Particle filter target tracking algorithm based on multiple features similarity function information fusion method

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To improve the accuracy and stability of the moving target tracking in optics target tracking testing system, this paper proposes a particle filter tracking algorithm by using multiple features similarity function information fusion method. Under the basic framework of particle filter, the weighted histogram of target color and edge are applied to describe target features, the edge feature was extracted by Sobel algorithm, then utilizes the edge feature to establish the target's edge observation model, analyzes the features correlation that is used to measure between different features prediction and observation states. Through the experiment and analysis, compared with the traditional particle filter algorithm, the optimized particle filter algorithm reduces the average error by 26.2 pixels, decreases the standard deviation by 24.7 pixels, the results show that the proposed particle filter target tracking algorithm not only can accurately track the moving target when the target and the background color are similar, but also can stably tracking target when the target rotates and the target is occludes partially, which can verify the method of the particle filter tracking algorithm based on the multiple feature similarity function information fusion is advanced.

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1. Introduction

Target tracking has always been the hot topic at home and abroad. Because of environmental factors, tracking framework factors and diversity of tracking targets, causing the targets tracking to unstably track and lose the target in different environmental conditions. The existing target tracking algorithms can get better results of target tracking and recognition under changeable environment [1]. At present the Particle Filter (PF) processing algorithm is widely used, it is a recursive method by using Monte Carlo method for solving Bayesian estimating problems, and for performing posterior estimation of parameters or states in case of nonlinear and non-Gaussian[2]. The state prior probability density was sampled by algorithm that using Monte Carlo method. The random sample is used to approximate the posterior probability density, so that the average value is replaced by the sample mean, these samples are called "particles"[3]. When the number of particles is large enough, this approximation estimate of particle is close to posterior probability density of the state, and the particle filter estimate reaches the best effect of Bayesian estimation. However, the traditional particle filter adopts the color feature histogram to filter particle weight, the result of target tracking is affected by misleading of target occlusion and similarity target features, partial attitude changes and complex background effects. Some experts have studied the particle filter target tracking algorithm based on fusion features, the target tracking algorithm by fusing Sobel Median Binary Pattern (SMBP) and H-S features is proposed, but, its core is to use the color feature of the target[4]. A particle filter-the Local Optimum Particle Filter (LOPF) algorithm for tracking object accurately and steadily in visual sequences in real time is presented, extracts the profile of the object by Sobel algorithm, only uses a single feature of the target[5]. A particle filter object tracking algorithm based on color and texture feature fusion is presented, the texture feature is described by global median local binary pattern(GMLBP), the color feature is described by HSV color characteristics [6]. In order to improve the tracking stability of particle filter algorithm in complex environment, this paper put forward particle filter target tracking algorithm based on fusion of multi-feature similarity function (PF-TBD) in the framework of particle filter[7][8]. The color observation model of target was established through RGB space. Using Sobel edge features to establish the edge observation model of target. The similarity function of candidate region and the target region calculated by integrating the color and edge features used for fusion, which obtain observation values of the particles in different feature spaces, achieve multi-factor fusion. According to the recursion formula, the particle weights are calculated and the current state of the target is estimated through the Bayesian theorem weighted average, and realizes target stably tracking.

2. Target image tracking based on particle filter

We denoted x_t as the state vector of target, Y_t as the observation information, $p(x_t|Y_t)$ as posterior probability density, then the tracking problem can be regarded as a process of inferring the target state value x_t

at time t, which from the obtained Y_t, that is the estimated $p(x_t \mid Y_t)$. According to Monte Carlo ideas[8], hypothesis N independent samples $\{x_t^{(1)}, x_t^{(2)}, \ldots, x_t^{(N)}\}$ is collected from $p(x_t \mid Y_t)$, the calculation of posterior probability can be expressed by formula(1).

$$p(x_t \mid Y_t) \approx \frac{1}{N}\sum_{i=1}^{N}\delta(x_t - x_t^{(i)}) \tag{1}$$

