Application Research on Sports Video Analysis using Object Segmentation Algorithms

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***Abstract* - When using background subtraction to segment the videos the errors that the background points are mistaken as foreground points will increase rapidly, causing bad segmentation effects. Therefore, this paper proposes a moving object segmentation algorithm for dynamic scenarios. Our scheme computes global moving parameters according to camera global moving model, to make pixels mapping among adjacent frames and acquire corresponding positions of pixel points between the adjacent two frames. Then three-difference method can be used to get the foreground of segmentation. On this basis, the pixel points segmented as background are mapped to adjacent frames to get mean of Gauss model and variance when the pixel points of each frame are taken as background. We also adopt particle filter to predict the foreground region of the next frame and compute the probability of each pixel point as foreground, to perform the segmentation of moving objects. The improved algorithm is implemented on sports video analysis and the segmentation results show that our scheme can eliminate cumulative errors caused by estimation bias of global moving model parameters effectively, and make moving objects segmentation with higher precision for sports videos.**

Keywords - The center point; Matlab; Tilt; Bending; Distortion

I. INTRODUCTION

In recent years, research on video analysis technology oriented to sports makes large progress, and related hardware and software system has been initially applied to a variety of sports training. Many scholars have made further study on athlete tracking, action events testing, sports analysis etc. Giancarlo [1] in Finland Helsinki University of Technology used video analysis technology which controlled by action and voice to sports training, and delayed video for feedback and evaluation athletes' complicated technical movements [2]. Ai [3] of Japan Nara Technology University Takai has developed a series of video analysis system for rugby football competitions. It uses computer graphics technology to display the competitions virtual scene on the huge screen cylinder in order to assist rugby players training. Chan al. [4] used layered behavior segmentation method to make dance movement sequence of dance posture automatic segmentation [5] in order to recognize and guide dance training. LIU et al. [6] of National University of Defense and Technology put forward the basic concept of semantic unit in sports videos "BSU", based on analyzing the basic characteristics of sports video. Then they propose sports video content analysis framework based on BSU. For example of football videos, it achieved a common sports video content analysis systems framework. All of these studies are based on computer simulation technique of digital three-dimensional human motion, the data of human motion biomechanics and the data of real human motion, and use the way of three-dimensional graphics for fidelity simulation, design, and technical moving analysis. They have powerful significance to guide sports program training.

The researches have shown that accurate track in athletes' motion parameter is important link in sports video analysis system [7-9]. By video tracking, the system could automatically capture the two-dimensional coordinate value of each joint, angles among the joints, jump height, body movement trajectory etc. These information could help coaches to make quantitative evaluation on athletes' sports process, so that the coaches' guidance to athletes will be more pertinent and scientific. Due to the complicate changes in the background and the high complexity of the body structure and motion process, human motion tracking based on the video is very difficult. For different tracking objects and different application scenarios, researchers have proposed different tracking methods. In recent years, particle filter [10] has been widely and effectively used in human motion tracking. Because of the adaptability of nonlinear and non-Gaussian system, particle filter shows its original advantages in fields of moving object tracking, state monitoring, fault detection, and computer technology. But particle filter algorithms have problems like intensive computation, bad real-time etc. To overcome these problems and improve the accuracy of the moving object extraction, this paper proposes a new algorithm for moving targets segmentation based on particle filter prediction. Firstly, the algorithm uses three-image difference method to segment foreground preliminarily. The pixel points to be segmented are taken as background based on camera global motion model mapping to adjacent frames to establish background image for each frame. Then it uses background subtraction for moving object segmentation. The implementation results of the algorithm on video object segmentation have shown that the improved algorithm effectively overcame the accumulated errors due to global motion model parameter estimation deviation. It can achieve higher precision of object segmentation in motion videos. This paper is organized as follows: section 2 analyzes the reason causing errors and proposes the principles and background of our segmentation algorithm. In section 3, an improved adaptive segmentation algorithm based on particle filter prediction is introduced to segment moving objects. Then in section 4, this paper provides some examples of the implementation of improved algorithm and verifies its performance compared to similar methods. At last, the conclusions are given in section 5.

