Multi-feature Fusion Tracking Based on A New Particle Filter

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***Abstract*—A new kind of particle filter is proposed for the state estimation of nonlinear system. The proposed algorithm based on Quadrature Kalman Filter by using integral pruning factor, which optimizes and reorganizes the integration point. New algorithm overcomes the particle degeneration phenomenon well by using Pruning Quadrature Kalman Filter to produce optimized proposal distribution function. In the improving particle filter framework, using color and motion edge character as observation model. Fusing feature weights through the D-S evidence theory, and effectively avoid the questions of bad robust produced by the single color feature in the illumination of mutation, posture change and similar feature occlusion. Experiment results indicate that the proposed method is more robust to track object and has good performance in complex scene.**

***Index Terms*—Particle Filter, Quadrature Kalman Filter, Object Tracking, Multi-feature Fusion, D-S Evidence Theory**

I. INTRODUCTION

Moving target tracking problem is a more difficult field of computer vision in complex environment. In recent years, many algorithms were proposed, which mainly based on motion model [1], optical flow [2], feature [3], image area information [4], and so on. The feature-based method is easy and robust. At present, the main fratures which used for tracking are color, texture, corner, edge and contour [5]. The color feature has been used widely, because of the strong robustness to the target rotation, posture changes, partial occlusion. However, it is not enough to use single color feature as the target observation model, especially when the background color is very similar to the object, or in the case of light mutation. Then the tracking error is large, or even failure.

At present, Particle filter (PF) is the main algorithm in researching object tracking, and get rapid development in this field [2-6]. The reason is that it can represent any form of probability distribution in theory. But the particle degradation is still one main barrier for this mechod go into practical application. [7] proposed an extended Kalman particle filter algorithm (EPF), which used Extended Kalman Filter (EKF) to optimize the importance probability density function. EPF can improve the filtering performance effectively, because the algorithm fused the new measurement information into the importance probability density function. But EKF linearization and Gaussian assumption in the model introduced too many errors of approximation. [8] proposed an Unscented Kalman Particle Filter (UPF), which used Unscented Kalman filter (UKF) to produce importance probability density function. This method has good estimation performance in the state estimation of nonlinear systems. But the complex transformation of UT leads the algorithm has a pool real time performance. [9] proposed an Quadrature Kalman particle filter (QKPF), which used Quadrature Kalman Filter (QKF) to produce the importance probability density function. This method obtained good filtering accuracy. But the method gave all integration points for a balanced weight distribution, ignoring the different weights have different values to the integral accuracy of integration points, and the filtering accuracy was weakened in some extent.

A new kind of particle filter is proposed for the state estimation of non-linear / non-Gaussian system which called Pruning Quadrature Kalman Particle Filter (P-QKPF). New algorithm overcame the particle degeneration phenomenon well by using Pruning Quadrature Kalman Filter (PQKF) to produce optimization proposal distribution function. In the framework of the new algorithm, color and movement edge were used as observation model, which is used to correct the predicted and actual value of the state. Finally, the two features were fused together with D-S evidence. This method effectively avoid the bad robust question which produced by the single color feature in the case of

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illumination mutation, posture change and similar feature occlusion. Theoretical analysis and experimental simulation show that the proposed method is more robust for tracking object in complex scene.

II PARTICLE FILTER ALGORITHM

A. Particle Filter Tracking Model

At present, PF algorithm is an effective method to solve nonlinear problems. It can approximate the continuous probability distribution by a set of discrete particles with the right weights. There is a particle degradation problem with the increases of time iteration. [7] overcome the weight degradation problem by introducing resample step to the algorithm, which access to a more successful application. We must first establish the appropriate target model for using this method to tracking target. The specific method described below [3]:

State model: In most cases, we can not get the accurate prior knowledge of the moving target. Many tracking algorithms are based on the assumption that we have get the similar model knowledge in current. So, we usually only consider the target's location information in video target trackingsystem, especially when there was one object.

So we can use a first-order recursive model to imitate the state spreading of the sample particles to spread:

$$\chi_k^i = \mathbf{A}\chi_{k-1}^i + v_k^i \qquad (1)$$

Where A is the state transition matrix, v_k^i is Gaussian noise.

