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Particle Filter Vehicles Tracking by Fusing Multiple Features

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ABSTRACT Real-time and accurate vehicle tracking by Cameras and Surveillance can provide strong support for the acquisition and application of important traffic parameters, which is the basis of the traffic condition evaluation and the reasonable traffic command and dispatch. To deal with difficult problems of vehicle tracking research in a complex environments, such as occlusion, sudden illumination change, similar target interference and real-time tracking, measures are taken as follows. Firstly, the existing color local entropy particle filter tracking method is improved. The symmetry of information entropy is used to overcome the tracking failure caused by large-area occlusion. Secondly, the SIFT feature tracking method is improved to enhance real-time performance and robustness. Thirdly, two tracking methods were combined according to their characteristics, aiming at effectively improving the quasi-determination and real-time performance of vehicle tracking. Fourthly, Kalman filter was used to predict the motion state of vehicles. According to the SIFT characteristics and license plate information of vehicles, the exact position of the lost target vehicles is quickly located. It has been verified by experiments that our method has effectively improved the accuracy and real-time performance of vehicle tracking in complex situations.

INDEX TERMS Particle filter, vehicle tracking, color local entropy, scale-invariant feature transform (SIFT), symmetry.

I. INTRODUCTION

In the modern road traffic environment, the use of computer vision technology to detect, track, and recognition vehicles in video surveillance has become the key application and research field of intelligent transportation system (ITS). Vehicles are the main objects in traffic surveillance. The acquisition of traffic parameters of the vehicle such as location, quantity, flow, speed, and density are based on the object tracking of the vehicle. Real-time and accurate vehicle tracking can provide reliable support for traffic behavior understanding and traffic operation status analysis.

There are complex environments for traffic video collection. The analysis of video files is greatly influenced by environmental factors. The study of vehicle tracking algorithms in complex environment is significant for accurate traffic information collection, effective traffic state assessment, and scientific traffic command and dispatch. To achieve long-term stable tracking of target vehicles in complex environment, the following three technical problems should be solved: (1) Adapting to changes of target's appearance and changes of illumination, updating target's model reasonably, suppressing the occurrence of tracking drifting; (2) Overcoming the interference of similar color and texture of targets; (3) Recapturing targets and continuing tracking quickly when the targets are lost.

Firstly, in order to deal with the tracking failure caused by large-area occlusion in the target tracking process, an improved particle filter tracking algorithm based on color is proposed. This algorithm uses the symmetry of information

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entropy. It solves problems of geometric distortion, partial occlusion and illumination change, moreover it effectively mitigates the impact of large-area occlusion of vehicles. Secondly, the particle filter tracking algorithm combines the color local entropy and the SIFT, to improve the processing speed. It uses symmetry to replicate symmetric eigenvectors in the aim of enhancing the robustness of the algorithm. Thirdly, we take the Kalman filter to predict the motion state. This helps to quickly search and locate for an accurate position of the lost target according to the SIFT and license plate characteristics of vehicles. Massive real-world experiments show that these methods can greatly improve the robustness and accuracy of tracking.

II. RELATED WORK

The research of target tracking is a very popular subject, which has attracted the attention of scholars from all over the world. Wax first proposed the basic principle of target tracking theory in 1955 [1]. Sittler proposed the concept of target point trajectory and the Bayesian theory about the optimal data association of target data path in 1964 which improved the target tracking algorithm. These theories laid the foundation for the development of the target tracking theory [2]. In the 1970s, Yaakov and Singer introduced the Kalman filtering algorithm and related mathematical theories into the target tracking algorithm, which led to the development of target tracking technology in this period [3], [4]. After the 1990s, Cheng, Kirubarajan, Mori and other researchers in the field of target tracking made outstanding contributions in several aspects such as mean shift theory, probability multi-hypothesis tracking, variable structure multi-model, and distributed target fusion, which promoted the great development of target tracking [5]–[8]. Especially in 1995, Cheng perfected the Mean shift theory, which greatly enhanced the timeliness and accuracy of moving target tracking [5]. In the 21st century, Doucet A, Gordon N, Godsll S J, Maskell S etc. applied the research results of particle filtering in the field of target tracking [9]–[11]. Particle filtering can be used to solve nonlinear and non-Gaussian distributions. The target tracking algorithm for particle filtering has received extensive attention from researchers in related fields [12]–[15].

Compared with Kalman Filter [16] and Mean Drift Algorithm [17], particle filtering algorithm can effectively deal with the state estimation problem of nonlinear and non-Gaussian systems. Moreover, it has good robustness to the local occlusion of the target and a wide range of application. The process of target tracking is to establish the target model, and the target model is a key problem of particle filtering algorithm. The color feature is often used as the target observation model because it is easy to be calculated with fast speed and insensitive to target deformation, rotation and partial occlusion. For example, Perez *et al.* [18] established the target color distribution model in HSV space and extended it to multi-target tracking. Nummiaro *et al.* [19] proposed a weighted color histogram model. However, the color histogram lacks spatial information about the target pixels and is sensitive to light changes. Therefore, in recent years, researchers have proposed many improved methods. For example, paper [20]–[22] proposed spatial color histogram models, which integrate spatial distribution information into the color histogram. The papers [23], [24] advocated the use of the optimal convex combination model to track the target, to establish a number of color models and improving the tracking accuracy, but a priori knowledge of the appearance of the target is required. The above algorithms have improved the tracking effect to a certain extent, but the light changes still have a serious of influences on the tracking results. Therefore, some researchers suggest combining color features with other features to improve the robustness of the target model. For example, the algorithm combing the color feature with one of features including texture [25], [26], contour [27], SIFT [28] and motion [29], also the algorithms combing the color feature with all features including contour, texture and motion [30]–[32]. Both types have achieved a good tracking effect. Those algorithms combine the advantages of many characteristics and have robustness. But, the extraction of various features and the calculation of combing strategy can easily lead to problems of oversized sample space, high complexity of the algorithm and real-time performance ensuring and so on.

