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Multi-features Fusion Tracking Method under Unknown Noise

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Abstract: In order to solve the problem of video target tracking problem, this study proposed a new kind of particle filter for the state estimation of nonlinear system when the statistical characteristics of the system are unknown. The proposed algorithm estimated and corrected the statistic characteristics of the system unknown noise in real-time by improved Sage-Husa estimator and produced optimal distribution function with unscented Kalman Filter. This novel algorithm reduced the estimation error effectively and improved the anti-noise ability of the system. Under the improving particle filter framework, this study used color and motion edge character as observation model and fused multi-features weights through the D-S evidence theory. The experiment results shows that the method in this study has high precision and strong robustness in target tracking under the complicated conditions.

Key words: Video target tracking, particle filter, adaptive filtering, multi-features fusion, D-S evidence theory

INTRODUCTION

Target tracking problem under complex conditions is a research focus in the fields of human-computer interaction and robot navigation. In order to achieve robust tracking of objects in different environments, researchers suggested many effective tracking methods (Morris and Trivedi, 2010; Doucet *et al*, 2000). Among them, filter estimate method was used widely. Because this method takes target tracking problem as a state estimation process and uses filtering technology to forecast and estimate the target state iteratively. In recent years, with the development of the nonlinear filtering technology, especially the proposed particle filter algorithm, target tracking technology under complicated conditions was promoted vigorously (Li *et al*., 2010; Luo and Wei, 2009; Doucet *et al*., 2000).

At present, Particle Filter (PF) is the main algorithm in researching object tracking and gets rapid development in this field (Julier and Uhlmann, 2004; Qu *et al*., 2010). The reason is that it can represent any form of probability distribution in theory. But in order to get easy way for sampling and calculating, the standard particle filter algorithm usually chooses the state transition probability density function as important sample probability density function. This method usually leads to the particle weights degeneration phenomenon, because it does not fuse the latest measurement information. So, this method is easy to cause the system model mismatch error after iterating many times and reduce the filter estimation precision. In order to improve this situation, researchers have put forward a variety of improved algorithm. Yu *et al*. (2011) proposed an extended Kalman particle filter algorithm (EPF) which used Extended Kalman Filter (EKF) to optimize the important probability density function. EPF can improve the filtering performance effectively, because the algorithm fused the new measurement information into the important probability density function. But EKF linearization and Gaussian assumption in the model introduced too many errors of approximation. Literature proposed an Unscented Kalman Particle Filter (UPF) which used Unscented Kalman filter (UKF) to produce important probability density function. This method has good estimation performance in the state estimation of nonlinear systems. But the complex transformation of UT made the algorithm have a pool real time performance (Gong *et al*., 2012). Liu *et al*. (2010) proposed a Quadrature Kalman Particle Filter (QKPF) which used Quadrature Kalman Filter (QKF) to produce the important 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 that had different values to the integral accuracy of integration points and the filtering accuracy was weakened in some extent.

Although the improved algorithms overcame the weight value degradation problems to some certain and promoted the overall filtering precision of the algorithm,

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all this improved algorithms were under the conditions that system noise was known exactly. But in general, this is unable to get the precise statistical properties of the noise of system. Especially under the complex scene, system model noise mismatch degree is high and tracking stability is bad. In view of this situation, this study proposed a new Adaptive Unscented Particle Filter (A-UPF) under the situation that the system noise was unknown. The proposed algorithm estimated the system noise in real-time by the improved Sage-Husa sub-prime unbiased estimator and optimized the sampling particles by combining with the Unscented Kalman Filter with recursive form. This method could generate optimization proposal distribution function and reduce the system estimate error. Considering the situation that the Sage-Husa filter was easy to divergent when there were too many unknown noise presence, this study used the method of covariance matching criterion to judge the situation of convergence or divergent of the filter and amended the forecasting error covariance by introducing the adaptive attenuation factor method. At last, this method adjusted the filtering gain, suppressed the filtering divergent phenomenon and further improved the ability of fast tracking filter.

THE THEORY OF ALGORITHM

Particle filter: 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. Literature (Yu *et al*., 2011) overcame the weight degradation problem by introducing resample step to the algorithm which accessed to a more successful application. We must firstly establish the appropriate target model for using this method to tracking target. The specific method described below (Li *et al*., 2010).

State model: In most cases, we could 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 just consider the target location information in video target tracking system, especially when there was only one object.