II. PRECONDITIONS

The algorithm uses three-image difference method [11] to segment the foreground preliminarily. We set the pixel points to be segmented as background base on camera global moving model mapping to adjacent frames, to establish background image for each frame. It adopts background subtraction for moving object segmentations. In this paper, the key technologies focus on following two aspects: firstly, reducing the deviation of moving objects taken as error when moving foreground is similar to background. We use the segmentation foreground regional coordinates, according to the particle filter, to estimate threshold value of each pixel in the next frame belonging to the background for an adaptive segmentation. Secondly, the moving object color models of moving foreground are adaptively constructed by the segmentation result in the upper frame automatically. We make modeling of the color of moving objects by hybrid Gaussian model [12]. We obtain the adaptive closed threshold between two Gaussian models according to FISher linear discriminant criterion [13]. Then iterative method is used to filter non-foreground site, and obtain their mean and variance by statistical methods. In order to adapt to illumination changes, the moving objects color model is updated by a simple adaptive filter. If the segmentation foreground is compared to people moving object color model for a test, the pixel points not complying moving object color model are taken as background points mistaken as foreground, to reduce the deviation of background points that are mistaken as the foreground.

Generally, with the existence of the camera noise, the background subtraction on the (x_i, y_i) obeys the distribution on $N(0,\sigma_b^2)$. However, in practice, due to matching blocks occur deviation in the searching process, the calculated data is not uniform between camera global moving parameters and actual values. It has big difference between construction background and practical background, while the background subtraction on the (x_i, y_i) does not always obey the distribution of $N(0,\sigma_b^2)$ [14]. Therefore, we could only make the distribution of the pixel value at background of each frame approximately obey $N(0,\sigma_b^2)$. u is the average value of background pixels. σ^2 is variance caused by noise, illumination change and mapping error. By statistical methods we can obtain the background model, that is, the sample space of background model establishment is composed of the pixels that are mapped to the pixel points and segmented as background preliminarily.

Since the actual camera global moving model parameter estimation has deviation, the construction of background model through frame mapping has greatly deviation between mean and actual value. If it is also in accordance with the fixed threshold segmentation in this situation, it will make segmentation accuracy decrease sharply. Even the background model parameter is more accurate, if the foreground and background pixel values are similar, it can also cause increasing probability of incorrect segmentation. Therefore, we refer to the adaptive threshold segmentation in literature [15]: although preliminary foreground/background has error segmentation condition， due to the factors like noise, frame mapping errors，it can be used as an adaptive threshold calculation standard after filtering. On the other hand, we use particle filter prediction mechanism base on current frame segmentation result to predict approximately areas of foreground in the next frame. Corresponding value for the probability of the pixel point is segmented as foreground in the next frame by pixel point and the deviation degree of foreground prediction areas. Therefore, this probability value can determine a segmentation threshold, and can also determine an adaptive threshold computing standard.

The probability of segmentation as background by three-difference method is:

$$P_{i,j} = \begin{cases} 0.1 & pixel\ point\ belonging\ to\ forehead \\ 0.5 & state\ of\ pixel\ point\ is\ unclear \\ 0.9 & pixel\ point\ belonging\ to\ background \end{cases} \quad (1)$$

From above equation we can get corresponding probability of pixel point segmentation. Since some of the pixel points have not mapping points, the state of it as background is not clear. Under such case we can assign a median to this pixel point and use mean filter to inhibit the noise. A $3*3$ filter can be adopted to get the probability of background after filtering:

$$P_{f(i,j)} = \frac{1}{p}\sum_{m=-1}^{1}\sum_{n=-1}^{1} P(i+m, j+n) \quad (2)$$

III. ADAPTIVE SEGMENTATION ALGORITHM BASED ON PARTICLE FILTER PREDICTION

The particle filter prediction process is depicted as figure 1: when predicting the foreground region, we use a particle set constituted by weighted particle to approximate the distribution of foreground region. The type of particles is vector, composed of horizontal and vertical coordinates of the upper left corner, bottom right corner, and horizontal and vertical velocity of upper left corner and the lower right corner. The segmented image computes the weight of each particle according to the coordinates of foreground region and performs re-sampling on the particles. The particles with large weight have higher probability to be selected. After the new particle set is acquired, we will predict the foreground region of the next frame based on system equations, to get the probability of each pixel points of the next frame as background.