III. IMPROVED COLOR LOCAL ENTROPY PARTICLE FILTER ALGORITHM

In paper [33], we propose a particle filter algorithm based on color local entropy. It combines color-weighted histogram features and local entropy. This method aims to the lack of spatial information of the target pixel and the sensitivity to the change of illumination. It realizes fast and effective tracking of the moving targets under partial occlusion, deformation, illumination changes, nonlinear motion, *etc*. However, when the target vehicles are blocked by a large area, the entropy value will change greatly, followed by tracking failure. We suggest tracking and updating the target template with the local characteristics of target, according to the appearance characteristics of target and the symmetry of information entropy.

A. PARTICLE FILTER ALGORITHM

In Bayesian filtering, we use the Bayesian formula to calculate the optimal prediction state of the system. It is the basic method for the nonlinear system prediction. Using this method, the recursive Bayesian filtering is produced by non-parameterized Monte Carlo method, and the posterior probability distribution is estimated by a randomly generated set of weighted particles.

In this paper, we use particle filtering algorithm as the tracking framework. The basic idea of particle filter algorithm can be described as: using a group of weighted particles to simulate the posterior probability distribution of practical problems, predicting the system state according to the particles and their weights, and updating the particles to ensure the effectiveness of the algorithm. Generic Particle Filter is as in

Equation 1:

$$\left\{(x_k^{(i)}, w_k^{(i)})\right\}_{i=1}^{N} = PF[\left\{(x_{k-1}^{(i)}, w_{k-1}^{(i)})\right\}_{i=1}^{N}, y_k] \tag{1}$$

The steps of the standard Particle Filter algorithm are as follows:

(1) Particle Set Initialization: $k = 0$, Sampling N particle samples $\left\{(x_0^{(i)}, \frac{1}{N})\right\}_{i=1}^{N} \sim p(x_0)$ from system prior density function $p(x_0)$, The weight of each particle is $1/N$, set $k = 1$.

For k=1, 2, 3, ..., perform the following loop to the end:

(2) Importance Sampling: Sample new particle samples $\left\{x_k^{(i)}\right\}_{i=1}^{N} \sim q(x_k \left| x_{k-1}^{(i)}, y_k \right.)$ from importance probability density function. Then calculate particle weights $w_k^{(i)}$ and normalize $\overline{w}_k^{(i)}$, last Calculate system posterior probability density based on $p(x_k |Y_k) \approx \widehat{p}(x_k |Y_k) = \sum_{i=1}^{N} \overline{w}_k^{(i)} \delta(x_k - x_k^{(i)})$,

$$\begin{aligned} w_k^{(i)} &\propto \frac{p(y_k \left| x_k^{(i)} \right.)p(x_k^{(i)} \left| x_{k-1}^{(i)} \right.)p(X_{k-1}^{(i)} |Y_{k-1})}{q(x_k^{(i)} \left| X_{k-1}^{(i)}, Y_k \right.)q(X_{k-1}^{(i)} |Y_{k-1})} \\ &= w_{k-1}^{(i)} \frac{p(y_k \left| x_k^{(i)} \right.)p(x_k^{(i)} \left| x_{k-1}^{(i)} \right.)}{q(x_k^{(i)} \left| X_{k-1}^{(i)}, Y_k \right.)} \end{aligned} \tag{2}$$

$$\overline{w}_k^{(i)} = \frac{w_k^{(i)}}{\sum_{i=1}^{N} w_k^{(i)}} \tag{3}$$

(3) Resampling: Calculate the number of effective particles $\widehat{N}_{eff}$, and set the particle threshold to N_T. If $\widehat{N}_{eff} < N_T$, resample particles $\left\{(x_k^{(i)}, w_k^{(i)})\right\}_{i=1}^{N} = \text{Resample}\left[\left\{(x_{k-1}^{(i)}, w_{k-1}^{(i)})\right\}_{i=1}^{N}\right]$. (Specific methods can be seen in paper [15]),

$$\widehat{N}_{eff} \approx \frac{1}{\sum_{i=1}^{N} (w_k^{(i)})^2} \tag{4}$$

(4) Output: Calculate the state estimation of the system at k-time, $\widehat{x}_k = \sum_{i=1}^{N} \overline{w}_k^{(i)} x_k^{(i)}$

END FOR

The essence of particle filter algorithm is to take random sample points in state space to approximate the posterior probability density function. When the size of sample is large enough, the real probability density is equal to the probability density obtained from the sample set, and the particle filter is also close to the optimal Bayesian filter.

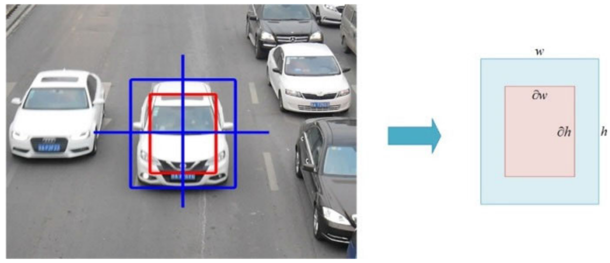

FIGURE 1. **Target area sketch.**

B. TARGET MODEL BASED ON COLOR LOCAL ENTROPY

1) THE FEATURES OF WEIGHTED COLOR HISTOGRAM

In the specific region with width w and height h, the weight function $k(r)$, the scale factor ∂, and the weighted color distribution of the target region centered at x_0 is:

$$k(r) = \begin{cases} 1, & 0 < r \le \partial \\ 1 - (\frac{r-\partial}{1-\partial})^2, & \partial < r \le 1 \end{cases} \tag{5}$$

$$p_u = C \sum_{i=1}^{n} k \left(\| \frac{x_i - x_0}{d} \|^2 \right) \delta \left[b(x_i) - u \right] \tag{6}$$

where ∂ is used to determine the pixel range that gives the highest weight (as in Figure 1); $d = 0.5\sqrt{w^2 + h^2}$ is the tracking window width; n is the total number of pixels in the target area; m is the color quantization level; $b(x_i)$ is the feature level corresponding to the pixel x_i; $\delta\left[b(x_i) - u\right]$ is the Dirac Function, which is used to determine whether the color of the pixel ix belongs to the b_{in} of u in the target area (equal to 1, otherwise 0): is normalization coefficient.