So, this study can use a first-order recursive model to imitate the state spreading of the sample particles to spread as formula (1):

$$\chi^i_k = A\chi^i_{k+1}+v^i_k \tag{1}$$

where, A is the state transition matrix, v^i_k is Gaussian noise.

Observation model: In the field of computer vision, most features which are used as observations in object tracking 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, this study define the following likelihood function:

$$p(z_k \mid x^i_k) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{l_i^2}{2\sigma^2}\right) \tag{2}$$

Formula (2) is one observation model for the system. l_i is the Bhattacharyya distance between the observed and real value of the ith particle. This study used Bhattacharyya 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 formula (3):

$$\omega^i_k = \omega^i_{k-1}p(z_k|x^i_k) \tag{3}$$

Unscented Kalman particle filter: UT transform is a kind of nonlinear change ideas which approximate Monte Carlo method. The main idea of it is to approximate the system state fully by the density function of the mean and variance of finite sample points. This method gives the corresponding sample points with the state and weight and maps with nonlinear by the direct state or measuring point of these samples equation. Finally, the sample points will be mapped to the corresponding values of weighted summation. Then can get the mean and variance of the nonlinear function of the state vector. Due to the change in the corresponding points directly on the characteristics of the transformation, the nonlinear approximate is better than EKF algorithm.

Assuming there is a random variables $x \sim N(\bar{x}, P_X)$, the corresponding non-linear function is y and y = f (x). Assuming the statistical properties of x is $(\bar{x}, P_X)$. According to the thought of UT transform, this study usually choose 2n+1 weighted points set to approximate the distribution of random variable x. Just as formula (4-9):

$$\chi_0 = \bar{x} \tag{4}$$

$$\chi_i = \bar{x} + (\sqrt{(n+\lambda)P_x})_i, i = 1,2,\cdots,n \tag{5}$$

$$\chi_{i+n} = \bar{x} - (\sqrt{(n+k)P_x})_i, i = n+1, n+2,\cdots,2n \tag{6}$$

$$W_0^m = \frac{\lambda}{\lambda+n} \tag{7}$$

$$W_0^c = W_0^m + (1-\alpha^2+\beta) \tag{8}$$

$$W_i^m = W_i^c = \frac{1}{2(\lambda+n)}, i = 1,2,\cdots,n \tag{9}$$

The proportion parameter is $\lambda = 1-\alpha^2+\beta$. The value of the proportion parameter usually depends on the parameters of the specific distribution of state x (Shi and Han, 2011). According to the experimental experience, this study can effectively reduce the system state error of forecasting by establishing reasonable proportion parameter. At the same time, this method also can adjust the high order moment features distribution of the system state online. $(\sqrt{(n+k)P_x})_i$ denotes the RMS values of the i line or i listed of matrix $\sqrt{(n+k)P_x}$. W_i^m denotes the weighted value of the system mean. W_i^c denotes the weighted value of the system covariance. This study can get the discrete points set $\{y_i\}$ by the transform of UT to approximate nonlinear points set. And this study know that:

$$y_i = f(\chi_i),\ i = 1,\cdots, 2n+1 \tag{10}$$

This study can calculate the statistical properties of y as formula (11-12):

$$\bar{y} = \sum_{i=0}^{L-1} W_i^m y_i \tag{11}$$

$$P_y = \sum_{i=0}^{L-1} W_i^c (y_i - \bar{y})(y_i - \bar{y})^T \tag{12}$$

The main idea of UT transform is to recursive and upgrading the state of system model and the error covariance through a kind of effective method of nonlinear change. This study can get the widely used UKF by using the UT transform to the Kalman Filter. Through the UKF algorithm, this study can get the system state and measurement information updates equation as follow:

Formulas (13-19) are state equation:

$$\chi_{k|k-1} = f(\chi_{k-1}) \tag{13}$$

$$\bar{x}_{k|k-1} = \sum_{i=0}^{2n} W_i^m \chi_{i,k|k-1} \tag{14}$$

$$\chi_{k|k-1} = f(\chi_{k-1}) \tag{15}$$

$$\bar{x}_{k|k-1} = \sum_{i=0}^{2n} W_i^m \chi_{i,k|k-1} \tag{16}$$

$$P_{k|k-1} = \sum_{i=0}^{2n} W_i^c [\chi_{i,k|k-1} - \bar{x}_{k|k-1}][\chi_{i,k|k-1} - \bar{x}_{k|k-1}]^T + Q \tag{17}$$

