Motion Detection and Tracking in Sports Videos using Particle Filter and Correlative Algorithm

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***Abstract* — With the improvement of the level of sports competition, the requirements of sports training have also improved. In the past, training based on the intuition of coaches has been ineffective to improve the competitive level. In order to adapt to this situation, computer vision technology is increasingly cited in sports training. Machine vision has better accuracy and memory than the human eye. It can capture moving objects quickly and efficiently, and can also record various movement data of the target. So it provides a more theoretical basis and data description for the movement of athletes. This paper proposes a moving object detection and tracking method based on particle filter and correlation algorithm. The particle filter algorithm satisfies the robustness and quasi real-time requirements of object tracking. The work also opens a new path for object tracking in sports video.**

Keywords-Particle filter; object detection; object tracking; sports video

I. INTRODUCTION

The spirit of competitive sports is "higher, faster, stronger". With the improvement of the level of sports competition, it is an urgent problem for athletes to know how to train athletes conveniently and quickly, to extract the parameters of motion and to help the daily training of athletes [1, 2]. In recent years, many countries have strengthened the field of sports science research. The sports training mode for coaches only relying on observation records and intuitive judgments has been unable to adapt to the ever-increasing competitive level needs. Since machine vision has better accuracy and memory than the human eye [3-5]. It can capture the moving object quickly and efficiently. It also can record various movement data of the target. By collecting a large number of video images of high-level athletes in regular training and large-scale events, this information can be effectively analyzed, which can change the shortage of the coaches 'manual observation and experience to guide the athletes' technical action. It also can greatly improve the athletes' training effect.

In recent years, with the continuous development of science and technology, moving target detection and tracking technology has matured [6, 7]. However, in sports video, athletes and background color of the venue may be more similar to each other between the athletes. The uniqueness of sports video brings a big challenge to target detection and tracking technology. Therefore, the purpose of this paper is to propose an efficient moving object detection and tracking algorithm, and verify the correctness of the algorithm.

Moving object detection and tracking system is based on digital image processing, pattern recognition, computer vision and other technology-based intelligent identification system [8]. This system can be widely used in traffic regulation, astronomical observation, biomedical research, traffic statistics and sports and other related fields. In the field of sports video analysis, the moving object detection and tracking technology plays an indispensable role. Through the real-time detection and tracking of the athlete's movements, the trajectory can be analyzed to facilitate the athletes in the training. This method is convenient to correct the difference in the training or in the game, which rely on the human eye can't perceive. Therefore, the method can improve the athlete's training effect and the competition result.

Aiming at the characteristics of sports video, this paper proposes a moving object detection and tracking method based on particle filter and correlation algorithm. We also deeply researches and discusses the target detection and tracking technology in sports video. In addition, the research in this paper will have a positive impact on other fields based on moving target tracking, and it also has important theoretical and practical value.

II. PARTICLE FILTERING AND RELATED ALGORITHMS

A. *Moving object detection and tracking*

Moving object detection in image sequence is a difficult and important research field. Generally speaking, the object detection in sports video is mainly to identify and analyze the moving object in the video stream, and filter out unrelated information in the moving object. So the movement of targets from the scene are isolated. Commonly used detection methods are: frame difference method, background elimination method, optical flow method, global motion estimation and target segmentation method [9, 10]. There are two main types of motion object segmentation methods:

motion segmentation and space-time segmentation. Among them, the optical flow method has the advantage of the image can be drawn for each pixel corresponding to the target motion information and parameters. But this also causes the optical flow method to calculate quite complex. The processing data quantity is too big. The computation time is longer. It is also very sensitive to the noise. Therefore, this method is relatively poor real-time. If there is no specific hardware support, this method is difficult to meet the real-time detection requirements of sports video. The frame difference method and the background subtraction method are relatively less computationally intensive. Their real-time processing ability is very stronger. Generally, the frame difference method and the background subtraction method are used in the real-time system to obtain the desired result.

Moving object tracking is mainly realized by two algorithms: tracking by target recognition and tracking by motion detection [11, 12]. Based on literature research, this paper summarizes the techniques of tracking moving object, which are divided into four categories: region-based tracking, model-based tracking, active model tracking, contour based tracking and feature-based tracking. With the emergence of various tracking methods, the development trend of target tracking is to combine the use of a variety of methods. In order to enhance the tracking accuracy, we can absorb the advantages of each method to better achieve the target tracking. In this paper, particle filtering and correlation algorithms are used to research and discuss the target detection and tracking technology in sports video.