Observation model: In the field of computer vision, the majority features, which are used as observations to track object, are color, contour and texture information. Usually, the difference between the predicted value of the system and the current state of the appropriate is corrected by these features. Here we define the following likelihood function.

$$p(z_k \mid x_k^i) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{l_i^2}{2\sigma^2}\right) \qquad (2)$$

(2) is one observation model for the system. l_i is the Bhattacharrya distance between the observed and real value of the i-th particle. We use Bhattacharrya distance l_i to ensure that the real situation is most close to the distribution of relatively large particles weight factor, and deviate the smaller weight particles. Here σ is the Gaussian variance.The corresponding distribution of particle weight update equation can be expressed as:

$$\omega_k^i = \omega_{k-1}^i p(z_k \mid x_k^i) \qquad (3)$$

B. Weights Update

According to the observation likelihood model defined by equation (2), we can recursively estimate the target particle's corresponding weights in accordance with (3). In this paper, the color histogram and motion edge features are used as observation model.

Weights update based on color histogram feature: At first, using the color histogram feature as the observation model. The initial target location is $\chi_0=(x,y)^T$, which used as the center of the object's location. We can search for the target effectively around the center of the images. Than calculate the target first characteristic probability density of the *u*-th in the feature space. The result can be expressed as:

$$p_u(y) = C_h \sum_{i=1}^{m} K\left(\frac{\| y - x_i \|}{a}\right) \delta(b(x_i) - u) \qquad (4)$$

Where, $C_h = \dfrac{1}{\sum_i^n K(\| x_i^* \|)}$ is the normalized factor of the probability density, the purpose is to make $\sum_{u=1}^{m} p_u(y) = 1$; a represents the whole area of the search, y represents the center coordinate of the search area; δ is Dirac function; m is the number of pixels in the search area; $b(x_i)$ is the target feature function value of x_i; $K(\bullet)$ is a weighting function. The purpose of the function is to give the true value near the center pixel greater weight, and give the true value which far away the center pixel smaller weight. And then deviate the smaller weight value. $K(\bullet)$ defined as follows:

$$K(s) = \begin{cases} 1 - s^2, s < 1 \\ 0, else \end{cases} \qquad (5)$$

We use statistical method to calculate the effective number of the feature in the region. The initial template of the target can be expressed as:

$$p(y) = \{p_u(y)\}_{u=1,\ldots,m} \qquad (6)$$

Assuming that in the k-frame, the position of the i-th particle parameters is $(x_k^i, y_k^i)^T$. The candidate matches $p(y_i)$ and target model $q(y_0)$ can be used to measure the distance Bhattacharrya:

$$d_i = \sqrt{1 - \rho(p,q)} \qquad (7)$$

Where $\rho(p,q) = \sum_{u=1}^{m} \sqrt{p_u(y) q_u(y_0)}$ is the corresponding Bhattacharrya factor. According to equation (2) and (3), we can get the weights update formula based on color histogram as:

$$\omega_{CLORk}^i = \omega_{CLORk-1}^i \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{d_i^2}{2\sigma^2}\right) \qquad (8)$$

Weights update based on motion characteristics of the edge:[11-13] give a very deep study on the integration of multi-feature tracking methods. Such as color and shape, or combinate color and texture feature together. But these features are static features. These features can not describe the object's movement. Therefore, this paper adopt the campaign character as the integration of edge

information, which can effectively describe the motion information of moving targets[3], but also highlight the edges and contours. We can get the feature by calculating as follows.

Assuming I_k, I_{k-1} is the k frame and k-1 frame of the video image, then the difference image $diff_k$ can be expressed as:

$$diff_k = | I_k - I_{k-1} | \quad (9)$$

The edges image of E_k of time k can be described as:

$$E_k = \nabla diff_k = \begin{bmatrix} \frac{\partial diff_k}{\partial x} & \frac{\partial diff_k}{\partial y} \end{bmatrix} \quad (10)$$

The direction angle θ can be described as:

$$\theta(x, y) = \arctan \left[\frac{\partial diff_k}{\partial y} \Big/ \frac{\partial diff_k}{\partial x} \right] \quad (11)$$

In the calculation process, the gradient direction angle is among $0 \sim 2\pi$. In the direction of the effective angle, we can get the target value. And also can get the corresponding code value. In order to get proper value we quantify the pitch angle of the direction as $\Delta\theta$. Then the direction of the code can be calculated as:

$$C_{ij} = \begin{cases} [\theta_{ij} / \Delta\theta], | \partial f / \partial y | + | \partial f / \partial x | > T \\ m, else \end{cases} \quad (12)$$