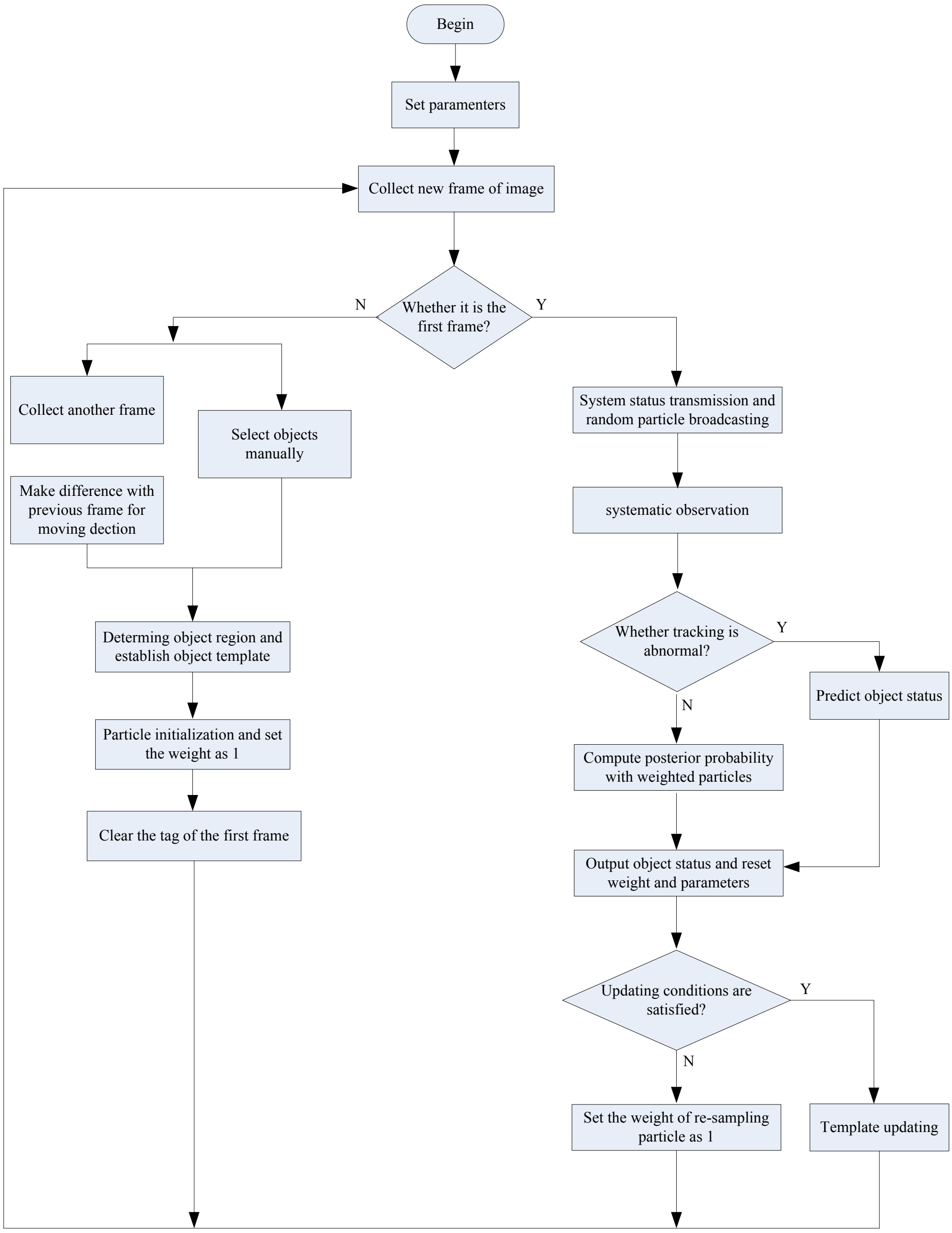


Fig. (1). Particle Filtering Process.