B. Description of particle filter algorithm

The core idea of particle filter is to generate a set of random samples in the state space. These samples are called particles. Then to obtain the samples that obey the actual distribution by adjusting the size and position of the weights on the basis of measurement. So the mean of the samples is taken as the system state estimation value. The algorithm is a recursive algorithm that is easy to solve the problem of prediction and smoothing. It is also suitable for the nonlinear system equations and the non-Gaussian noise. A general description of the algorithm is given below [13].

Initialization: take $k = 0$, according to $p(x_0)$ extract N samples:

$$x_0^{(i)},\ i = 1,...,N \tag{1}$$

Importance sampling:

$$\begin{aligned} \tilde{x}_k^{(i)} &\sim q(x_k|\mathrm{x}^{(i)}_{0:k-1}, z_{1:k}), \\ \tilde{x}_{0:k}^{(i)} &= (x_{0:k-1}^{(i)}, \tilde{x}_k^{(i)}),\ i = 1,2,...,N \end{aligned} \tag{2}$$

Calculating weight:

$$w_k^{(i)} = w_{k-1}^{(i)} \frac{p(z_k{}^{(i)}|x_k{}^{(i)})\, p(x_k{}^{(i)}|x_{k-1}{}^{(i)})}{q(x_k{}^{(i)}|x_{0:k-1}{}^{(i)}, z_{1:k})} \tag{3}$$

If the posterior state distribution is shifted by one step, the formula can be simplified as:

$$w_k^{(i)} = w_{k-1}^{(i)} p(z_k{}^{(i)}|x_k{}^{(i)}) \tag{4}$$

Normalized weight：

$$\tilde{w}_k^{(i)} = \frac{w_k^{(i)}}{\sum_{j=1}^{N} w_k^{(j)}} \tag{5}$$

Resampling: copy according to the size of their normalized weight $\tilde{w}_k^{(i)}$ / discard sample $\tilde{x}_{0:k}^{(i)}$, N samples $x_{0:k}^{(i)}$ with approximate $p(x_{0:k}^{(i)}|z_{1:k})$ distribution are obtained.

Output: the output of the algorithm is the particle set $\{x_{0:k}^{(i)} : i = 1, 2, ...N\}$, which can be used to approximate the posterior probability and the expectation of the function $g_k(x_{0:k})$:

$$E(g_k(x_{0:k})) = \frac{1}{N}\sum_{i=1}^{N} g_k(x_{0:k}^{i}) \tag{6}$$

$K = K + 1$, repeat steps (2) through (6).

Figure 1 is a schematic diagram of a standard particle filter algorithm. The prior probabilities at k-1 are approximated by a number of particles with weights 1/N.

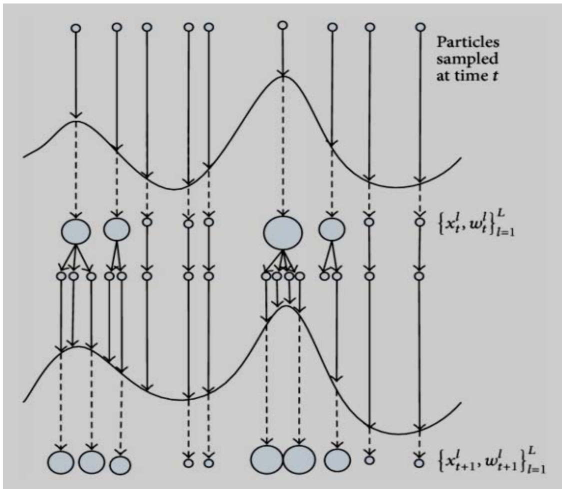

Figure 1. A schematic diagram of a standard particle filter algorithm

The first step is to observe the system and calculate the weight of the particle $\tilde{w}_{k-1}^{(i)}$. Compared with the actual situation of the particle (peak particle) is given greater weight (in the diagram for large particles), and deviate from the actual situation of the particle (trough particle) is given less weight (in the diagram for the small size of the particles).

The second step is the process of re-sampling. Large weight particles are derived from more "offspring" particles. Small weight particles corresponding "offspring" particles are rare. The "offspring" of the particle weights is reset to 1/N.

The third step is the state transition process of the system. It predicts the state of each particle in K time by adding random variables.

The fourth step is the process of K time observation system. It is same to the first step. The final expression of the target state is obtained by the weighted number of particles.

The flow chart of the target tracking algorithm based on particle filter is shown in Figure 2, which mainly includes three steps: the prediction of particles, the updating of particles and the resampling of particles.