2) IMAGE LOCAL ENTROPY

Let image size be $M \times N, f(x, y)$ representing the pixel value at the point (x, y), then:

$$H_f = -\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} p_{ij} \log p_{ij} \tag{7}$$

$$p_{ij} = f(i,j) / \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i,j) \tag{8}$$

where H_f is the entropy of the image, the probability p_{ij} in the local entropy is the ratio of the single pixel gray value to the sum of local gray level.

3) COLOR LOCAL ENTROPY

Combining the weighted color histogram with the image local entropy, the feature of color local entropy (CLE) is proposed. In the specific region with width w and height h, the color local entropy H_c of the image is:

$$\begin{aligned} H_c &= -\sum_{u=1}^{m} p_u \log p_u \\ p_u &= C \sum_{i=1}^{n} k \left(\| \frac{x_i - x_0}{d} \|^2 \right) \delta \left[b(x_i) - u \right] \end{aligned} \tag{9}$$

where m is the quantization level of color space, $p_u$is as defined in (5)&(6).

Considering the logarithm operation of the formula, the round off high-order items can be expanded using the Taylor series at the time of engineering application, then the approximate formula follows:

$$H_c = -\sum_{u=1}^{m} p_u(p_u - 1) \tag{10}$$

where p_u is the color distribution of the current state of the target. H_c is color local entropy of the target in current state. p_{ref} is the color distribution of the target reference model. H_{ref} is the color distribution and color local entropy of the target reference model.

In the tracking process, the similarity of the target reference model and the current state is described in terms of Euclidean distance: $d_t^2 = \|H_{ref} - H_c\|^2$, according to particle filtering algorithm, the observation probability of particle x^i is:

$$p(y_k \left| x_k^i \right.) = \frac{1}{\sqrt{2\pi}\sigma} \exp(-\frac{d_t^2}{2\sigma^2}) \tag{11}$$

C. MODEL UPDATING METHOD AND DYNAMIC ADJUSTMENT OF PARTICLE QUANTITY

The shape of vehicle is axisymmetric with the central axis of the license plate. The symmetry determination method of the target's feature is: by referring to paper [34], we use the color of license plate, geometric characteristics and Chinese character features to detect the license plate position of the target ahead, and using the extension line of the license plate as the center axis of the vehicle. The entropy value of the center axis are and H_{right}, the symmetry parameter is S, when $d_s \leq \delta$, the target is symmetrical, then set $S = 1$; when $d_s > \delta$, the target is asymmetrical, then set $S = -1$; If condition is unknown, which the license plate position is not located, then set $S = 0$. δ is the decision threshold of similarity, and $d_s^2 = \|H_{left} - H_{right}\|^2$. If H_{ref} is the target reference model, H_c is the color local entropy of the current state, $w^{(i)}$ is the weights of the current state particles, the updating algorithm of the target template are as follows:

(1) If $S_{ref} = -1, 0\&S_c = -1, 0\&\max(w^{(i)}) \geq \lambda_1$, we update the template by $H_{ref,t+1} = (1-a)H_{ref,t} + aH_{u,t}$.

(2) If $S_c = -1, 0\&\max(w^{(i)}) < \lambda_2$, stop updating the template, increase the number of particles. Set the particle number to be $N + K$ in next frame till no longer meets this condition, and then set the number to be N.

(3) If $S_c = 1$, updating the template by $H_{ref,t+1} = (1-b)H_{ref,t} + bH_{u,t}$.

(4) If $S_{ref} = 1\&S_c = 0\&\max(w^{(i)}) \geq \lambda_1$, updating the template by $H_{ref,t+1} = (1-c)H_{ref,t} + cH_{u,t}$.

(5) If $S_{ref} = 1\&S_c = -1\&\max(w^{(i)}) \geq \lambda_1$, defining$d_{left}^2 = \left\|H_{left}^{ref} - H_{left}^{c}\right\|^2$ and $d_{right}^2 = \left\|H_{right}^{ref} - H_{right}^{c}\right\|^2$,

① if $d_{left}^2 > d_{right}^2$, $H_{ref,t+1} = (1-e)H_{ref,t}^{right} + eH_{u,t}^{right} + H_{u,t}^{left}$.

② if $d_{left}^2 < d_{right}^2$, $H_{ref,t+1} = (1-e)H_{ref,t}^{left} + eH_{u,t}^{left} + H_{u,t}^{right}$.

The forgetting factor a, b, c, e and thresholdλ_1, λ_2 were set according to the experiment.

D. ALGORITHM STEPS

In this paper, we use target's external rectangular box to describe the state of the moving target. The system state vector is defined as $X(k) = [a_x(k), a_y(k), v_x(k), v_y(k), w(k), h(k)]^T$, in which $a_x(k), a_y(k)$ represent the x and y coordinates of the target centroid. $(v_x(k), v_y(k))$ represents the speed in the corresponding direction, and $(w(k), h(k))$ represents the width and height of the tracking window. In the video target tracking, the speed of the moving vehicle in the tracking scene can be approximately uniform, and the first order motion model is adopted in this paper. The system state equation is:, where A is the state transfer matrix, B is the particle propagation radius, and $w(k)$ is the Gaussian noise with a mean value of zero. The concrete implementation steps of the particle filtering algorithm to improve the color local entropy are as follows:

Step 1. Initializing Particle: $k = 0$, the initial particle number is N. Manually select the tracking target, and calculate its weighted color distribution q_u and color local entropy H_u. Establis the initial state sample set $\left\{(x_0^{(i)}, 1/N)\right\}_{i=1}^{N} \sim p(x_0^{(i)})$, setting $k = 1$.