According to experience, we set this quantitative threshold T = 5, and quantify the direction of the selection as 16.Then the u-th direction coded statistical probability can be calculated as:

$$f(u) = \sum \delta(u - c_{ij}) \quad (13)$$

Where, δ is the delta function. In order to get the statistical probability, we normalized the function. We use sub-Bart Charlie distance to measure the similarity of the two plans. The detail calculation formula is described as:

$$D_k = \sqrt{1 - \sum_{u=1:m} \sqrt{f_p^{(u)} f_q^{(u)}}} \quad (14)$$

According to equation (4) and (5), we can get the weights update formula based on motion characteristics of the edge as (15).

$$\omega_{DIFFk}^i = \omega_{DIFFk-1}^i \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{D_K^2}{2\sigma^2} \right) \quad (15)$$

C. Weights Fusion

At present, the main methods for multi-feature fusion are product feature fusion and sum feature fusion [11]. The product feature fusion method can effectively improve the tracking accuracy, but it easy to zoom in noise. The sum feature fusion obtained the sum weights of the features by the weighted sum total method. According to the different characteristics of the feature, we get the adjustment factor weights of each feature. Sum fusion is not sensitive to noise, but it can't improve the credibility of fusion. Taking into account the advantages of D-S evidence theory in information processing, we use D-S evidence theory to fuse two features weights.

For example, for N samples in terms of particles, the color histogram features and the edge features weights are normalized. We can get:

$$\omega_{di} = \omega_{COLORk}^i / \sum_{i=1}^{N} \omega_{COLORk}^i \quad (16)$$

$$\omega_{Di} = \omega_{DIFFk}^i / \sum_{i=1}^{N} \omega_{DIFFk}^i \quad (17)$$

Based on the D-S evidence theory ideas, the above two normalized measures of the particle are used as the basic probability assignment to χ_k^i, the weight of the particles can be re-calculated as:

$$\omega_i = \frac{\omega_{di}\omega_{Di}}{\omega_{di}\omega_{Di} + (1 - \omega_{di})\omega_{Di}} \quad (18)$$

Finally, then the right values are normalized as (19), that is to be used for the final weight of the resampling particles:

$$\omega_i = \omega_i / \sum_{i=1}^{N} \omega_i \quad (19)$$

III. PROPOSED PARTICLE FILTER ALGORITHM

A. Quadrature Kalman Filter (QKF)

I. Arasaratnam first proposed the QKF algorithm in [14], by using a Statistical Linear Regression (SLR) method, using a cluster of approximately Gaussian Gauss - Hermite integration points to estimate the state of the posterior probability density function, and detailed proof that the algorithm is superior to EKF, UKF algorithm. The algorithm works as TABLE Ⅰ:

TABLE I.
QKF ALGRITHM

(1) Time update

Supposed at time k, the system's posterior probability density function is:

$$p(x_{k-1} | z_{1:k-1}) = N(\hat{x}_{k-1|k-1}, P_{k-1|k-1})$$

The corresponding factorization is describled as

$$P_{k-1|k-1} = S_{k-1|k-1} S_{k-1|k-1}^T$$

We calculate the grade point as

$$\{X_{j,k-1|k-1}\}_{j=1}^m$$

$$X_{j,k-1|k-1} = S_{k-1|k-1}\xi_j + \hat{x}_{k-1|k-1}$$

We can get the integral points

$$X_{j,k|k-1}^* = f(X_{j,k-1|k-1}), j = 1, \cdots, m$$

The predictive value and corresponding error covariance can describle as:

$$\hat{x}_{k|k-1} = \sum_{j=1}^{m} \omega_j X_{j,k|k-1}^*$$

$$P_{k|k-1} = Q_k + \sum_{j=1}^{m} \omega_j (X_{j,k|k-1}^* - \hat{x}_{k|k-1})(X_{j,k|k-1}^* - \hat{x}_{k|k-1})^T$$

Here, m is the number of integration points, Q_k is the covariance of the process noise in the time period, and we can get the forecasted probability density function of the system in the update times.