$$\gamma_{i,k|k-1} = h(\chi_{i,k|k-1}) \tag{18}$$

$$\bar{y}_{k|k-1} = \sum_{i=0}^{2n} W_i^m \gamma_{i,k|k-1} \tag{19}$$

Formulas (20-24) are measurement equation:

$$P_{yy} = \sum_{i=0}^{2n} W_i^c [\gamma_{i,k|k-1} - \bar{y}_{k|k-1}][\gamma_{i,k|k-1} - \bar{y}_{k|k-1}]^T + R \tag{20}$$

$$P_{xy} = \sum_{i=0}^{2n} W_i^c [\chi_{i,k|k-1} - \bar{x}_{k|k-1}][\chi_{i,k|k-1} - \bar{x}_{k|k-1}]^T \tag{21}$$

$$\bar{x}_{k|k} = \bar{x}_{k|k-1} + K_k (y_k - \bar{y}_{k|k-1}) \tag{22}$$

$$P_{k|k} = P_{k|k-1} - K_k P_{yy} K_K^T \tag{23}$$

$$P_{xy} = \sum_{i=0}^{2n} W_i^c [\chi_{i,k|k-1} - \bar{x}_{k|k-1}] \tag{24}$$

In order convenient, the standard particle filter algorithm usually choose prior probability density function as $q(x_k|x_{k-1}, y_k) = p(x_k|x_{k-1})$. This important distribution function is convenient for sampling. But this method let the filtering and predicting rely heavily on the state of the system model, because the function lacks of real-time measurement updating of the information. Therefore, there are weights degradation problems.

The filter usually is not convergence and even divergence when the system model is not accurate or the system noise statistical characteristics are unknown. So, many researchers tried to use adaptive method to solve this contradiction. Yang and Gao (2006) used the Sage-Husa sub-prime unbiased great checking method to estimate the system noise statistical properties on-line and got good performance. But this method also exist certain shortage. Sage-Husa estimator is easy to incline to expand when the system noise and measurement noise all have larger error. Therefore, this study tried to judge the filter divergent condition by introducing covariance matching algorithm when this study tried to estimate the system noise statistical properties on-line.

Noise estimation: The main idea of the Sage-Husa estimation is to use the estimated value $\hat{x}_{j|j}$ or the predicted value $\hat{x}_{j|j-1}$ of the system to replace the complex smooth estimated value $\hat{x}_{j|k}$. Then this study can get the statistical properties of the system noise based on the basis of prior estimation. The specific expression as Formula (25-26):

$$\hat{q}_k = \frac{1}{k}\sum_{j=1}^{k}[\hat{x}_{j|k} - \Phi_{j-1}\hat{x}_{j-1|k}] \quad (25)$$

$$\hat{Q}_k = \frac{1}{k}\sum_{j=1}^{k}[\hat{x}_{j|k} - \Phi_{j-1}\hat{x}_{j-1|k} - \hat{q}_k]\times[\hat{x}_{j|k} - \Phi_{j-1}\hat{x}_{j-1|k} - \hat{q}_k]^T \quad (26)$$

The effective method to overcome the particle filter algorithm weights degradation problem is to enhance the amend effect of latest measurements and to highlight the latest information in system noise statistical feature updating and to weaken the past information on system noise characteristics of interference. Therefore, this study gave different weights to the latest measurement information and past information in the period of noise estimate. This method effectively weakened the interference of the past information to the system noise estimation. The specific mathematical expression of the estimated statistical characteristics of noise as Formula (27-28):

$$\hat{q}_k = (1-d_{k-1})\hat{q}_{k-1} + d_{k-1}[\hat{x}_{k|k} - \Phi_k\hat{x}_{k-1|k-1}] \quad (27)$$

$$\hat{Q}_k = (1-d_{k-1})\hat{Q}_{k-1} + d_{k-1}[K_k v_k v_k^T K_k^T + P_{k|k} - \Phi_k P_{k-1|k-1}\Phi_k^T] \quad (28)$$

where, $d_{k-1} = (1-b)/(1-b^k)$, j = 0.1.⋯, k-1 and b is called forgetting factor. According to relevant research experience value, the value of b is $0.95<b<0.99$. Here, this study describe the specific value method. This study must give the forgetting factor larger value when the system noise changes greatly and the mismatch degree is high. Then this study can improve the correction action of the current measurement information. This study must give the forgetting factor smaller value when the system noise changes litter. Then this study can strengthen the maintain effect of the past information, so as to achieve the statistical characteristics of system noise real-time updates effectively.