Step 2. Predicting Target State: Estimate the state of particle $x_k^{(i)}$ according to the system state equation and particle $x_{k-1}^{(i)}$.

Step 3. Calculating Particle Weights: Calculate and normalize the particle weights by formula.

Step 4. Updating Model and Determining Particle Number: Dynamically update the target reference template and the number of particles using the updating methods mentioned in section 3.2.

Step 5. Calculating Target Symmetry: If $S_c = 0, 1$ go to Step 6; if $S_c = -1$,

$d_t^2 = 2 \cdot \min(\left\|H_{ref}^{left} - H_c^{left}\right\|^2, \left\|H_{ref}^{right} - H_c^{right}\right\|^2)$.

Step 6. Outputting: The particle state with the largest weight value is output as the tracking result, and the target tracking region is obtained.

Step 7. Resampling Particle: Resample particle based on the principle of materiality [34]. Set, and turn into Step 2 to continue the next frame of tracking.

IV. IMPROVED SIFT FEATURE PARTICLE FILTERING TRACKING ALGORITHM

A. TARGET MODEL BASED ON SIFT

Assuming that the target model contains m SIFT feature points, and using S to represent the target model, then $S = \{f_i\}_{i=1}^{m}$, where f_i represents an eigenvector of a SIFT feature point. Assuming that S_k represents the candidate target model in the k frame target image, there is E, where F is a set of eigenvectors of the SIFT feature point.

In the case of occlusion and deformation, not all feature points in the target model can find the matching feature point in the candidate target S_k^i. In this paper, the matching points of feature points are calculated by using the methods mentioned in literature [35]. For any feature point $f_i, f_i \in S$, we calculate the shortest Euclidean distance and sub-short Euclidean distance of all feature points in S_k^i. If the ratio of the shortest Euclidean distance to the sub-short Euclidean distance is less than a certain threshold (literature [35] taking 0.4), it shows that feature point f_i has matching feature points in S_k^i, and the Euclidean distance between f_i and matching feature points is the shortest Euclidean distance. By using the number of matching feature points between the target model and the candidate target model, the similarity between the models is described, and the observation likelihood function is defined as follows:

$$p\left(Z_k \middle| X_k = S_k^i\right) = 1 - \exp\left(-\sum_{j=1}^{m} d\left(f_j, map\left(f_j\right)\right)\right) \tag{12}$$

where $f_i \in S$, $map(f_j)$ is used to calculate the mapping of eigenvectors, and $map(f_j) \in S_k^i$; $d(\bullet)$ is defined as:

$$d\left(f_j, map\left(f_j\right)\right) = \begin{cases} 1, & if\ map\left(f_j\right) \neq \varnothing \\ 0, & otherwise \end{cases} \tag{13}$$

When the target changes, such as deformation, the model will change accordingly. Then the tracking should rely more on the feature points that have occurred more frequently in the recent period (there are matching feature points), which is stable feature points. In order to describe the stability of feature points, a weight is introduced with each eigenvector f_i as a feature point, and π_i in k frame image is defined as follows:

$$\pi_k^i = \frac{\Phi_{k-t}^{k-1}(f_i)}{\sum_{i=1}^{m} \Phi_{k-t}^{k-1}(f_i)} \tag{14}$$

where $\Phi_{k-t}^{k-1}(f_i)$ represents the number of occurrences of the feature point f_i in the most recent t frame image, and t is a weight statistic parameter, $0 < t < k$. If a feature point f_i appears more frequently in a historical frame, it corresponds to a larger weight π_i, then the target model can be defined as: $S = \{f_i, \pi_i\}_{i=1}^{m}$, and the observation likelihood function is rewritten as:

$$p\left(Z_k \middle| X_k = S_k^i\right) = 1 - \exp\left(-\sum_{j=1}^{m} \left(\pi_i d\left(f_j, map\left(f_j\right)\right)\right)\right) \tag{15}$$

The particle weight based on the SIFT feature is:

$$\begin{aligned} w_k^{[i]} &= w_{k-1}^{[i]} p\left(Z_k \middle| X_k = S_k^i\right) \\ &= w_{k-1}^{[i]} \left\{1 - \exp\left[-\sum_{j=1}^{m} \left[\pi_i d\left(f_j, map\left(f_j\right)\right)\right]\right]\right\} \end{aligned} \tag{16}$$

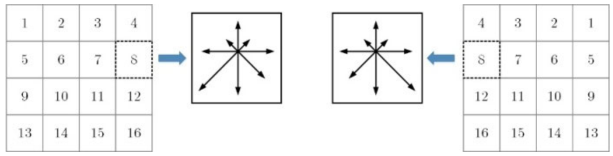

FIGURE 2. Symmetric coding of eigenvectors.

B. MODEL RENEWAL STRATEGY AND DYNAMIC ADJUSTMENT OF PARTICLE NUMBER

When the target changes in state during tracking, the SIFT features also change, so the target model needs to be updated, which includes adding or removing feature points and updating feature vectors of feature points.

(1) Deleting Feature Points: If a feature point repeats very few times within a past t frame, the feature point can be removed from the target model, which means that at the time $\pi_i < \tau$ (τ as a variable), the feature point i can be removed from the target model.

(2) After obtaining the target of the k frame, it is usually necessary to add new feature points to reflect the change of the target. However, a new feature point should be added in this process, in order to prevent the outer point be added to the target model (a feature point that is not part of the target), which means that at the time $\pi_i > \varsigma$(ς as a constant), the new feature point is i.