In (1), $\delta(x_t - x_t^{(i)})$ is Dirac function, then introduces a set of supporting particles $\{(x_t^{(i)}, \omega_t^{(i)}), i = 1,2,\ldots, N\}$, $(x_t^{(i)}, \omega_t^{(i)})$ expresses sampling of particles from the importance density function, $x_t^{(i)}$ expresses a possible state of the *I*-th particle at time t, its weight is $\omega_t^{(i)}$, which indicates the degree of the particle approached true state of target[9]. Thus, the posterior density function can be expressed as a weighted approximation using the results of sample; it can be expressed by formula (2).

$$p(x_t \mid Y_t) \approx \sum_{i=1}^{N}\omega_t^{(i)}\delta(x_t - x_t^{(i)}) \tag{2}$$

In (2), $\omega_t^{(i)} \propto \dfrac{p(x_t \mid Y_t)}{q(x_t \mid Y_t)}$. With the iterative loop of state propagation and observation updates, the particle sample set will obey the distribution described by Bayesian estimation. On the basis of Bayes theorem [10], the tracking result of target can be shown by weighted average of the particles, which can be expressed by formula (3).

$$\hat{x}_t = \frac{1}{\sum_{i=1}^{N}\omega_t^{(i)}}\sum_{i=1}^{N}\omega_t^{(i)}x_t^{(i)} \tag{3}$$

3. Target image multiple features description

3.1. Weighted color histogram

The spatial distribution of colors in an image may be expressed as calculating ratio of different colors in entire image. The ratio is called color histogram, which divides the entire color space into cells, and every color interval is called bin. The RGB color histogram of target is selected as one of the target extraction features [11]. R channel is quantified L Levels, G *and* B Channels are quantified as $L/4$ rank, so the number of bin is $L \times (L/4)^2$.

Assuming the number of pixels in the target area is n, the pixels of the target area are $\{x_i\}, i = 1,2,\ldots n$. The center coordinates of the target area are x_0. The eigenvalue of the target template component of R is $\{u = 0,1,2\ldots, L-1\}$. The eigenvalues component of G and B are $\{u = 0,1,2\ldots, L/4-1\}$. In order to make the extracted color features play more favorable role, the influence of pixels closer to the tracking frame is weighted, and establishes the kernel function weighted histogram. Therefore, the weighted RGB color histogram can be expressed by formula (4).

$$\begin{cases} p_c(u) = \sum_{i=1}^{n} K\left(\left\|\dfrac{(x_i - x_0)}{w_t}\right\|^2\right) & b(x_i) = u \\ 0 & other \end{cases} \tag{4}$$

In (4), $K(\cdot)$ is Kernel function of the weight value of each pixel, therefore, the closer the target center, the higher the pixel weight value and the lower the impact of the external environment on the target area. w_t is the window bandwidth, $b(x_i)$ is the eigenvalue at x_i point. Therefore, the size of the Kernel function is mainly affected by the pixel set of the target area and the window bandwidth is set by the system.

3.2. Weighted edge histogram

In the Sobel operator, the edge gradient values can be decomposed into two categories, horizontal and vertical [12]. The two gradient values have respective templates, denoted as G_x and G_y. When the first frame is detected, the image is diarized, and the G_x and G_y templates can be used to calculate G and θ_e by equation (5),which can be express by formula (5).

$$\begin{cases} G = \sqrt{{G_x}^2 + {G_y}^2} \\ \theta_e = \arctan\left(\dfrac{G_y}{G_x}\right) \end{cases} \tag{5}$$

In (5), G is the gradient magnitude of the target image at the edge, θ_e is the edge direction of the target image at the edge, the range of the edge direction is $\left(-90^\circ, 90^\circ\right)$. n' is the total number of edge pixels, $\{x_g\}, g = 1,2,\ldots n'$ is the edge pixel set, x_0 is the center coordinates of the target area, the edge direction quantified into M_e equal division, so the eigenvalue of the target template on the edge of each equal edge is $\{u = 0,1,\ldots,180/M_e - 1\}$. Similarly, the distribution function of weighted aerial histogram of the target can be described by formula (6).

$$\begin{cases} p_e(u) = G\sum_{g=1}^{n'} K\left(\left\|\frac{(x_g - x_0)}{w_t}\right\|^2\right) & b(x_g) = u \\ 0 & other \end{cases} \quad (6)$$

In (6), $b(x_g)$ is eigenvalue at the x_g pixel. The kernel function is influenced by the pixel set of the target edge area, and the window bandwidth is set by the system.