Considering the algorithm for nonlinear systems, this study used UKF algorithm to calculate the estimation of (27) and (28). This method reduced the model error of the nonlinear system and enhanced the accuracy and robustness of the filter algorithm.

The judgment and inhibition of filter divergent: According to the divergent problem of Sage-Husa estimator, this study used covariance matching method to judge the actual situation of filter divergent. The specific formula just as follows:

$$\tilde{y}_k^T \tilde{y}_k \le S\,\mathrm{tr}\left[E\left(\tilde{y}_k \tilde{y}_k^T\right)\right] \quad (29)$$

The adjustment coefficient S is a prior initial value by set. In general, this study require S>1. The residual sequence of the system is $\tilde{y}_k = y_k - h(\bar{x}_{k|k-1})$. If the real-time calculation results of the system show Formula (29) is right and this study think that the overall performance of the system is convergence. This study can estimate the noise characteristics by the Sage-Husa estimator. But this study should to revise $P_{k|k-1}$ when the judge result is not right. The correction method of concrete is to introduce attenuation factor of memory adaptive weighted coefficient λ_k. The specific definition shows as follow:

$$\lambda_k = \begin{cases} \lambda_0, \lambda_0 \ge 1 \\ 1, \lambda_0 < 1 \end{cases} \quad (30)$$

The concrete fixed formula is:

$$P_{k|k-1} = \lambda_k \sum_{i=0}^{2n} W_i^c[\chi_{i,k|k-1} - \bar{x}_{k|k-1}]\times[\chi_{i,k|k-1} - \bar{x}_{k|k-1}]^T + Q_{k-1} \quad (31)$$

Where:

$$\lambda_0 = \frac{\mathrm{tr}(C_{0,k} - R)^T}{\mathrm{tr}(\sum_{i=0}^{2n} W_i^c[\gamma_{i,k|k-1} - \bar{y}_{k|k-1}][\gamma_{i,k|k-1} - \bar{y}_{k|k-1}])^T} \quad (32)$$

$$C_{0,k} = \begin{cases} \tilde{y}_k \tilde{y}_k^T, k = 1 \\ \dfrac{\rho C_{0,k} + \tilde{y}_k \tilde{y}_k^T}{1+\rho}, k > 1 \end{cases} \quad (33)$$

The main function of the attenuation coefficient ρ is to enhance the fast tracking ability of the filter. When the value of ρ is larger, the weights of the present moment information is larger and also more highlight the residual current information to estimate the effect of system. Therefore the coefficient effectively ensures the tracking ability of the system to the changes and mutations. Usually, the scope of ρ is $0<\rho\le 1$ and this study let $\rho = 0.95$ in this study.

THE REALIZATION OF MULTI-FEATURES FUSION TRACKING

Weights update: According to the observation likelihood model defined by Eq. 1, this study can recursively estimate the target particle corresponding weights in accordance with (2). In this study, the color histogram and motion edge features are used as observation model.

Weights update based on color histogram feature: At first, by 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 location. This study can search the target effectively around the center of the images. Then calculate the target first characteristic probability density of the uth in the feature space. The result can be expressed as:

$$p_u(y) = C_h \sum_{i=1}^{m} K\left(\frac{\| y - x_i \|}{a}\right) \delta(b(x_i) - u) \tag{34}$$

Where:

$$C_h = \frac{1}{\sum_{i}^{n} K(\| x_i^* \|)}$$

is the normalized factor of the probability density, the purpose is to make:

$$\sum_{u=1}^{m} p_u(y) = 1$$

α 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(.) 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 it deviates the smaller weight value. K(.) is defined as follow:

$$K(s) = \begin{cases} 1 - s^2, s < 1 \\ 0, \text{else} \end{cases} \tag{35}$$

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

$$p(y) = \{p_u(y)\}_{u = 1, \cdots, m} \tag{36}$$

Assume that in the k-frame, the position of the ith particle parameters is (x^i_k, y^i_k)T. The candidate matches $p(y_i)$ and target model $q(y_0)$ can be used to measure the Bhattacharyya distance:

$$d_i = \sqrt{1 - \rho(p,q)} \tag{37}$$

Where:

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

is the corresponding Bhattacharyya factor. According to Eq. 2 and 3, this study can get the weights update formula based on color histogram as:

$$\omega^i_{CLORk} = \omega^i_{CLORk-1} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{d_i^2}{2\sigma^2}\right) \tag{38}$$