(1) Particle initialization

The initialization process aims to approximating the distribution of X_k with initialized particle set, according to observing equations [16]. In this paper we set the observing equation as $Y_k = X_k + V_k$. V_k is observing noise and obeys normal distribution. The detailed operation: the coordinates of foreground region in the segmentation results of the first frame constitute N 8-dimensional state vectors, recorded as ($x_0, y_0, u_0, v_0, x_1, y_1, u_1, v_1$) . (x_0, y_0) is the upper left coordinate of object region; (u_0, v_0) is the upper left horizontal velocity and vertical velocity of object region; (x_1, y_1) is bottom right coordinate of object region; (u_1 , v_1) is bottom right corner horizontal velocity and vertical velocity of object region. Initially, $(u_0, v_0) = (0,0)$ and $(u_1, v_1) = (0,0)$. The state vectors are added with normal random noise to get N new state vectors. Each vector is assigned with weight $\frac{1}{N}$ and the initialized particle set of particle filter can be acquired.

(2) Computation of prediction pixels points in foreground region belonging to background

According to system equations, this paper uses initial particle set or particle set acquired by re-sampling to predict the foreground region of the next frame:

$$\begin{cases} x_0^{k+1} = \alpha(x_0^k + \mu_0^{k+1}\Delta t + w_k) + b(y_0^k + v_0^{k+1}\Delta t + w_k) + e \\ y_0^{k+1} = c(x_0^k + \mu_0^{k+1}\Delta t + w_k) + d(y_0^k + v_0^{k+1}\Delta t + w_k) + f \\ \mu_0^{k+1} = \mu_0^k \\ v_0^{k+1} = v_0^k \\ x_1^{k+1} = \alpha(x_1^k + \mu_1^{k+1}\Delta t + w_k) + b(y_1^k + v_1^{k+1}\Delta t + w_k) + e \\ y_1^{k+1} = c(x_1^k + \mu_1^{k+1}\Delta t + w_k) + d(y_1^k + v_1^{k+1}\Delta t + w_k) + f \\ \mu_1^{k+1} = \mu_1^k \\ v_1^{k+1} = v_1^k \end{cases} \tag{3}$$

The parameters in the equations α , b , c , d and e are parameters in global moving model of acquired k_{th} frame. The velocity u_0 , v_0 , u_1 , v_1 are computed as the following equation:

$$v = (d_c - d_0) - (x_c - x_0) \tag{4}$$

d_c is the abscissa which is segmented as the pixel points of upper left of foreground in current frame. d_0 is the abscissa which is segmented as the pixel points of upper left of foreground in previous frame. x_c is the abscissa which is segmented as the pixel points of upper left of foreground in next frame. x_0 is the coordinate mapped on current frame according to camera global moving model. So to speak, if the moving foreground does not move, $(d_c - d_0)$ equals to $(x_c - x_0)$.

We can get N prediction value of foreground region in the next frame. Since the weigh of each particle is $\frac{1}{N}$, the probability that each pixel point in the foreground region corresponding to this particle is also foreground will be $\frac{1}{N}$. Therefore, the probability that the pixel points in corresponding foreground region of N particles belonging to foreground will be added $\frac{1}{N}$ respectively. Then the probability that each pixel point is the foreground can be finally acquired.

(3) Computation of the particle weight

The weight value of particle is computed as equation 5:

$$w_i = \frac{P(Y_k / Xk^*(i))}{\sum_{j=1}^{N} P(Y_k / Xk^*(j))} \tag{5}$$

We compute the accuracy of prediction results and find that the particles with higher accuracy have bigger weights. In our algorithm, Xk^* denotes the prediction value of each particle to predict the foreground region, Y_k denotes the foreground region value in segmentation results and $P(Y_k / Xk^*(i))$ denotes the probability of true value under prediction. That is to say, when the prediction value is approaching to true value, the value of $P(Y_k / Xk^*(i))$ is bigger. In this paper we set $P(Y_k / Xk^*(i)) = R_i / R_d$. R_i is the intersection of predicted foreground region and true segmentation foreground region. R_d is the difference of union of predicted foreground region and true segmentation foreground region, and intersection of predicted foreground region and true segmentation foreground region.