(3) Updating Eigenvectors: After obtaining the target state of the k frame, when the feature points in the target model have corresponding feature points in the candidate target, it is necessary to update the eigenvector of the feature point, that is, the gradient direction histogram. The formula is as follows:

$$bin(f_i, j) = (1 - \omega)bin(f_i, j) + \omega bin(mapf_i, j) \tag{17}$$

where ω is a constant, and $bin(f_i, j)$ represents the value of the j of the bin in f_i, which reduces the impact of local noise.

(4) Using Symmetry To Replicate Eigenvectors: On the basis of the established database of the SIFT feature, the robustness of the system is enhanced by using symmetry to replicate the eigenvectors of higher weights.

SYMMETRIC CODE OF EIGENVECTORS

Symmetrically encoding the whole 16 seed vectors, which each original eigenvector includes 4×4 eigenvectors p_i with 8 directional vectors; at the same time, symmetrically encoding the 8 directional vectors within the seed point, resulting in new 4×4 eigenvectors q_i with 8 directional vectors. The eigenvectors p_i and q_i are asymmetrical to the axis of the license plate, as in Figure 2.

V. VEHICLE TRACKING BASED ON MULTI-FEATURE FUSION PARTICLE FILTER

In section II, the particle tracking algorithm based on color local entropy can track the target in real-time under the conditions of occlusion and illumination change. But the long-time tracking performance would be influenced by the particle degradation in the process of color local entropy tracking. The use of this algorithm would be affected by factors such as particle quantity, search range and motion model, and the failure of tracking would happen under the conditions of sudden target acceleration, the large area occlusion of the target and the sudden change of illumination. Moreover, the failure of tracking would happen when there are similar color targets near the candidate target. In this case, using the tracking method based on the SIFT feature point should be a better choice.

In section III, the method of the particle filter tracking based on SIFT feature points has good robustness to the tracking performance when the target is under the conditions of local occlusion, sudden illumination change, rotation and so on. When the target is too small or the target texture is almost consistent, it is impossible to use SIFT feature points to describe the target because there are not enough valid feature points. In this situation, the advantage of using the tracking method based on color local entropy is more obvious. In addition, here are some shortcomings in real-time tracking performance due to the huge amount of calculation of the SIFT feature point description.

To maintain a long-time stable tracking of the target in the complex environment, there are three technical problems need to be solved: (1) How to adapt to the changes of the appearance of the target, to update the target model reasonably, and to suppress the emergence of tracking drift phenomenon; (2) How to overcome the interference of similar color and texture target; (3) How to recapture the target quickly and continue tracking when the target is lost.

In order to deal with the above problems, two methods are proposed in this chapter: Firstly, use the particle filter tracking method combined with the SIFT characteristics and color local entropy; Secondly, detect the license plate or SIFT characteristics of the target vehicle in the target area of the Kalman filter prediction to reacquire the location of the target.

A. COLOR LOCAL ENTROPY PARTICLE FILTERING WITH SIFT FEATURES

Considering the above problems, we propose, in this chapter, a color local entropy particle filtering algorithm that combines the characteristics of the SIFT. The final weight of the particles calculated by the new algorithm is determined by the particle weight $w_k^{[i]}$ based on the color local entropy and the particle weight $w_k^{(i)}$ based on the SIFT features. Therefore, the final weight of the particle is:

$$w_k^i = \alpha w_k^{(i)} + (1-\alpha) w_k^{[i]} \tag{18}$$

where α is the dominant weight of the color local entropy, $0 \leq \alpha \leq 1$.

The state estimation equation for the k frame is:

$$\hat{w}_k^i = \sum_{i=1}^{N} w_k^i X_k^i \tag{19}$$

where α represents the proportion of two weights with different characteristics, which should be selected according to the specific situations.

(1) When the target is far away, the value of α should increase. In order to reduce the calculation amount of the system, the value of τ should increase correspondingly, and the value of t should decrease correspondingly, thus the calculation amount of the SIFT feature model would decrease.

(2) When the target is affected by large area occlusion or sudden illumination ($\max(w^{(i)}) < \lambda_2$), as well as the local sample entropy particles are seriously degraded, the value of α should be reduced appropriately, and the value of τ should decrease correspondingly, as well as the value of t would increase t correspondingly.

B. TARGET SEARCHING

When the target is lost, traditional methods tend to detect the target in the area with a radius of r, which the center of the area is the target center point of the previous frame. In order to ensure that the moving target can appear in the searching area, the searching radius must be long enough, but the longer searching radius will inevitably make the scanning window increase greatly, resulting in an increase in the calculation. The method based on motion parameter prediction uses state space to describe the motion characteristics of the tracked target. Filter is an algorithm for linear minimum variance prediction of state sequences of dynamic systems, which has the characteristics of small calculation and strong practicability. What's more, it can accurately predict the position and speed of the target in the next moment.

In this chapter, the way to search for the lost target is the Kalman filter method combined with the recognition information of the target license plate and the SIFT features. Filtering theory can be used to accurately predict the motion position of the tracking target. The neighborhood area with prediction point as the center can be used as the searching window, which is very effective, to locate the license plate accurately, which can greatly simplify the calculation. The specific approaches are as follows: predict the state value of the target on the frame according to the state value of the target on the k frame, and detect the license plate in the specified prediction area of the $k+1$ frame. Then obtain the exact position of the target in the frame. The new position is used as the observation value of the filter process to update the filter parameters, which is the initial state of predicting at the next moment.