$$p(x_k \mid z_{1:k-1}) = N(\hat{x}_{k|k-1}, P_{k|k-1})$$

（2）Measurement update

the corresponding factorization of predicted value

$$P_{k|k-1} = S_{k|k-1} S_{k|k-1}^T$$

the set of integration points

$$\{X_{j,k|k-1}\}_{j=1}^m$$

$$X_{j,k|k-1} = S_{k|k-1}\xi_j + \hat{x}_{k|k-1}$$

the corresponding set of measurement points

$$\{Z_{j,k|k-1}\}_{j=1}^m$$

$$\{Z_{j,k|k-1}\}_{j=1}^m = h(X_{j,k|k-1}),\ j = 1, \cdots, m$$

estimates of measuring

$$\hat{z}_{k|k-1} = \sum_{j=1}^m \omega_j Z_{j,k|k-1}$$

state updation and the corresponding covariance estimation

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - \hat{z}_{k|k-1})$$

$$P_{k|k} = P_{k|k-1} - K_k P_{zz,k|k-1} K_k^T$$

factorization of the $P_{k|k}$

$$P_{k|k} = S_{k|k} S_{k|k}^T$$

the system probability density can be expressed as

$$p(x_k \mid z_{1:k}) = N(\hat{x}_{k|k}, P_{k|k})$$

B. Quadrature Pruning Factor

From the probability sense, the different weights assigned to the integral contribution to the integration points are also different: the weight of the larger integration point for a greater contribution to the integral operation, the weight of the smaller integral points on integral operator contribution is small, and have bad impact on the algorithm for operation time. Based on this, the quadrature pruning factor θ_m is introduced into the algorithm. Linear optimization is adapt for the re-integration point.

For the m integration points, the corresponding quadrature pruning factor θ_m can be expressed as integral

$$\theta_m = \frac{\omega_1 \omega_{[\frac{m+1}{2}]}}{m} \tag{20}$$

Integral correction is based on the main idea: the integral points corresponding weight ω_i and the quadrature pruning factor θ_m are compared, if the integration point weight $\omega_i \geq \theta_m$, keep integration points for the corresponding integral operator; if the integration point weight $\omega_i < \theta_m$, then abandon the integration points ξ_i, and keep it as following linear optimization and reorganization of the way.

$$\xi_i' = \xi_\alpha + L(\xi_\alpha - \xi_i) \tag{21}$$

Among them, ξ_i' is the new integration points by optimized the future emergence; ξ_α is the effective integration point for integration; ξ_i is the integration points which was abandoned, L is the appropriate step of $(\xi_\alpha - \xi_i)$.

Assuming m is the number of Gauss - Hermite integration points, n_x is the representative of the state space dimension, ω is the representative of any integral point of integration points within the field of spatial probability distribution, then the step can be calculated as:

$$L = [\frac{1}{m\omega}]^{1/n_x} \tag{22}$$

Theorem 1 Assuming m is the number of integration points which came from the probability density of $p(x)$, n_x is the representative of the state space dimension, then any integration point within the field of integration points between the average distance can be expressed as:

$$L = [\frac{1}{mp(x)}]^{1/n_x} \tag{23}$$

It can be seen, the theoretical step calculation is used in the calculation of integration points within the field of computing, in fact, each new integration points are calculated over this field.

C. Pruning Quadrature Kalman Particle Filter (P-QKPF) Tracking Algorithm

Considering the above theoretical analysis, this paper adopted the revised importance of the PQKF to produce the probability density function, and proposed a new particle filter which called Pruning Quadrature Kalman Particle Filter (P-QKPF). The new particle filter greatly improved the system's state posterior probability density function.The concrete realization of the new algorithm as TABLE Ⅱ:

TABLE II
P-QKPF ALGRITHM

（1）Filter initialization

$$\hat{x}_0^{(i)} = E[x_0^{(i)}]$$

$$P_0^{(i)} = E[(x_0^{(i)} - \hat{x}_0^{(i)})(x_0^{(i)} - \hat{x}_0^{(i)})^T]$$

$$P_0^{(i)} = S_0^{(i)}(S_0^{(i)})^T$$

the initial weights：

$$\omega_0^{(i)} = 1/N$$

（2）Using Pruning Quadrature Kalman Filter to produce optimized proposal distribution function for the set of particles $\{x_{k-1}^{(i)}, \omega_{k-1}^{(i)}, i = 1, ..., N\}$ of K-1, and get

the estimated state $\hat{\mathbf{x}}_{k|k}^{(i)}$ and covariance $\mathbf{p}_{k|k}^{(i)}$ at time k of each particle.