4. Target tracking algorithm of Particle filter based on fusion of multiple features similarity function

4.1. State model of moving target

For the video target, the mobility of the target motion is not large between adjacent frames. In most cases, the motion law is described by the first-order constant-velocity model [13]. We denoted (x, y) as the center coordinates of the tracking box at time t, V_x and V_y as the velocity of the target in the *x* and *y* directions, h_x and h_y as respectively half of the length and width of the tracking frame. Assuming the target is moving with uniform linear motion, the state of the moving target can be expressed by formula (7).

$$x_t = [x, V_x, y, V_y, h_x, h_y]^T \quad (7)$$

Assuming the target status transformation meets the first-order auto-regressive model, that is, the target state at the current time is only related to previous moment, and the time varied state of target can be described by equation (8).

$$\begin{aligned} x_t &= f_{t-1}(x_{t-1}, w_{t-1}) = f_{t-1} \cdot x_{t-1} \\ &= \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} x_{t-1} \end{aligned} \quad (8)$$

In (8), x_t and x_{t-1} are the target vector at time t and time $t-1$, $f_{t\text{-}1}()$ is a transfer function of system state, w_t is the Gaussian noise with system mean of 0.

4.2. Fusion observation model with multiple features similarity functions

The particle state would changes after it is propagated through the state transfer model, but the weight of the particle is not updated. In order to make the distribution of the propagated particles closed to the target true posterior density distribution, the particle weights need to be corrected by the observation model that is endowed with the corresponding probability values[14]. Essentially, this is process of similarity measurement that is measuring the degree of similarity between the target prediction state and the real state through observation.

Obviously, the quality of the observation model determines the target tracking performance. By comparing the target region feature of the next frame with distribution of the current frame, the strategic strategy model can effectively distinguish tracking target and non-tracking, which is a good measurement model [15].

The feature information of the current frame target region is the color and edge information, the information is extracted in the previous frame image area. As the true distribution of the target state, the obtained information of color and edge are referred to target templates. First, a sub-model of target is constructed by spatial kernel weighted histograms of individual features, then each sub-model is assembled into a set to establish a target template.

1) Color feature observation template of target. Calculate the color probability distribution histogram of the target region on the three components of R, G, and B($p_c^R(u) \in R^{L\times 1}$, $p_c^G(u) \in R^{(L/4)\times 1}$, $p_c^B(u) \in R^{(L/4)\times 1}$). The overall color probability distribution histogram is the color feature observation template of target, it can be expressed formula (9).

$$p_c = \frac{1}{3}\left[\left[p_c^R(u)\right]^T, \left[p_c^G(u)\right]^T, \left[p_c^B(u)\right]^T\right]^T \in R^{(3/2L)\times 1} \quad (9)$$

2) Target edge feature observation template. Similarly, the target's overall edge probability distribution histogram can be expressed by formula (10).

$$p_e = \left[p_{e1}, p_{e1}, \ldots, p_{e1}\right]^T \in R^{M_e \times 1} \quad (10)$$

Because of the diversity of the target tracking environment, the description ability of each feature of target model is changing dynamically. In order to stably track method of particle filter tracking with the frame pre and post similarity function, the overall histogram distance measure corresponding to the two distributions can be calculated by inter-feature similarity function of the frames, and by calculating the observation likelihood function of fusion to achieve multi-cue fusion tracking .