1) KALMAN FILTER TARGET STATE PREDICTION

In the video target tracking, the target vehicle can be approximated seen as moving in uniform between the adjacent two frames, so this section uses the first order motion model. Define the target state vector as $X_k = [x(k), y(k), v_x(k), v_y(k)]$, the observation vector as $Z_k = [x(k), y(k)]$, where $x(k), y(k), v_x(k), v_y(k)$ are as the coordinates and velocity of the center position of the target in the image, then the Kalman state equation and the measurement equation in the k moment are:

$$\begin{aligned} X_k &= A_k x_{k-1} + W_{k-1} \\ Z_k &= C_k X_k + V_k \end{aligned} \tag{20}$$

where W_{k-1} is process noise and V_k is observed noise. W_{k-1} and V_k select Gaussian white noise with a mean value of zero, T represents the time interval of two adjacent frames, represents the system state transfer matrix, $C(k)$ represents the observation matrix, $A(k) = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$, $C(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$. The position of the target in the current frame is predicted by the following 5 formulas of the Kalman filter.

$$\begin{cases} X_{k|k-1} = A_k X_{k-1|k-1} \\ P_{k|k-1} = A_k P_{k-1|k-1} A_k^T + Q_{k-1} \\ H_k = P_{k|k-1} C_k^T \left(C_k P_{k|k-1} C_k^T + R_k \right)^{-1} \\ X_{k|k} = X_{k|k-1} + H_k \left(Z_k - C_k X_{k|k-1} \right) \\ P_{k|k} = \left(1 - HkCk \right) P_{k|k-1} \end{cases} \tag{21}$$

where $X_{k|k-1}$ is the system predictive state vector, $X_{k|k}$ is the system correction state vector, $P_{k|k-1}$ and $P_{k|k}$ are the priori error covariance matrix and the posterior error covariance matrix, H_k is the gain matrix of the Kalman filter, Q is the process noise covariance matrix, R is the observation noise covariance matrix, the position of the target center in $X_{k|k-1}$ is the search center of the plain Bayesian classifier.

2) TARGET SEARCH STEPS

Step 1. Use Kalman Filter to predict the target position $X_{k|k-1}$ in the k frame of the lost tracking target $Veh1$ in the $k-1$ frame;

Step 2. Establish a planar coordinate system with central position $X_{k|k-1}$ as searching center O_{k-1}^k, r_1 as searching radius, (x, y) as target centroid coordinate. Then establish a searching area equation by using the symmetry of the searching region:

$$\begin{cases} x^2 + y^2 = {r_1}^2 \ , \quad -r_1 \le x \le r_1, -r_1 \le y \le r_1 \\ r_1 = t_{k-1}^k \sqrt{{v_x}^2(k) + {v_y}^2(k)} \end{cases} \tag{22}$$

Step 3. Set $Lpn1$ as the license plate number of the vehicle $Veh1$, jump to Step 6 while detecting $Lpn1$ in the searching area defined in Step 2;

Step 4. Compare the SIFT feature point set $S_{Veh1} = \{f_i\}_{i=1}^m$ of $Veh1$ with the foreground target features in the searching radius to find the matching target, then jump to Step 6;

Step 5. Turn to Step 1 to predict the target position $X_{k+1|k}$ in the $k+1$ frame of $Veh1$;

Step 6. According to the relative coordinate invariance of the matching SIFT feature point and the target centroid and the reference coordinate system in Step 2, calculate the coordinate of the target centroid.

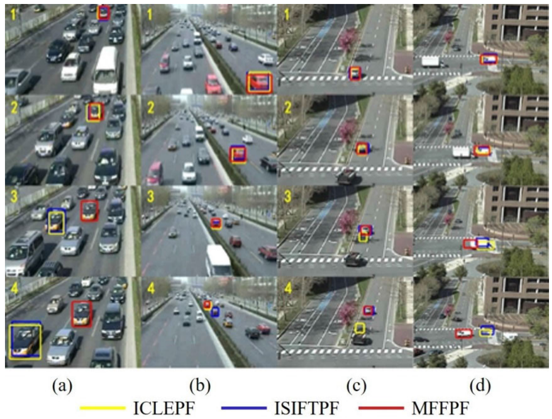

FIGURE 3. Tracking result with the proposed three methods and ICLEPF in four traffic sequences. (a) Background clutters. (b) Scale variation. (c) Illumination variation. (d) Occlusion.

VI. IMPLEMENTATION AND RESULTS

The implementation of algorithm is derived from OpenCV3.1.0 and Visio Studio 2013. The experimental testing is performed on a system using Intel® Core™ i7-6900K CPU 3.50 GHz (8 cores) with 32 GB of RAM, and NVIDIA GeForce GTX 1080Ti (3584 CUDA cores) with graphics memory of 11 GB.

A. QUALITATIVE EVALUATION

1) EXPERIMENT 1: COMPARISON BETWEEN PROPOSED METHODS

In order to verify the robustness of the three methods we proposed in this paper, four test video sequences are selected from two self-mining public surveillance video as shown in Figure 3(a) and Figure 3(b), besides MIT traffic dataset [36] as shown in Figure 3 (c) and Figure 3(d), including the interference situation, such as Figure 3(a) the background near the target has the similar color or texture as the target; Figure 3 (b) the ratio of the bounding boxes of the first frame and the current frame is out of the range; Figure 3 (c) the illumination in the target region is significantly changed; Figure 3 (d) the target is partially or fully occluded.

The yellow tracking box stands for improved color local entropy particle filter tracking algorithm (ICLEPF), the blue tracking box stands for the tracking effect of improved SIFT feature particle filtering tracking algorithm (ISIFTPF), and the red tracking box stands for the tracking effect of multi-feature fusion particle filter (MFFPF).

Figure 3 (a) represents background clutters challenge, the similar features near the target, result in the failure of ICLEPF and ISIFTPF. Figure 3 (b) shows scale variation challenge. as the target is farther away from the camera, not enough effective SIFT features, which results in the failure of ISIFTP. Figure 3 (c) compares illumination

FIGURE 4. **Tracking effect comparison of ten methods on OTB dataset.**

variation challenge, after the target enters the shaded area, ICLEPF failed. Figure 3 (d) is occlusion challenge, during the tracking process, the target is occluded, and MFFPF can continue to track the target through the target relocation strategy.