（3）Using:

$$q(\mathbf{x}_k^{(i)} \mid \mathbf{x}_{k-1}^{(i)}, \mathbf{z}_{1:k}) = N(\hat{\mathbf{x}}_{k|k}^{(i)}, \mathbf{p}_{k|k}^{(i)})$$

as the importance probability density function and sampling

（4）the particle weights:

$$\omega_k^{(i)} = \omega_{k-1}^{(i)} \frac{p(\mathbf{z}_k \mid \mathbf{x}_k^{(i)}) p(\mathbf{x}_k^{(i)} \mid \mathbf{x}_{k-1}^{(i)})}{q(\mathbf{x}_k^{(i)} \mid \mathbf{x}_{k-1}^{(i)}, \mathbf{z}_k)}$$

Normalize as:

$$\bar{\omega}_k^{(i)} = \omega_k^{(i)} \Big/ \sum_{i=1}^{N} \omega_k^{(i)}$$

（5）Resampling

In order to determine whether need to re-sample, we set the threshold N_{th} for a given initial particle number. When $N_{eff} < N_{th}$, let $\bar{\omega}_k^{(i)} = 1/N$,and need for resampling

（6）Filter estimated output

$$\hat{p}(x_k \mid z_{1:k}) = \frac{1}{N_m} \sum_{i=1}^{N} \delta(x_k - x_k^{(i)})$$

$$\hat{x}_k = \frac{1}{N_m} \sum_{i=1}^{N} x_k^{(i)}$$

$$P_k = \frac{1}{N_m} \sum_{i=1}^{N} (\hat{x}_k - x_k^{(i)})(\hat{x}_k - x_k^{(i)})^T$$

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experiments are based on the Matlab R2007a simulation environment, and the computer is frequency for 1.8Hz, 1.5GB RAM laptop.

A. Simulation

First of all, we validate the accuracy and computational complexity of the proposed algorithm by the simulation experiments. In order to effectively reflect the improved results, respectively, we use PF, EPF, UPF, QKPF and the improved algorithm (P-QKPF), five kinds of filtering methods to estimate the same non-linear system, and compare the filtering accuracy.Experimental system used (24) shows the mean estimate, and define an independent test of the mean square error as (25) below.

$$\hat{x}_t = \frac{1}{N} \sum_{j=1}^{N} x_t^j \qquad (24)$$

$$MSE = (\frac{1}{T} \sum_{t=1}^{T} (\hat{x}_t - x_t)^2)^{1/2} \qquad (25)$$

In order to test the new algorithm's improved results in estimating the strongly nonlinear system, the Univariatc Nonstationary Growth model (UNG) was chosen as the system model for the simulation experiments. It can be seen from (26) that the UNG model is a highly non-linear, dual-mode model, the model's Dynamic State Space (DSS) equation can be described as:

$$\begin{cases} x_k = 0.5x_{k-1} + 25\dfrac{x_{k-1}}{1+x_{k-1}^2} + 8\cos(1.2(k-1)) + v_{k-1} \\ y_k = \dfrac{1}{20}x_k^2 + 8\cos(k) + \omega_k, k = 1,...,T \end{cases} \qquad (26)$$

It can be seen from (26) that the system has strong nonlinearity. When the given value y_k , there are two possible values of x_k , the system equations and observed values are present in the quadratic function. This model is a strongly nonlinear system, which need to solve more difficulties. The initial state is set as $\hat{x}_0 = 0.1$, Observation time T = 60s, the number of sampling particles N = 100.