In the frame of particle filter algorithm, the region of each particle of the next frame is used as the candidate target region, which are respectively defined c_j and e_j as the *j*th candidate regional observation templates of color and edge features. The similarity function based on color features are calculated with histogram intersection method, it can be expressed by formula (11).

$$f_c(p_c,c_j)=\frac{\sum_{i=1}^{3/2L}\min(p_{c,i},c_{j,i})}{\sum_{i=1}^{3/2L}p_{c,i}} \tag{11}$$

In (11), $p_{c,i}$ is the ith element of p_c, $c_{j,i}$ is the ith element of c_j, the large $f_c(p_c,c_j)$, the more similar the color features of the candidate region to the target. Similarly, the similarity function of the edge feature is:

$$f_e(p_e,e_j)=\frac{\sum_{i=1}^{M_e}\min(p_{e,i},e_{j,i})}{\sum_{i=1}^{m}p_{e,i}} \tag{12}$$

In (12), $p_{e,i}$ is the ith element of p_e, $e_{j,i}$ is the ith element of e_j. To use multiple features information fusion to accomplish target synchronization tracking, the weighted strategy of fusion is embedded in the particle filter tracking framework. The similarity function of the color and edge features is observed with a weighted linear method. For multiple observational features, combined with formula(12), the global similarity functions of the target and candidate can be described as formula(13),which can be express as

$$\begin{cases} f_{his}=\lambda_c f_c(p_c,c_j)+\lambda_e f_e(p_e,e_j) \\ \lambda_c=\dfrac{f_c(p_c,c_j)}{f_c(p_c,c_j)+f_e(p_e,e_j)} \\ \lambda_e=\dfrac{f_e(p_e,e_j)}{f_c(p_c,c_j)+f_e(p_e,e_j)} \end{cases} \tag{13}$$

In (13), λ_c and λ_e are the weighted value of the corresponding feature respectively, and $\lambda_c+\lambda_e=1$. The overall distance measure of the histogram of target area and the candidate area can be calculated by formula (14).

$$D_{his}=\frac{1}{2}\left[\lambda_c^{\ 2} f_c^{\ 2}(p_c,c_j)+\lambda_e^{\ 2} f_e^{\ 2}(p_e,e_j)\right] \tag{14}$$

The overall distance measure of the histogram is also called Bhattacharyya distance. According to the result of Bhattacharyya distance, these particles are given the corresponding weights. Meantime, because some particles have very small weights, occupy resources and waste time in calculation, if the variance of particle weights increases with time, the number of effective particles decreases, and the number of particles with small weights increases, the results is that the particle weights begin to degenerate, it is necessary to use the resampling method by discarding the particles with small weights and replacing with new particles, ensure timely correct particle weights, reduce the amount of calculation and improve the real-time performance of system.

Combined with the overall distance measure of the histogram of two distributions, we can fuse the observation models of particles in different feature spaces to achieve multi-cue fusion, and thus establish a multi-feature joint observation likelihood function for particle weights, which can be express by formula (15).

$$p(y_t|x_t)\propto N(D_{his};0,\sigma^2)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{D_{his}^{\ 2}}{2\sigma^2}\right) \tag{15}$$

In (15), σ^2 is the Gaussian variance.

The larger the value of formula (13), the more similar the fusion histogram features of the candidate target and the target template and the more likely the candidate target is a real target. With the arrival of fused observations in equation (15), the weights corresponding to the particles can be calculated, and then combined with equation (3) to obtain the recursive estimation of target state expectation.

4.3. Implementation of tracking algorithm

The flow chart of particle filter tracking algorithm based on multi features fusion is shown in Fig. 1.

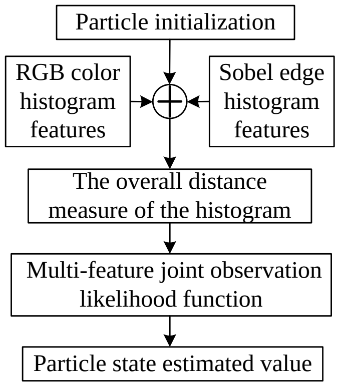

Fig. 1. The flow chart of particle filter tracking algorithm based on multi features fusion

Select the two complementary features of the target color and edge to track[16], give the number of features n=2, the RGB color space of color feature L=16, and the histogram of edge features M_e =36. Assume that the initial state of the target is $\{x_0^{(i)},\omega_0^{(i)}\}$, the specific steps of the algorithm implementation as follows:

1) Calculate the histogram sub-model of each feature of the target template p_c,p_e, and initialize their weights $\lambda_c=\lambda_e=1/2$, randomly sample based on the initial probability distribution of the target state to establish the initial particle set $\{x_t^{(i)},\omega_t^{(i)}\}$, where target status is $x_t^{(i)}, i=\{1,2,\ldots,N\}$, Particle weight is $\omega_t^{(i)}=1/N$.