2) EXPERIMENT 2: COMPARISON ON OBT DATASET

To perform the comparative evaluation, we consider nine trackers: CF2 [37], CCOT [38], LCT [39], KCF [40], CNN_SVM [41], SAMF [42], CLEPF [33], MEEM [43], Staple [44]. Eight test attributes were selected on OBT dataset [45], which represents the challenging aspects in visual tracking, were named Background Clutters (BC), Deformation (DEF), Fast Motion (FM), In-Plane Rotation (IPR), (Illumination Variation (IV), Occlusion (OCC), Out-of-View (OV), Scale Variation (SV). Tracking effect comparison of ten methods on OTB dataset presented in Figure 4, Ten videos from top to bottom named: BlurCar1, BlurCar2, BlurCar3, Blurcar4, Car1, Car2, Car4, Car24, Car Dark, Car Scale, which were selected from OBT Dataset.

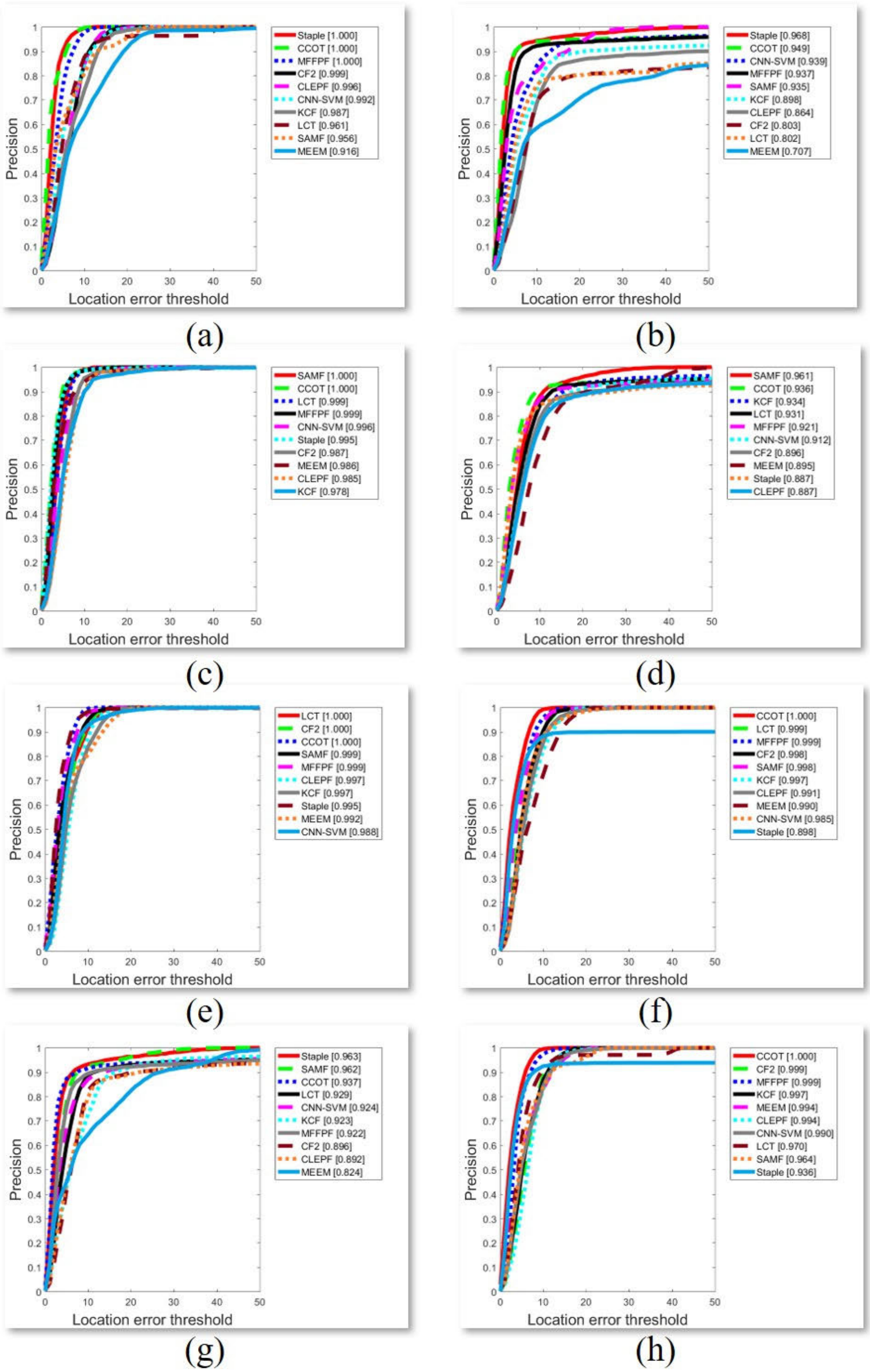

FIGURE 5. **Precision plots of 10 tracking algorithms on 8 attribute OTB dataset. (a) Background clutter; (b) deformation;(c) fast motion; (d) illumination variation; (e) inplane rotation; (f) occlusion; (g) out of view; (h) scale variation.**

B. QUANTITATIVE EVALUATION

1) PERFORMANCE ON OBT DATASET

We will quantitatively analyze the effect of the algorithm from four aspects: Location error threshold, precision, overlap threshold, success rate. Eight attributes test sequences were selected, which represents the challenging aspects in visual tracking. Figure 5 clearly illustrates the precision of the OPE on eight different attributes.