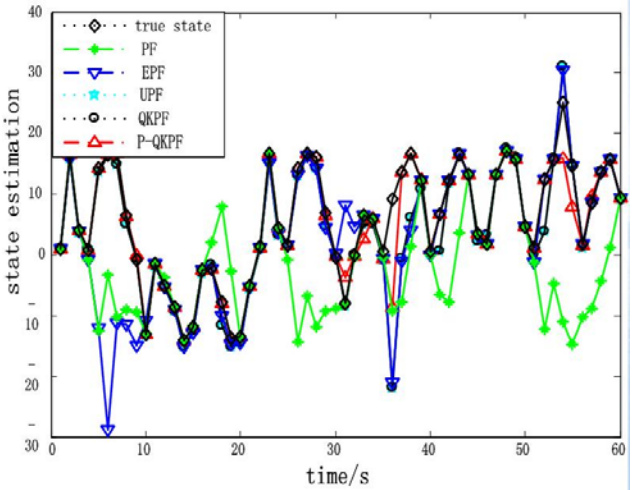


Figure 1 The system state estimation

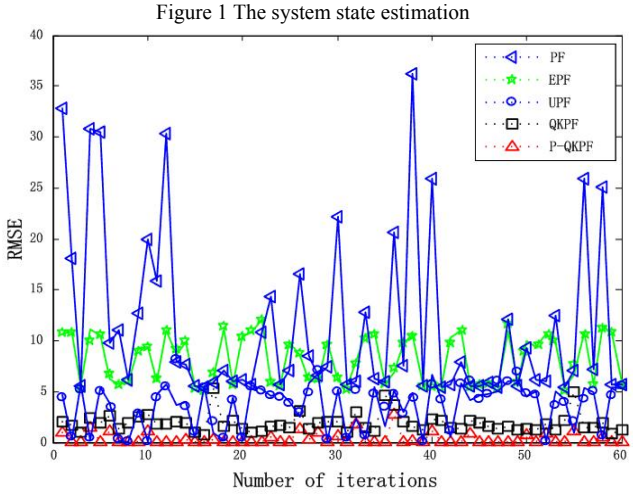


Figure 2 RMSE curve

Simulation A: First, the iteration time is once step, given the system model 60 seconds forecast tracking, get the system tracking curve shown in Figure 1. It can be seen, several improvements of the particle filter in tracking accuracy is obviously better than the standard particle filter. And the proposed algorithm P-QKPF showed a high filtering precision, estimated state is coincident with the true trajectory.

Simulation B: Experiments using 60 steps of time iteration, each time run 60 seconds, respectively, the root mean square error of the mean and variance and the

corresponding average time consumption of several improved particle filter were compared. The root mean square error curve is shown in Figure 2, and the TABLE Ⅲ shows the root mean square error of the mean and variance and the corresponding average time consumption.

TABLE Ⅲ
COMPARING THE STATISTICAL PROPERTIES OF THE ALGORITHM

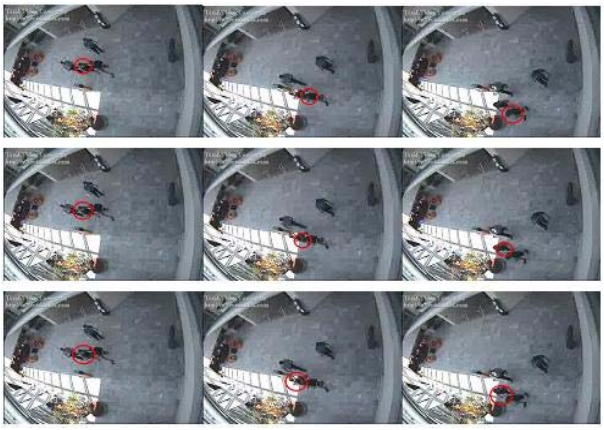
Algorithm	Performance Indicators		
	RMSE	Variance of RMSE	Average time consumption (s)
PF	0.37736	0.08731	3.2716
EPF	0.31313	0.08089	6.7992
UPF	0.09647	0.00760	17.2189
QKPF	0.08771	0.00623	17.3321
P-QKPF	0.04128	0.00461	16.8174

It is clear that several improved particle filters were fused into the latest measurements, filtering accuracy is better than standard particle filter algorithm, just as show in Figure 2 and TABLE Ⅰ. As a result of , the proposed algorithm by introducing the online self-adjustments of quadrature pruning factor θ_m to ensure the efficient sampling of particles and diversity at the same time, did not increase the algorithm's time loss.

B. Video Tracking Experiments

Within the framework of the new algorithm, we conducted different environments of video tracking experiment. This article chose target colors and movement edge characteristics as the observation model to track the moving target. In experiments, three different video sequences of complex situations, respectively, mutations on the light, similar to the background block and attitude change in three different cases, test the tracking results, and the proposed algorithm test results were compared with the single color feature based on PF and multi-features fusion based on PF methods (Top: single color feature based on PF; Middle: multi-features fusion based on PF; Bottom: multi-features fusion based on proposed algorithm), further illustrates the superiority of the proposed method.

The first video sequence used a standard video sequence "Meet_Crowd.mpeg" test, which was provided by the CAVIAR project team [16]. The experimental result is shown in Figure 3. Image size is 384 × 288, frame rate is 20 frames / sec. Because of a dramatic change in light in the frame 140, the method based on a single color characteristic led to fail. However, the metod which based on multi-features fusion is still able to accurately track the target. The proposed method is obviously better than the first two methods, which can effectively track the target in the whole process.