2) The state transition equation is used to propagate the

particles in the next frame of the image to obtain new particles.

3) Calculate the similarity function of color and edge features, use equation (13) fusion operations to generate overall histogram distance measure of the target and candidate region, then obtain the multiple features joint observation likelihood function with equation (15).

4) Calculate the particle weight, and substitute the formula (3) to calculate the final estimated value of the target state.

5) Calculate effective sampling coefficient of particle. If the effective sampling coefficient is less than the threshold set, the system need to be resampled the particle set, otherwise, the system does not need to be resampled.

6) Judge whether follows target tracking after next time. If the system tracks the target, jumps to the second step of the algorithm, otherwise, the system ends the target tracking.

The particle filter target tracking of the multi-features similarity function can be completed by the above six steps.

5. Experimental results and analysis

5.1. Contrasting experiment of tracking

In order to verify the performance of the algorithm, the traditional particle filter target tracking algorithm (PF-TBD), the particle filter target tracking algorithm combined with the color and edge features (multi-features fusion PF-TBD) are used in the same video file for comparison experiments. The experimental software platform was simulated in Opencv2.410 conjunction with Visual Studio 2012. The video comes from a standard video sequence “Car” intercepted the CAVIAR item. The reasons for selecting the image sequence are as follows: First, there are non-similar targets occluded and false targets in the scenes included in the image sequence, in which the false targets respectively include the color and the edges feature similarity target; Second, the background of the image sequence is complex and drastically changes.

The image sequence of “Car” is 320×240 pixels. The tracking target is a white SUV. The initial target region is set to 100 initial particles. Tracking the scene as follows: In the target tracking process, there are edge similar features and the image sequence with complex background, Variant, non-similar targets local occlusion, similar color targets, and target part attitude change. Fig. 2 shows some representative experimental results extracted from the PF-TBD algorithm target tracking process. Fig. 3 shows that the multiple features fusion with the PF-TBD algorithm tracking result. From left to right and top to bottom, the number of video image frames is 71st, 106th, 160th, 218th, 256th, 389th, 470th, 760th and 855th frames respectively.