(4) Re-sampling.

The calculated particle weights are normalized. Then the accumulated weights of each particle will be computed. The accumulated weight separate space [0,1] to N regions. N random numbers are generated by uniform sampling in [0,1]. Thus, corresponding particles in some region that these numbers belong to will copy to one particle concentrated by new particles. The particles with bigger weight have larger space area during the process of re-sampling, and they have bigger probability to be copied to new particles.

By the following equation we get the probability that pixels belongs to background:

$$P_b = [P_f(i,j) + P_s(i,j)]/2 \tag{6}$$

If pixel point (i,j) falls in the interval decided by $P(x_1 < X < x_2) = P_b$, it belongs to background; otherwise it belongs to foreground. x_1 and x_2 are computed as:

$$\begin{cases} \int_{x_2}^{-\infty} f(x)dx = 1-(1-P_b)/2 \\ x_1 = 2\mu - x_2 \end{cases} \tag{7}$$

IV. EXPERIMENTS

We adopt OpenCV + VC6.0 to realize the prototype program of the algorithm in this paper and use different action video sequences to test its effectiveness. The computer configuration in this experiment is PIV3.0GHZ / 1024M and the image resolution is 352*240. To compare the superiority of the improve method we also verify CSY algorithm [18] in the experiments. CSY algorithm is an ideal algorithm in current video moving object segmentation. It combines three-frame difference with background subtraction to perform static scenarios moving

The detailed process of improved scheme is depicted as follows:

Step 1: Connected component analysis is performed, to eliminate the pixel points in the component group whose components are smaller that some threshold, as background;

Step 2: Test the moving object color model to eliminate the pixels points which do not meet the moving object color model, as background;

Step 3: Connected component analysis is performed again. After above tests, some larger blocks of background mistakenly segmented as foreground may be separated into several smaller blocks. Then connected component analysis can effectively eliminate these background points. If the iteration process is convergent it exits the segmentation of the next frame and the moving object color model established in this process will be taken as the test model for the next frame;

Step 4: Using mathematical morphology opening and closing operations and processing operations to eliminate the cavity in foreground;

Step 5: Establish new moving object color model by the new segmented foreground images after the background points are eliminated and repeat step 2.

object segmentation, and it has achieved better results. During the experiments, when camera moving model is acquired, we apply CSY algorithm to segment the moving object in the video: Figure 3(a) depicts the original videos respectively for a movement at different hours. Figure 3(b) depicts the results of moving videos with CSY segmentation. Figure 3(c) depicts the segmentation results using our algorithm. Figure 4 shows video segmentation error result and the incorrect segmentation rate equals to incorrect segmentation pixel point/(352*240). The green curve is CSY algorithm error segmentation rate and black curve is error segmentation rate for the algorithm proposed in this paper.