Frame 85 Frame 140 Frame 178

Figure 3 Track results of lighting mutation

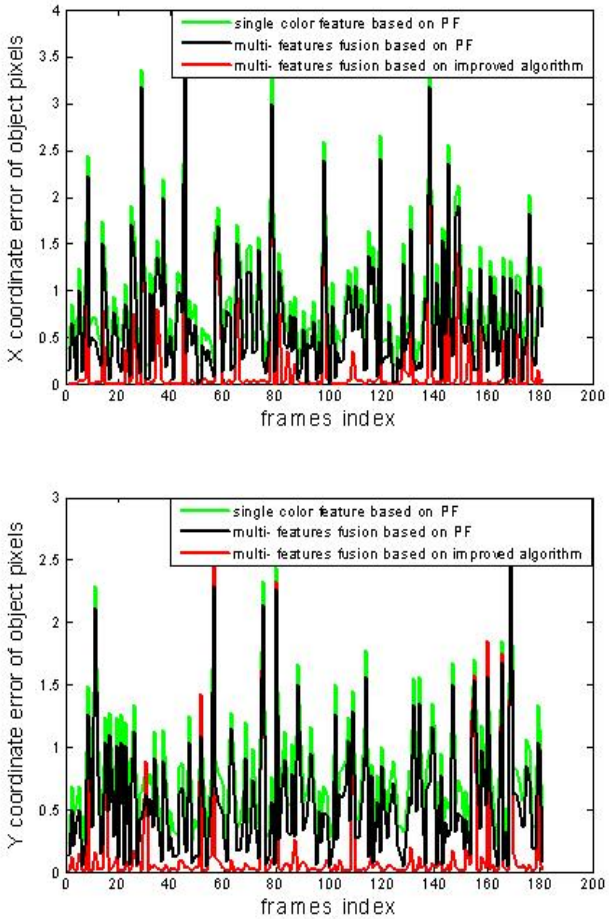


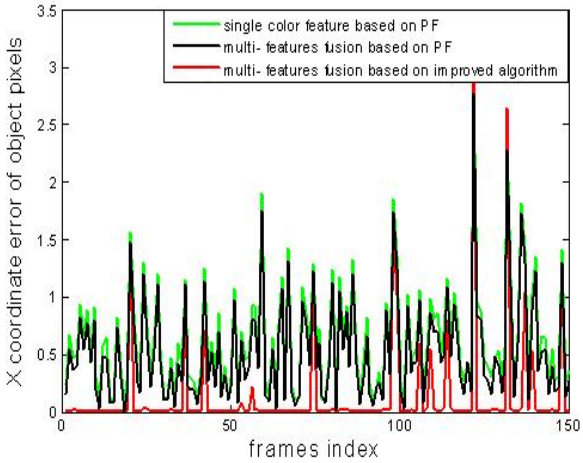
Figure 4 Comparison of tracking errors in X and Y coordinate of the three algorithms in lighting mutation

The second video sequence used a standard video sequence " One Stop Move No Enter 2 cor. Mpeg" test, which was provided by the CAVIAR project team [16]. The experimental result is shown in Figure 5. Image size is 384 × 288, frame rate is 25 frames / sec. In the first 99 frame, because of the emergence of similar color target block, the tracking error becomes large, then in 135 frame, when the color characteristics of the method based on a single track to fail. However, the metod which based on multi-features fusion is still able to accurately track the

target, and continue to show good robustness, which could be seen from Figure 6. And the proposed method is superior to the standard particle filter method, the whole process are to maintain a high tracking accuracy.

Frame 27 Frame 99 Frame 135

Figure 5 Track results of similar features block



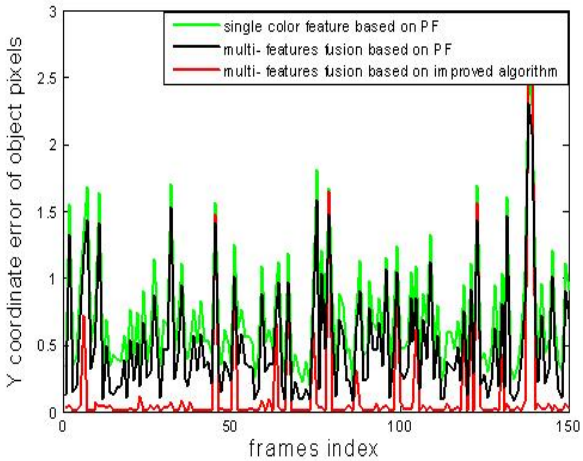
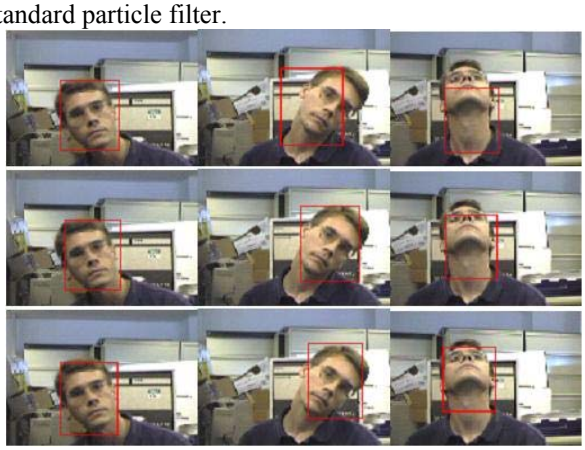