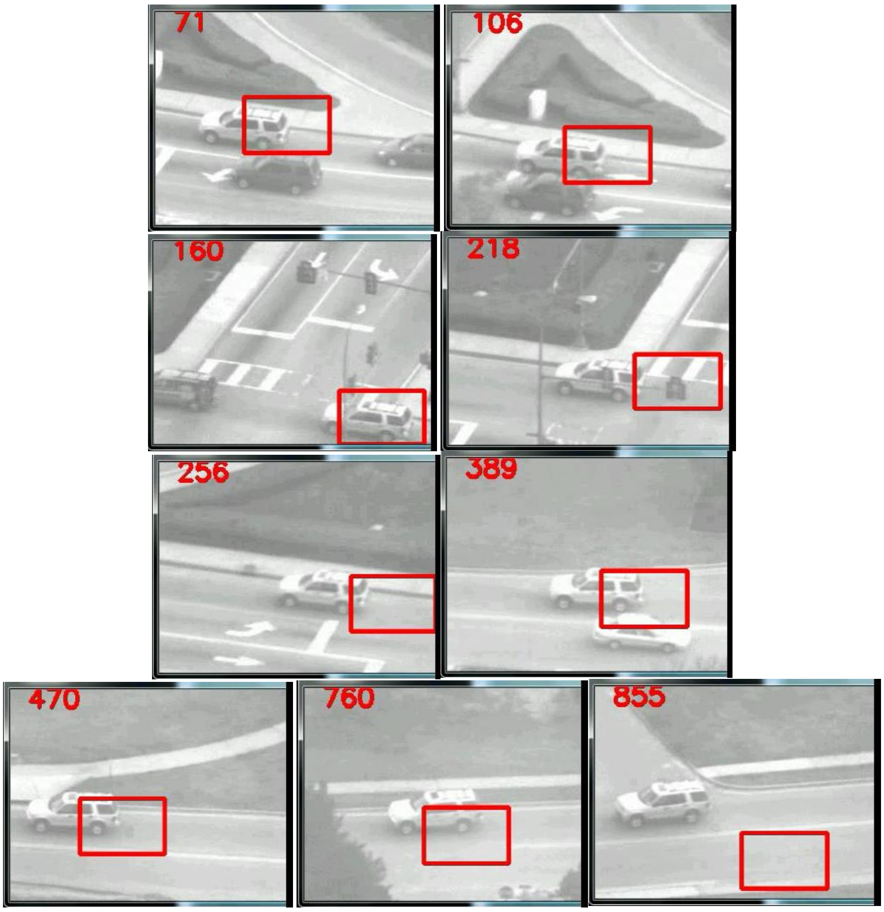

Fig. 2. Experimental results of PF-TBD target tracking algorithm

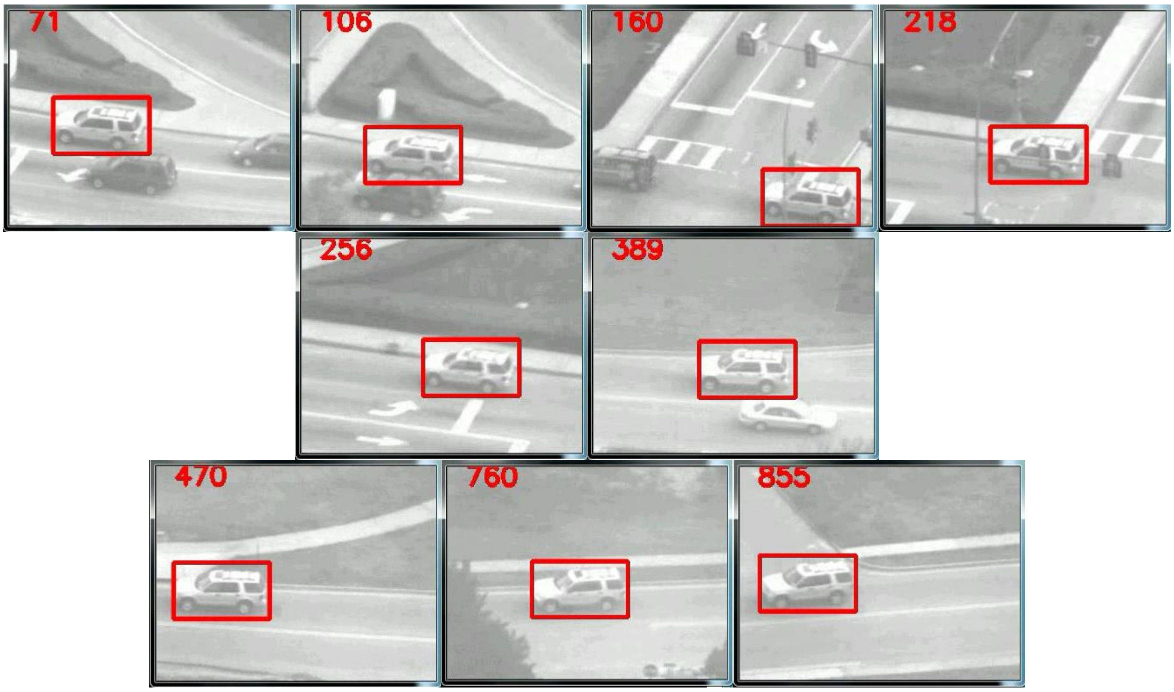

Fig. 3. Partial experimental results of PF-TBD tracking algorithm with multiple features fusion

Fig. 2 shows the PF-TBD target tracking algorithm. Fig. 3 shows the multi-features fusion target tracking method with PF-TBD. By analyzing the video, we can see that in the 71st and 106th frames of the image sequence, there is a black SUV that the edge feature similarity. Because of the algorithm used to the color feature of target in the initialization phase, therefore, both algorithms can track the real target. Although Fig. 2 does not lose the tracking target, there is a large deviation in the tracking of the target. In this case, since the edge feature information is integrated in Fig. 3, tracking accuracy of target is relatively improved. Therefore, tracking target with single feature is not enough. When the 160th frame has a large background change, the particle filter can overcome such problems. So, the tracking effects of the two algorithms are almost the same, and the multi-features fusion PF-TBD algorithm has higher accuracy of relative tracking.