Weights update based on motion characteristics of the edge: Gu *et al.* (2011), Wang and Tang (2010) and Brasnett *et al.* (2007) gave a very deep study on the integration of multi-feature tracking methods. Such as color and shape or combine color and texture feature together. But these features are static features. These features could not describe the object movement. Therefore, this study adopt the campaign character as the integration of edge information which can effectively describe the motion information of moving targets (Kim and Park, 2004), but also highlight the edges and contours. This study 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:

$$diff_k = |I_k - I_{k-1}| \tag{39}$$

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

$$E_k = \nabla diff_k = \begin{bmatrix} \frac{\partial diff_k}{\partial x} & \frac{\partial diff_k}{\partial y} \end{bmatrix} \tag{40}$$

The direction angle θ can be described as:

$$\theta(x,y) = \arctan\left[\frac{\partial diff_k}{\partial y} \Big/ \frac{\partial diff_k}{\partial x} \right] \tag{41}$$

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

$$C_{ij} = \begin{cases} [\theta_{ij} / \Delta\theta], |\partial f / \partial y| + |\partial f / \partial x| > T \\ m, \text{else} \end{cases} \tag{42}$$

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

$$f(u) = \Sigma\delta(u\text{-}c_{ij}) \quad (43)$$

where, δ is a delta function. In order to get the statistical probability, this study normalized the function. This study used sub-Bart Charlie distance to measure the similarity of the two plans. The detail calculation formula is described as:

$$D_k = \sqrt{1-\sum\nolimits_{u=1:m}\sqrt{f_p^{(u)}f_q^{(u)}}} \quad (44)$$

According to Eq. 4 and 5, this study can get the weights update formula based on motion characteristics of the edge as (15):

$$\omega_{DIFFk}^{i} = \omega_{DIFFk-1}^{i}\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{D_K^2}{2\sigma^2}\right) \quad (45)$$

Weights fusion: At present, the main methods for multi-feature fusion are product feature fusion and sum feature fusion (Gu *et al*., 2011). The product feature fusion method can effectively improve the tracking accuracy, but it is 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, this study got the adjustment factor weights of each feature. Sum fusion is not sensitive to noise, but it could not improve the credibility of fusion. By the advantages of D-S evidence theory in information processing, this study used 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 were normalized. Then this study got:

$$\omega_{di} = \omega_{COLORk}^{i} / \sum_{i=1}^{N}\omega_{COLORk}^{i} \quad (46)$$

$$\omega_{Di} = \omega_{DIFFk}^{i} / \sum_{i=1}^{N}\omega_{DIFFk}^{i} \quad (47)$$

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_{ik}, the weight of the particles can be re-calculated as:

$$\omega_i = \frac{\omega_{di}\omega_{Di}}{\omega_{di}\omega_{Di}+(1-\omega_{di})\omega_{Di}} \quad (48)$$

Finally, then the right values are normalized as (49) which are used for the final weight of the resampling particles:

$$\omega_i = \frac{\omega_i}{\sum_{i=1}^{N}\omega_i} \quad (49)$$

EXPERIMENT RESULTS AND ANALYSIS

Experiments were based on the MATLAB R2007a simulation environment and the computer was 1.8 Hz, 1.5 GB RAM laptop. Within the framework of the new algorithm, this study conducted different environments of video tracking experiment. This study chose target colors and movement edge characteristics as the observation model to track the moving target. In the experiment, two different video sequences of complex situations were similar to the background block and attitude change in two different cases, respectively. This study tested the tracking results and the proposed algorithm test results were compared with the single color feature based on PF and multi-features fusion methods. This step illustrated the superiority of the proposed method.

The first video sequence used a standard video sequence "One Stop Move No Enter 2 cor. Mpeg" test which was provided by the CAVIAR project team (Wu and Han, 2010). The experimental result is shown in Fig. 1. The image size is 384×288; frame rate is 25 frames/sec. In the first 124 frame, because of the emergence o f similar color target block, the tracking error becomes large, then in 158 frames, when the color characteristics of the method based on a single track to fail. However, the method which based on multi-features fusion was still able to accurately track the target and continue to show good robustness which could be seen from Fig. 2. And the proposed method was superior to the standard particle filter method, the whole process are to maintain a high tracking accuracy.

The second 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 and the frame rate is 20 frames/sec. It can be seen in Fig. 3, 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, this study can see that the tracking accuracy of the proposed method was significantly higher than the standard particle filter.