Figure 6 Comparison of tracking errors in X and Y coordinate of the three algorithms in similar

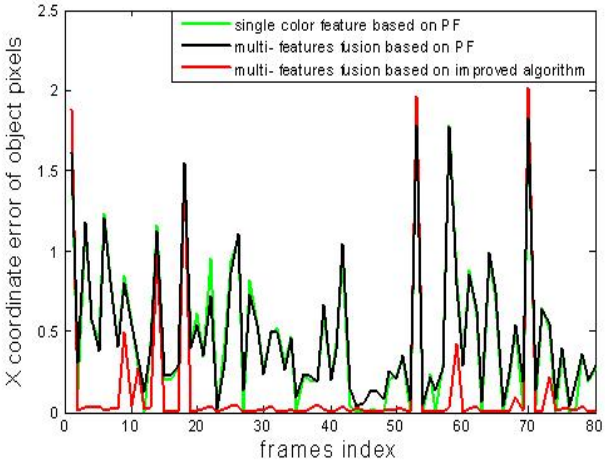
features block

The third video sequence is about the face tracking in the office. Image sequences from the Stanford University faces test sequence, the image size is 256 × 192, frame rate is 20 frames / sec. It can be seen from Figure 7, in the first 53 and 62 frame, the method which use the single color feature led to large errors. As the multi-feature fusion method combines the features of the target edge of the movement, showing a strong tracking robustness. At the same time, we can see that the tracking accuracy of the proposed method was significantly higher than the standard particle filter.



Frame 31 Frame 53 Frame 62

Figure 7 Track results of attitude change



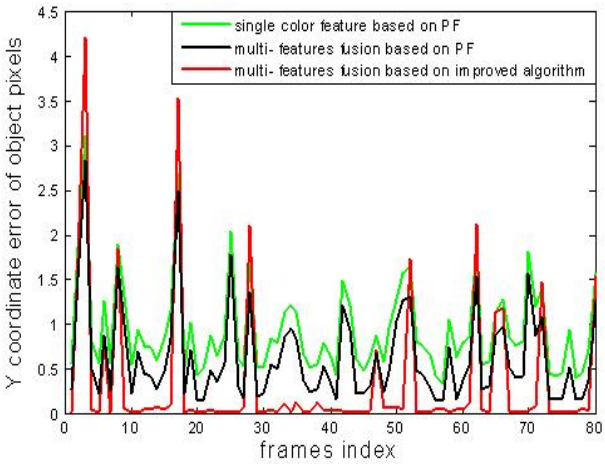


Figure 7 Comparison of tracking errors in X and Y coordinate of the three algorithms in attitude change

V. CONCLUSION

This paper presents a new particle filter algorithm, and uses the D-S evidence theory to sport a multi-features fusion target tracking scenario. This paper mainly showed the following three characteristics: (1). Introduced the

quadrature pruning factor θ_m in to the QKF, and optimized the restructuring of the integration points, using a pruning QKF to produce the optimal proposal distribution function, well overcome the particle degradation, and effectively improve the filtering accuracy; (2). Using the color characteristics and motion edge features as observation model to calculate the filter particles weights; (3). Using D-S evidence theory approach to fuse the characteristics of the weights for the integration process, through the fused weights to estimate the target's posteriori state, effectively overcome the additive integration and by fusion defects. Theoretical analysis and experimental simulation showed that the proposed method effectively overcomed the weakness of object tracking in complex environment when the light mutation, attitude change, and some shading similar model.

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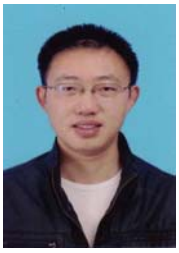

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