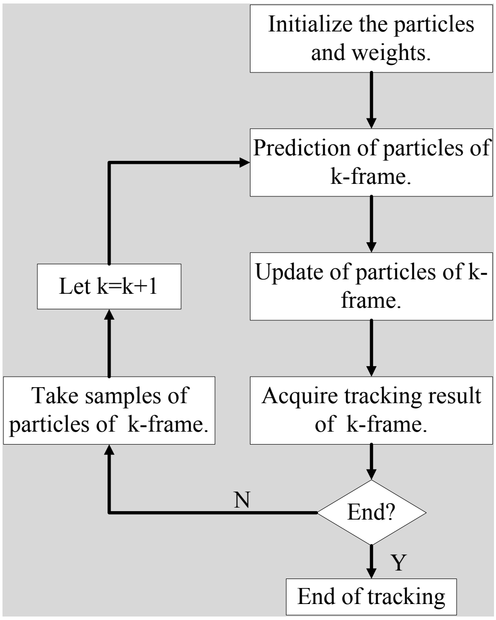

Figure 2. Flow chart of the target tracking algorithm based on particle filter

III. RESEARCH AND IMPLEMENTATION OF PARTICLE FILTER FOR MOVING TARGET TRACKING IN SPORTS VIDEO

A. Target model

HSV color space is used in this paper. The color histogram is normalized by the kernel function, and the color distribution of the target is extracted. In order to increase the adaptability of the tracking algorithm to illumination variation, this paper minimizes the influence of the luminance component V by increasing the proportion of the chrominance component H. The color histogram is composed of $m = 64 \times 8 \times 1 = 512$ columns.

The color distribution is calculated in a rectangular region. In order to increase the reliability of the color distribution when the boundary pixel belongs to the background or occlusion, the pixels farther from the center of the target will be given a smaller weight. To achieve this, the weighting function is used:

$$k(r) = \begin{cases} 1 - r^2 & , \quad 0 < r < 1 \\ 0 & , \quad other \end{cases} \tag{7}$$

In the formula (1), r is the ratio of the distance from the center of the pixel to the parameter a (a, the size of the target region). The color distribution of the particles in the rectangular area with center point y is $p_y = \left\{ p_y^{(u)} \right\}_{u=1,\dots,m}$, the formula is:

$$p_y^{(u)} = C \sum_{i=1}^{N} K\left(\frac{\|y - x_i\|}{a}\right) \delta[h(x_i) - u] \tag{8}$$

Where N is the number of pixels in the region; δ is the Kronecker impact function; $\|y - x_i\|$ is the distance between the pixel point x_i and the center position (x, y) of the particle y, measured by the number of pixels; $h(x_i)$ assigns the color of the x_i point to the corresponding color histogram in the color histogram; C is the normalization factor:

$$C = \frac{1}{\sum_{i=1}^{N} k\left(\frac{\|y - x_i\|}{a}\right)} \tag{9}$$

Make $\sum_{u=1}^{m} p_y^{(u)} = 1$.

In the tracking process, the hidden target state probability distribution is updated by obtaining new observations. To be able to compare the similarity between the candidate model and the target model, we need to define a similarity measure based on the color distribution. In this paper, the method of calculating the similarity of two distributions is Bhattacharyya coefficient, and its form is as follows:

$$\rho[p, q] = \int \sqrt{p(u) q(y)} du \tag{10}$$

We get the color histogram with a vector of m components. The component is discrete. The discretization of $p = \{p(u)\}_{u=1,\dots m}$ *and* $q = \{q(u)\}_{u=1,\dots m}$, the correlation coefficient is defined as:

$$\rho[p, q] = \sum_{u=1}^{m} \sqrt{p(u) q(y)} \tag{11}$$

The larger the coefficient is, the more similar the two probability distributions are. When two histograms are equal ρ=1, it implies that the two match exactly. Define the distance between two probability distributions-Bhattacharyya distance is:

$$d = \sqrt{1 - \rho[p, q]} \tag{123}$$

In this way, the particles are weighted based on the Bhattacharyya distance.

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B. Motion Model

The target motion model is one of the basic elements of the target tracking theory. Any tracking algorithm is based on one or some of the models of the target motion. In the establishment of target motion model, the general principle is that the established model should not only meet the actual situation, but also to facilitate mathematical processing. For the target in the video, between the adjacent image frames, if the mobility of the target motion is not very large, the mathematical model of (7) or (8) is used to describe the motion law.