Fig. 1(a-c): Track results of human movement in the similar background environment (a) Single color feature based on PF, (b) Multi-features fusion based on PF and (c) Multi-features fusion based on proposed algorithm

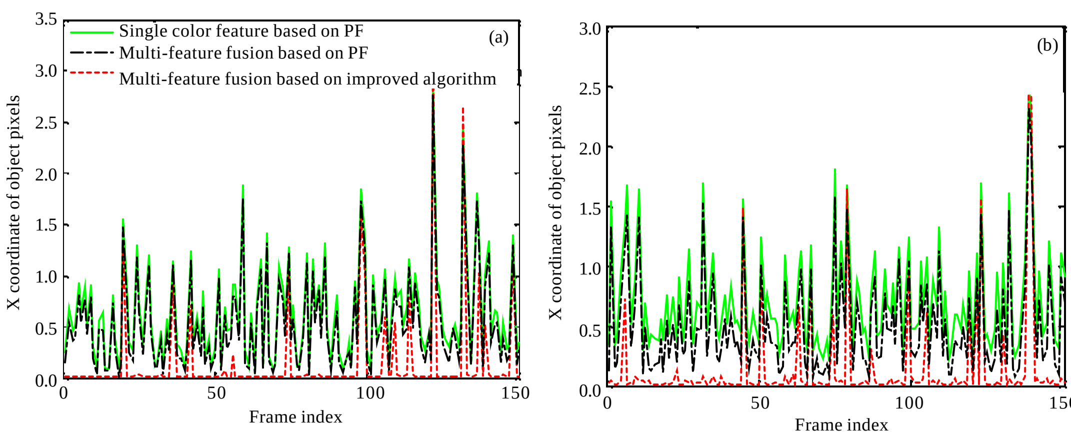

Fig. 2(a-b): Comparison of tracking errors in (a) X and (b) Y coordinate

Fig. 3(a-c): Track results of face movement when attitude changed (a) Single color feature based on PF, (b) Multi-features fusion based on PF and (c) Multi-features fusion based on proposed algorithm

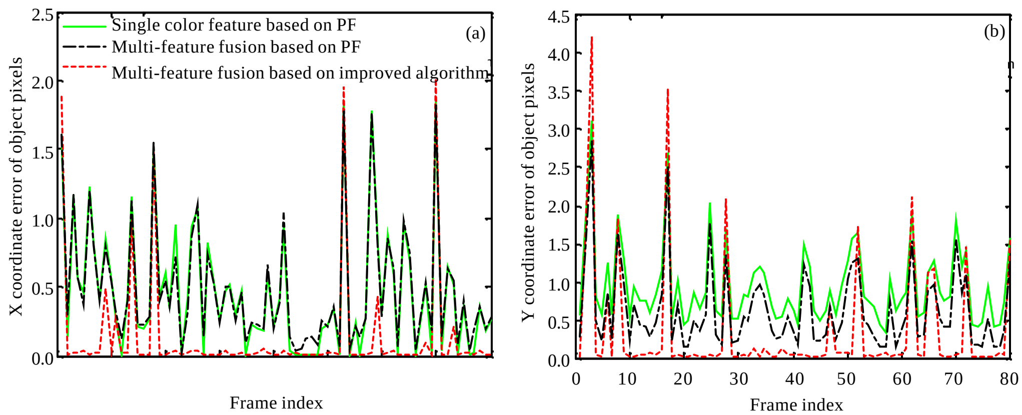

Fig. 4(a-b): Comparison of tracking errors in (a) X and (b) Y coordinate

However, the method which based on multi-features fusion was still able to accurately track the target and continue to show good robustness which could be seen from Fig. 4. And the proposed method was superior to the standard particle filter method, the whole process are to maintain a high tracking accuracy.

CONCLUSIONS

In order to solve the problem of video target tracking problem, this study proposed a new kind of particle filter for the state estimation of nonlinear system when the Statistical characteristics of the system were unknown. The proposed method mainly showed the following four characteristics: (1) This study estimated the system noise in real-time by the improved Sage-Husa sub-prime unbiased estimator and optimized the sampling particles by combining with the Unscented Kalman Filter in recursively form; (2) This study used the covariance matching criterion method to judge the situation of convergence or divergent of the filter and amended the forecasting error covariance by introducing the adaptive attenuation factor method; (3) Calculated the filter particles weights based on the color characteristics and motion edge features as observation model; (4) Fused the characteristics of the weights for the integration process by D-S evidence theory approach and estimated the target's prior state by the fused weights to. This could effectively overcome the additive integration and by fusion defects. The experiment results show that the method proposed in this study has high precision and strong robustness to video target tracking under the complicated conditions.

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