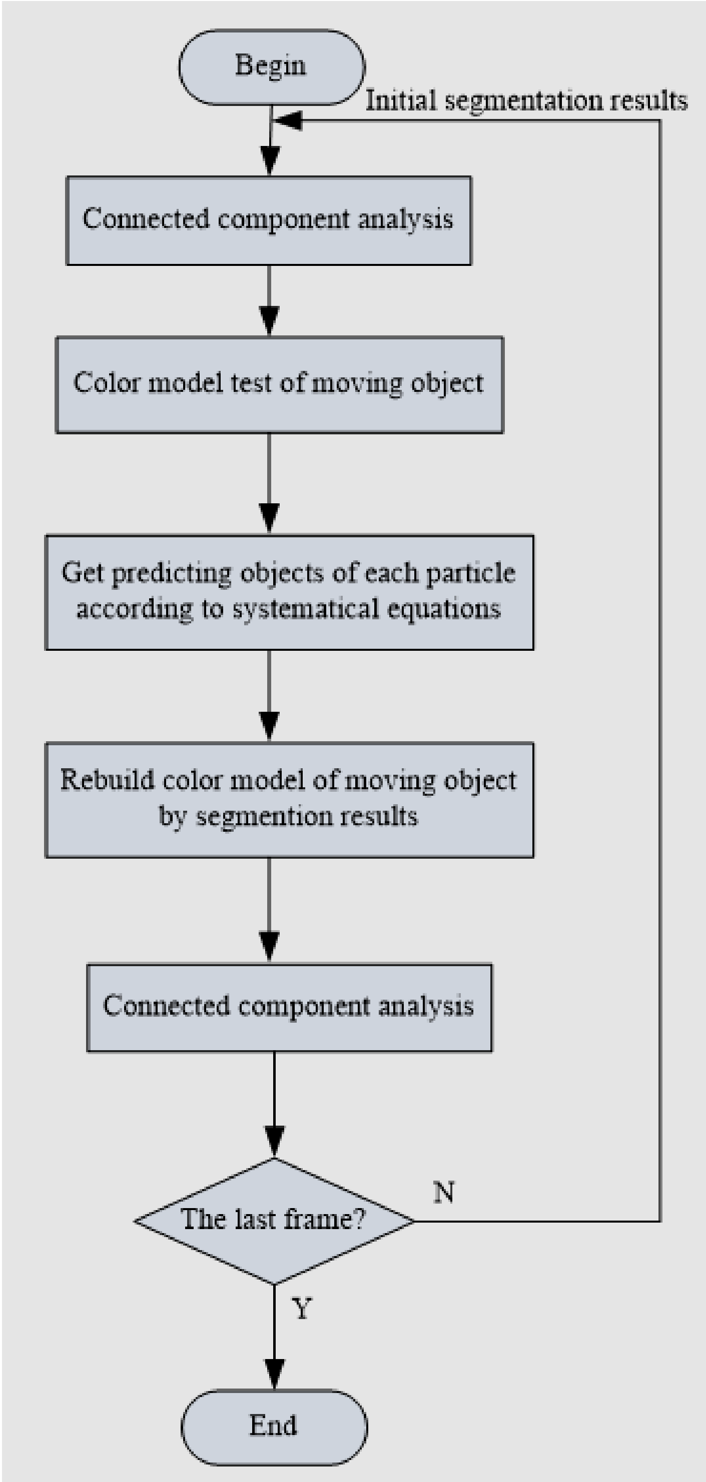
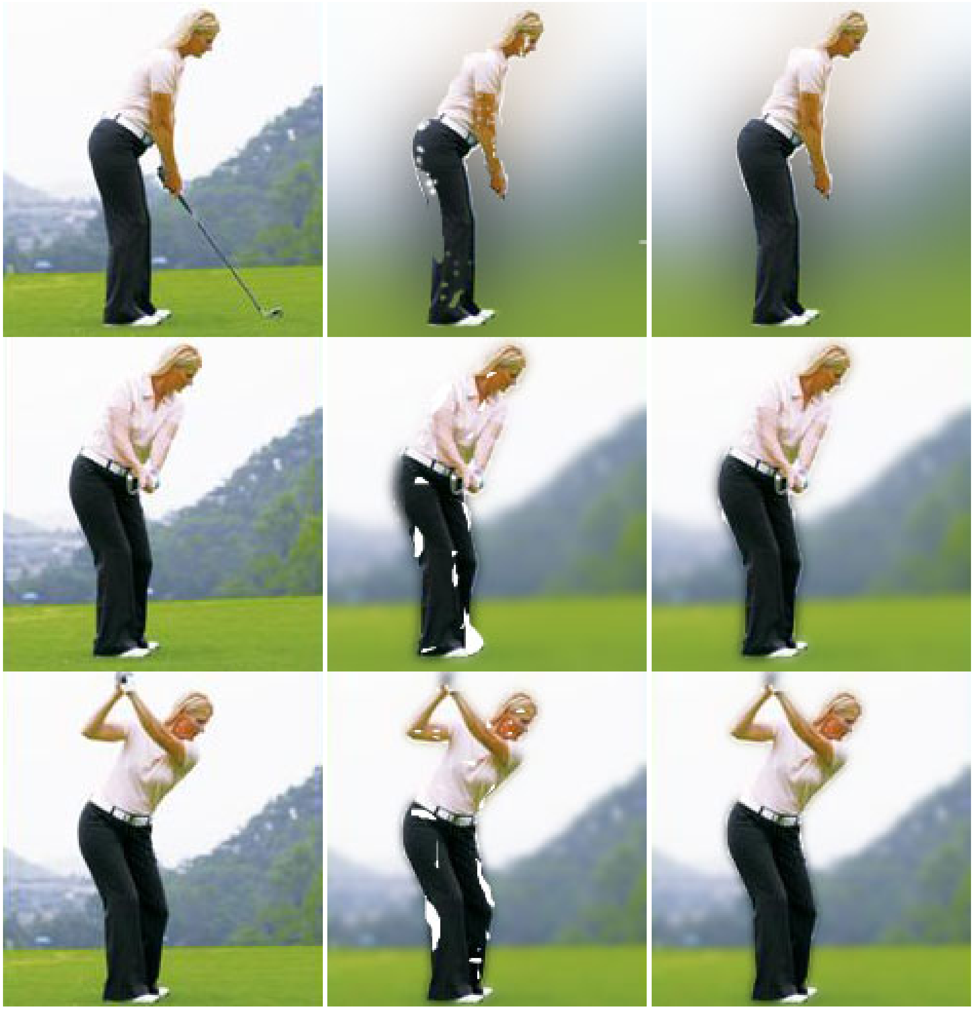