In order to predict the position of the moving object in the video sequence, suppose sample $s = \{x, y, x^{'}, y^{'}, h_x, h_y\}$,

Where x, y is the center position of the moving object, x', y' is the horizontal and vertical velocity of the moving target respectively, h_x, h_y is the width and height of the moving object respectively. The propagation of the sample set is represented by the moving model of the target. The simple system can represent for a first-order system:

$$s_t = As_{t-1} + Bw_{t-1} \tag{13}$$

Where, A, B are constants, $w_{t-1} \sim N(0, \sigma^2)$ is the system Gaussian random noise, the variance σ determines the range of particle motion, to a certain extent determines the diversity of particles and effectiveness.

If you consider the target acceleration, you can use second-order system:

$$s_t = As_{t-2} + Bs_{t-1} + Cw_{t-1} \tag{14}$$

In order to simplify the calculation process, the motion model in this paper adopts the formula (7).

C. Implementation of particle filter

- Initialization process

In order to simplify the tracking process, this paper adopts manual initialization. For the tracking algorithm in this paper, it is necessary to form the particle set representing the distribution model in the initial image frame according to the requirements of the motion model. This is done by marking the position of the tracking point in the first frame of the tracked sequence and calculating the color histogram of the tracking area with the tracking point as the center, and saving the position of the tracking point as the state vector of the starting frame. N state vectors (N particles) are constructed by adding normal random noise to each component of the state vector. Finally, we assign a weight to each state vector, the size is 1/N. Then we form an estimate of the distribution model with N number of state vectors. This distribution model is used as the posterior model of the first frame, directly as a priori model of the second frame.

- Update of observation model

In order to ensure that the tracking algorithm is no longer in the new model update after losing the target object, this paper adopts the update condition: $\pi_{E(s)} > \pi_t$

Where, is the average state of the observed probability; is the threshold value, which can be specified according to the experience or the mean of the tracking results of the t previous multi frame.

The update of the target model is achieved by the following formula:

$$q_t^{(u)} = \begin{cases} (1-a)q_{t-1}^{(u)} + ap_{E(s_t)}^{(u)} & if \ \pi_{E(s)} > \pi_t \\ q_{t-1}^{(u)} & else \end{cases} \tag{15}$$

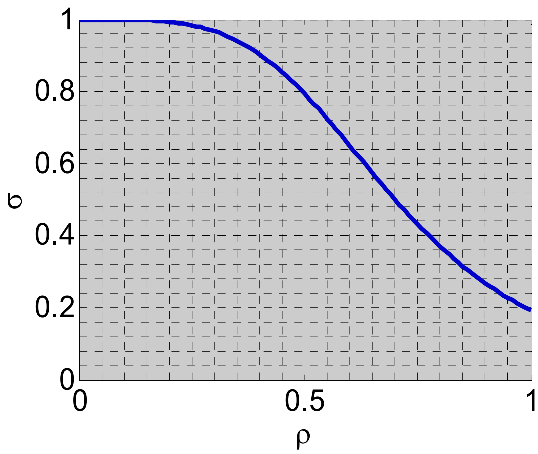
For each lattice in the color histogram u, a is the color histogram $p_{E(s_t)}$ contribution factor of the mean state.

- Self-adaptive selection of relevant parameters

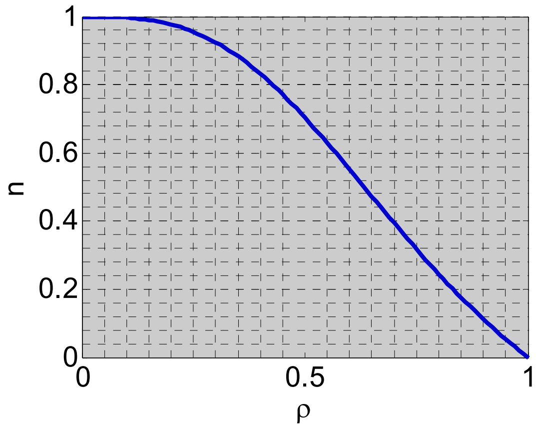
When the target is deterministically predicted, the histogram matching degree ρ , the variance σ and the number of particles N of the template as a function of ρ are calculated by the formula (5). It should have the property of monotonously decreasing. In this way, the prediction is more accurate, σ and N are smaller when ρ is larger, and σ and N are larger when the prediction is not accurate, when ρ is small. The relationship between ρ and σ, N is expressed by the following monotone decreasing function.

$$y = \frac{a_y}{1 + \exp[(\rho - 0.75) * b_y]}, \quad y = \sigma, N \tag{16}$$

Experiments show that the parameter $a_\sigma = 5,\ b_\sigma = 8,\ a_N = 60,\ b_N = 6$, which makes $\sigma \in [0.6, 5],\ N \in [11, 60]$. This range can satisfy the principle of particle validity under the condition of high sampling rate, and ensure the quality of particles and the real-time property of target tracking. Under the above parameters, relation curve of ρ and σ, N are shown in Figure 3.