When the 218th frame of the image sequence is partial occlusion, and the zebra crossing with occluded targets forms a false target, causing the PF-TBD algorithm to be misleading makes tracking target could be lost. In the 256th frame, the PF-TBD algorithm still follows the tracking error; in the 389th frame, there is a false target with similar color characteristics in the same color car. Obviously, the PF-TBD algorithm is insensitive to the target edge information, and is susceptible to interference. However, the PF-TBD algorithm of multiple features fusion keeps stably tracking. Therefore, the single feature can not effectively track; in the 470th to 855th frame images, the tracking target part of the attitude changes, PF-TBD algorithm track box fluctuations, the tracking effect of the real target is not ideal and even tracking failure. Besides, multi-features fusion the tracking frame of the PF-TBD algorithm has almost no fluctuations. It can be seen from the experimental results that the multi-features fusion PF-TBD algorithm has small deviation in the tracking process, which can effectively improve the target tracking performance in the presence of similar targets.

5.2. Simulation and comparing analysis

In order to further verify the performance of the algorithm, we use motion trajectory and tracking error to compare different target tracking algorithms. Since target coordinate of thalamus needs to manually judge. In order to simplify the workload, the target centroid is measured at per 15 frames and corresponding coordinate data is obtained. The video sequence "Car" has 855 frames. Therefore, the video sequence can obtain 57 sets data, including the x-direction and y-direction pixel value of the target, as shown in Fig. 4 and Fig. 5.

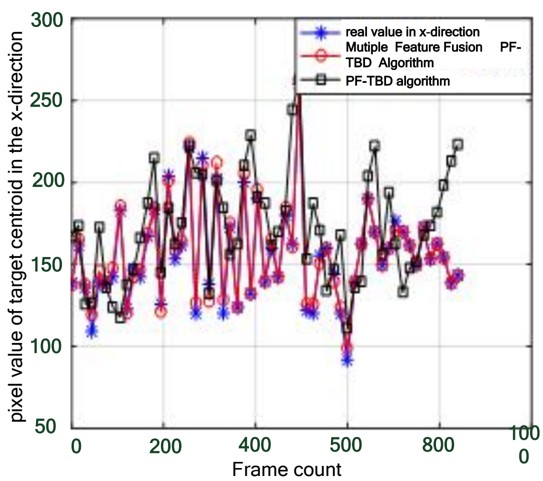

Fig. 4. Target centroid x direction coordinate data

The result of Fig. 4 contains the real value in x direction, the pixel value in x direction obtained by the multi-features fusion PF-TBD algorithm, and the pixel value in x direction obtained by the traditional PF-TBD algorithm, these results can show that the error between the traditional PF-TBD algorithm and the real value in x direction, the error between the multi-features fusion PF-TBD algorithm and the real value in x direction.

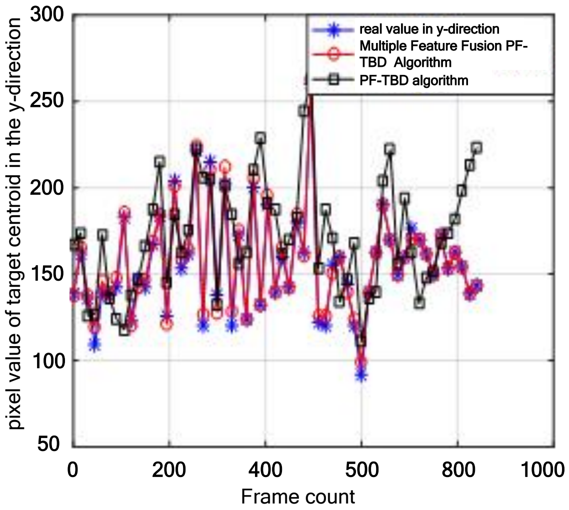

Fig. 5. Target centroid y direction coordinates data

The result of Fig. 5 contains the real value in y direction, the pixel value in y direction obtained by the multi-features fusion PF-TBD algorithm, and the pixel value in y direction obtained by the traditional PF-TBD algorithm, these results can show that the error between the traditional PF-TBD algorithm and the real value in y direction, the error between the multi-features fusion PF-TBD algorithm and the real value in y direction.