Fig. (2). Flowchart of Post-processing

By comparison results of two algorithms of video segmentation, it can be seen that the segmentation results obtained by CSY algorithm has obvious cavities. However, the results obtained our scheme is relatively complete and clear.



Original video (b) CSY (c) Particle filter

Fig. (3). Sports Video Segmentation Results.

Figure 4 shows the error segmentation rate of us is about 1% in most cases. The error segmentation rate has slightly increased from 300_{th} frame to 450_{th} frame, caused by that each frame background changes rapid during this period time. The estimation deviation of camera global moving model parameters causes significant effects to subsequent processing. By comparison of figure 4, we can see that the CSY algorithm is more sensitive and its incorrect segmentation rate is increasing rapidly. But the error segmentation rate of improved algorithm is not increased significantly, so our scheme can effectively inhabit the accumulated error due to estimation deviation of camera global moving model by frame mapping. It also reduces the errors of mistaking foreground points as background points, and background points as foreground points.

Illustrated by the above data and analysis, we can draw the following conclusions:

Compared the improved algorithm to CSY algorithm, our method shows a lower segmentation rate among the frames, and it has higher segmentation accuracy. We can see that CSY algorithm for each frame in moving video segmentation has a lower error segmentation rate. Figure 3 and 4 also reflects the superiority of its advantage. Moreover, we find that this superiority shown in figure 3 is more prominent. The video shown in figure 3 is in high speed. It occurs in a short time and its action response rapidly so it has been regarded as a video segmentation nodes for a long time.

The superiority of the segmentation in this paper is that it focuses on the movement with large changing amplitude, and for the condition that information of body surface changes greatly. The adaptive segmentation algorithm based on particle filter prediction aims to reducing the error of movement target which is incorrectly segmented as background in the condition that moving object is similar to background. It uses segmentation foreground regional coordinate in accordance with the particle filter to estimate each pixel point in the next frame belonging to the thresholds of background for adaptive segmentation, so its advantages are obvious.

This paper makes modeling of the color of moving object by hybrid Gaussian model, the model composed by Gauss model of athlete pixel points, hair and clothing. The key of our algorithm is adaptive moving target color model which is the moving foreground automatically constructed by foreground point in the upper frame segmentation results. In order to be adapted to illumination changes, the moving target color model is updated by a simple adaptive filter. We test the segmentation foreground with moving object color model testing and regard pixel points which does not comply moving target color models as background that is segmented incorrectly as foreground. So it reduces the deviation of background points which are incorrectly segmented as foreground points and improves the accuracy of algorithm.