(a)The function curve o ρ *and* σ



(b) The function curve of ρ and n.

Figure 3. Relation curve of ρ and σ 、 n.

- Algorithm implementation flow

The flow of particle filter algorithm in this paper is as follows:

(1) Initializing. Selecting the tracking area and calculating the color histogram of the area;

(2)From the sample set $S_{t-1} = \{s_{t-1}^{(n)}\}_{n=1,\ldots,N}$, select N samples of the probability distribution π_{t-1}^{n}.

Calculate the cumulative probability distribution C_{t-1} :

$$C_{t-1}^{(0)} = 0$$

$$C_{t-1}^{(n)} = C_{t-1}^{(n-1)} + \pi_{t-1}^{n}$$

$$C_{t-1}^{'(n)} = \frac{C_{t-1}^{(n)}}{C_{t-1}^{(N)}}$$

Generate N random numbers $r_n \in [0,1]$, they are uniformly distributed.

In the set $\{C_{t-1}^{'(j)}\}$, select the minimum j that satisfies the condition $\{C_{t-1}^{'(j)}\} \geq r_n$, let $S_{t-1}^{'(n)} = S_{t-1}^{(j)},\ 0 \leq n \leq N$.

(3)From the set $S_{t-1}^{'} = \{s_{t-1}^{'(n)}\}_{n=1,\ldots,N}$, use the motion equation (7) to generate the next set of images in the sample set $S_t = \{S_t^{(n)}\}_{n=1,\ldots,N}$. The color histogram of the region where the particles are located in the sample set is calculated. The probability weight of the sample points is calculated according to formula $\pi^n = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{d^2}{2\sigma^2}}$, and normalized.

(4)Predicting the position of the target in the next frame of the image.

The mean of the states of all particles is solved, and the final result is determined by each particle according to its importance. The program structure of the system is shown in Figure 4.

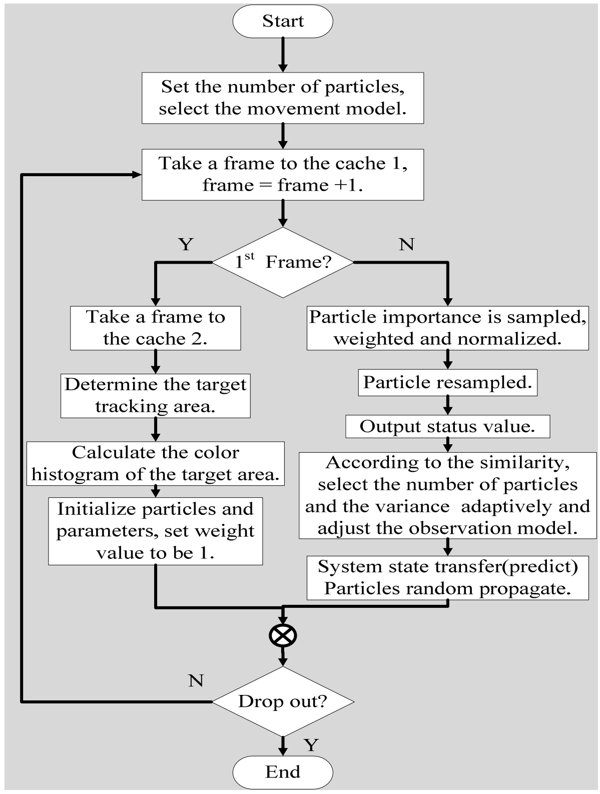


Figure 4. System program frame map

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the effectiveness of the above methods, three videos (man, young man and car) were used to track the moving object with the particle filtering method described above. At the same time, this method were compared with the HPFMS method and APF method [14, 15]. Their positioning accuracy error are shown in Figure 5 and Figure 6.