Comparing Fig. 4 and Fig. 5, the multiple features fusion PF-TBD algorithms is closer to the real target trajectory. The error of the PF-TBD algorithm in the x direction is larger than the y direction. The x and y direction data are integrated to calculate tracking accuracy of an algorithm with tracking error.

The tracking error is defined by comparing the difference between the actual value of the actual tracking target centroid and the theoretical value in the experimental data. (x, y) indicates the center coordinate of the tracking frame obtained by the experiment in the t-th frame. (x_{to}, y_{to}) represents the centroid coordinate of the target in the actual image sequence. The center offset distance can be expressed as $e(t) = \left[(x_t - x_{to})^2 + (y_t - y_{to})^2\right]^{1/2}$. The smaller offset distance, the smaller tracking error and the higher the tracking accuracy. The calculated center offset distance is as shown in Fig. 6.

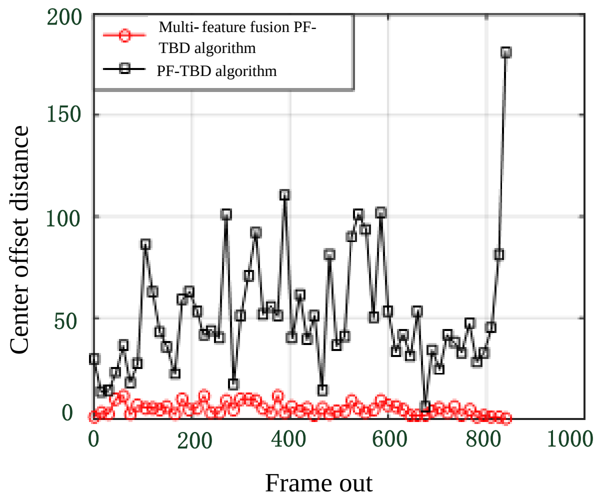

Fig. 6. Target Center Offset Distance

According to the center offset distance of Fig. 6, the center tracking error value of the multiple features fusion PF-TBD algorithm is significantly smaller than that of the PF-TBD algorithm. The average tracking error and standard deviation of the PF-TBD algorithm is 31.294 and 27.750 pixels respectively. The tracking error and standard deviation of multiple feature fusion PF-TBD algorithm is 5.095 and 3.051 pixels respectively. The multi-features fusion PF-TBD algorithm can effectively improve the target tracking accuracy, and its motion trajectory trend is more suitable to the actual motion trajectory trend.

6. Conclusions

The target tracking results are affected by misleading of sheltered targets and similarity targets, partial attitude changes and complex background, there is provides multi-features fusion method based on particle filter framework. On the basis of particle filter theory, the color and edge histogram features are selected for studying multi-features weighted fusion. In this method, the feature's tracking effect is adaptively weighed with the minimum Bhattacharyya Distance of the feature distribution, because these particles are given the corresponding weights according to the result of Bhattacharyya distance. The PF-TBD tracking algorithm for multi-features fusion is much better than the traditional algorithm for different scenes, such as, the similar edge-targets, complex background of image sequence, multiple changes, partial occlusion of similarity, similarity of color features and changes in the attitude of the target part. In the tracking process, the multi-features fusion PF-TBD algorithm has higher accuracy and stability. In the simulation comparison analysis, the multi-features fusion PF-TBD algorithm is closer to the real target trajectory, and the multi-features fusion PF-TBD algorithm is meaner than the PF-TBD algorithm. Therefore, multi-features fusion PF-TBD algorithm can effectively improve the accuracy of target tracking, the trend of its trajectory more accordance with the actual trend of the target trajectory.

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