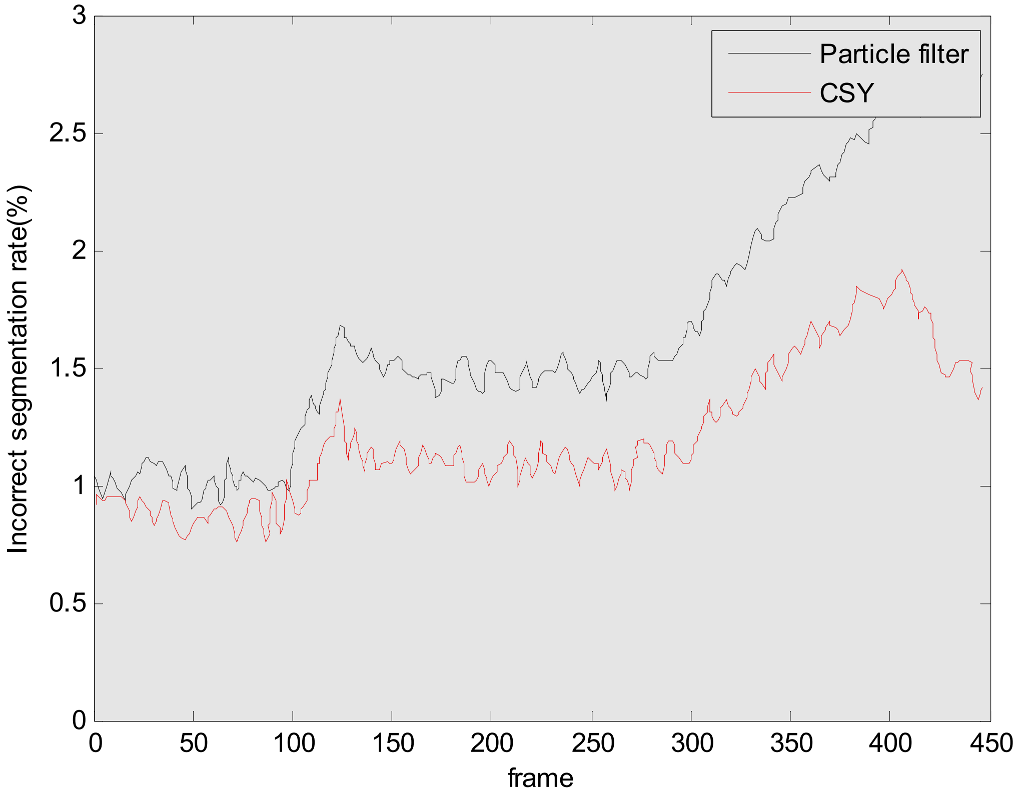


Fig. (4). Incorrect Segmentation Rate of Each Frame.

V. CONCUSION

This paper proposes a new segmentation algorithm for moving object which is suitable to field state and scenario. Firstly, it uses three-image difference method to get preliminary foreground. The pixel points to be segmented are taken as background use adjacent frames to obtain mean and variance of Gaussian model, when each frame's pixel point is background. It uses particle filter to predict the next frame foreground field, and whether the pixel points in the next frame at the preliminary segmentation are foreground. Then it calculates the probability of each pixel point that is foreground, and makes adaptive moving object segmentation. In the extraction process of video objects, in the post-processing, we set the pixel points to be segmented as foreground for the moving object color model testing according to the characteristics such as skin color, hair style, etc., eliminating those pixel points not passing the moving target color model testing which are taken as error segmentation foreground of the background. The experimental results have shown that the improved algorithm in this paper can effectively overcome the accumulated error due to global moving model parameter estimation deviation after frame mapping. It can also implement segmentation on the video of moving objects accurately. So our adaptive moving segmentation algorithm based on particle filter prediction can extract the moving objects from the video more effectively.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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