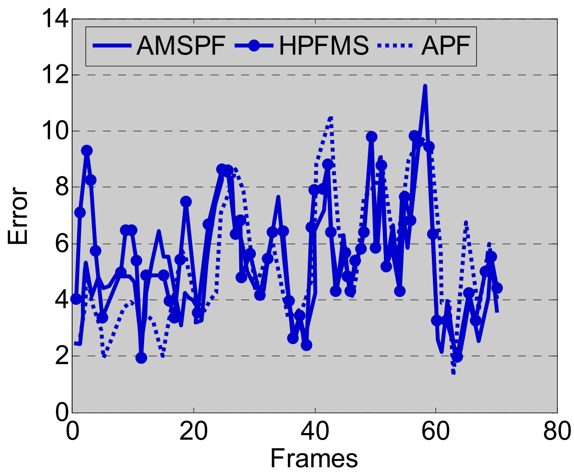


Figure 5. A comparison between AMSPF and HPFMS and APF in man vedio.

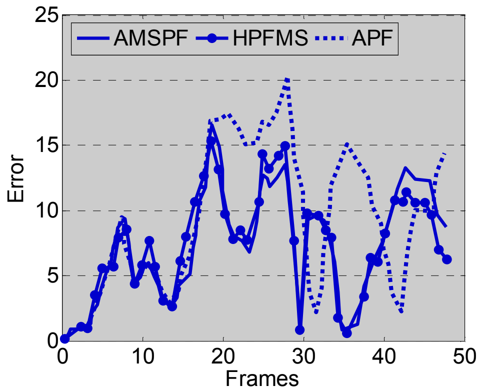


Figure 6. A comparison between AMSPF and HPFMS and APF in Car Video

In addition, UPF utilizes the state estimation results of Unscented Kalman filter (UKF) to compute the important density function and generate tentative distribution. The UPF is a newer algorithm, while the regular particle filter (RPF) is raised to solve the problem of loss of diversity due to resampling. In this paper, the UPF and RPF methods are compared. The average error of the positioning accuracy of the five methods is shown in Table 1. It can be seen from the table, tracking effect in AMSPR and other three methods (APF, UPF, RPF) is better. Although tracking effect in HPFMS method is very close to the above method, real-time in AMSPR is better. The average calculation time comparison is shown in table 2.

TABLE I. COMPARISON OF AVERAGE DEVIATIONS TRACKING IN EXPERIMENTAL RESULTS. (UNITS: PIXELS).

Algorithm	Man	Young Man	Car
AMSPF	3.80	8.32	8.77
HPFMS	4.26	8.21	8.65
APF	3.97	9.55	10.84
RPF	4.28	10.32	11.27
UPF	4.71	10.41	8.88

TABLE II. COMPARISON OF COMPUTING TIME IN EXPERIMENTAL RESULTS. (UNITS: MS)

Algorithm	Man	Young Man	Car
AMSPF	176.45	208.22	229.20
HPFMS	318.13	412.28	406.80

Further, in order to verify the effectiveness of this algorithm, we also test a variety of different sports types and different resolution of sports video sequences. Experimental results show that the proposed particle filter algorithm has achieved very good results. The following is the technical parameters of the test process.

TABLE III. THE APPLICATION OF THE PROPOSED PARTICLE FILTER ALGORITHM IN SPORTS VIDEO SEQUENCE.

Test Video	Ping-Pong	Horizontal Bar	Football	Weightlifting
Resolution	352×288	560×381	352×288	720×576
Frames	85	87	81	78
Bin Number	4*4*4	8*8*4	8*8*8	8*8*8
Sample Number	100	200	400	400
Average Iteration Number	6	4	5	4
Calculation Time	3542	5074	7253	12931

V. CONCLUSIONS

Particle filter technology for non-linear system and non-Gaussian environment has a high degree of adaptability. It can solve the problem with accuracy is not high or even divergent, which overcomes the shortcomings of poor reliability. In this paper, we focus on the tracking of targets based on the characteristics of color, and focus on solving the problem of particle tracking in target tracking in sports video. This paper designs and implements a particle filter algorithm based on color feature. Then the update mechanism of the observation model is established. Finally, we analyzes the relationship between the histogram matching degree ρ, variance σ and the number of particles n.

Thus, it provides theoretical guidance for the adaptive selection of the above parameters. Experimental results show that the proposed method can solve the problem of target occlusion and target tracking loss. It also has quasi real-time property. So the proposed method in this paper can track the target of interest in sports. However, this method has the drawback of relying too much on the color of the moving object. Once the background color is close to the moving object or the object with similar color exists in the background, it is easy to disturb the tracking result. In the future, we would tap other new features as a tracking condition to improve the tracking effect.

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