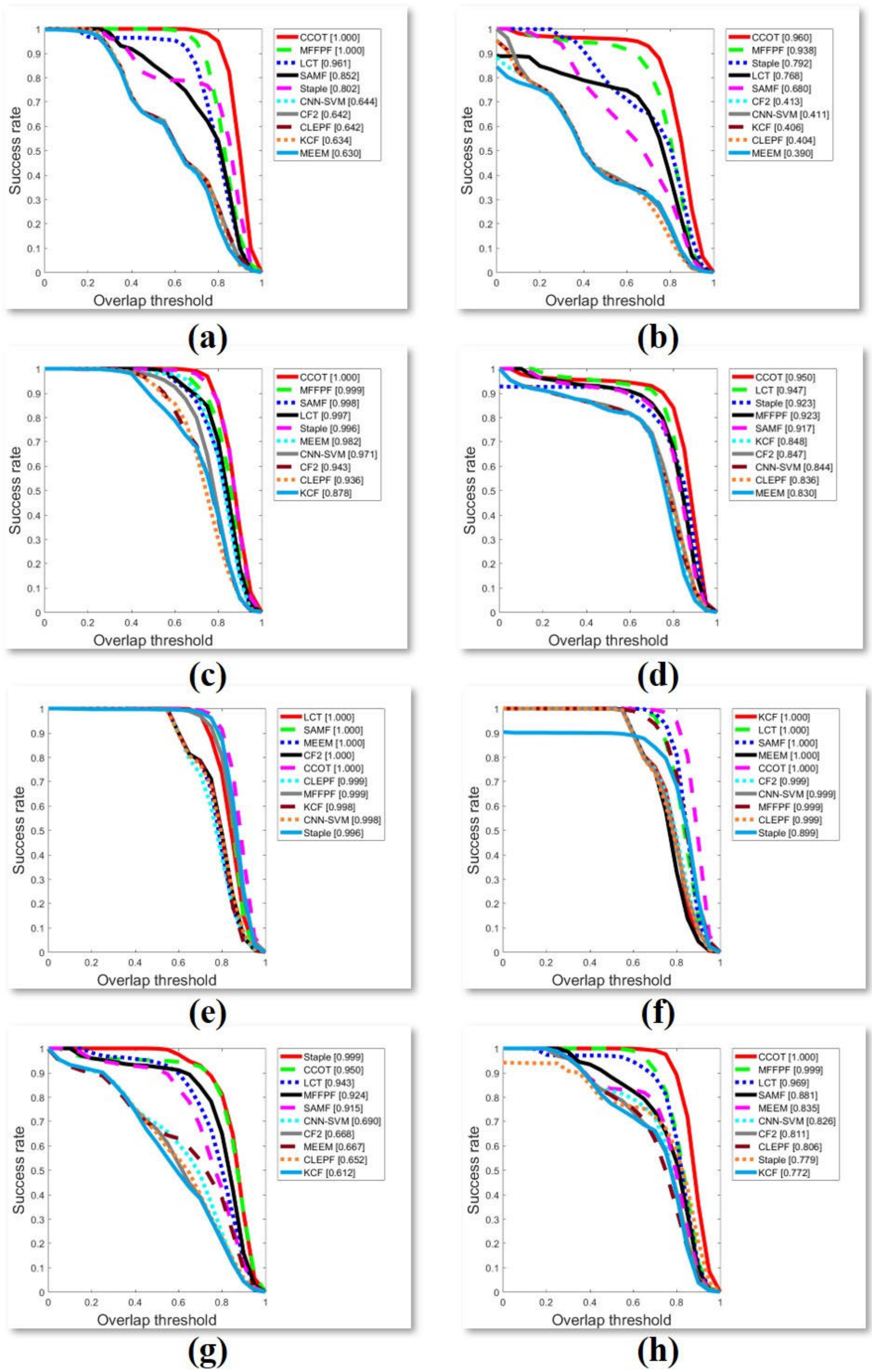

FIGURE 6. **The success plots of 10 tracking algorithms on OTB dataset eight different. (a) Background clutter; (b) deformation; (c) fast motion; (d) illumination variation;(e) inplane rotation; (f) occlusion; (g) out of view; (h) scale variation.**

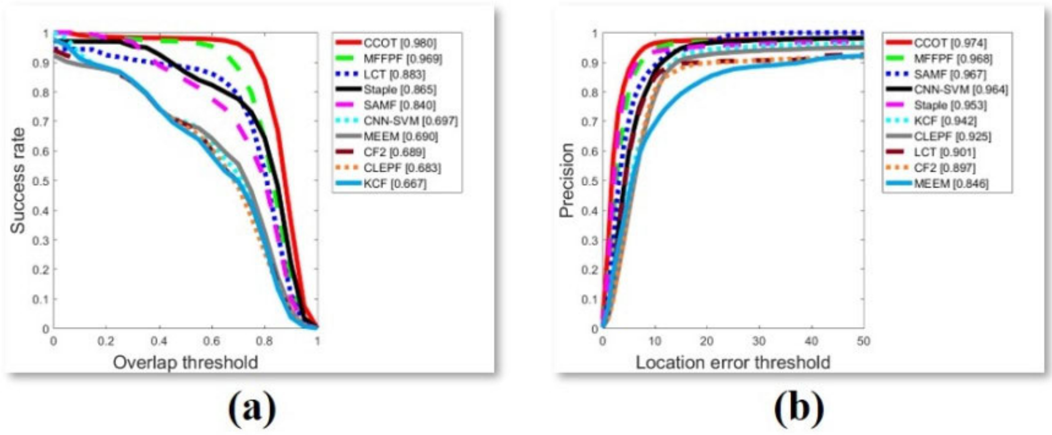

FIGURE 7. **Tracking effect comparison of ten methods on OTB dataset. (a) Average success rate with OPE. (b) Average precision with OPE.**

Figure 7 explicitly shows the comparison results on OBT Dataset in terms of the average precision plots (PP) and average success plots (SP) of one pass evaluation (OPE). As shown in Figure 7, our algorithm MFFPF achieves a comparable result.It gets the second place in both precision and success.

VII. CONCLUSION

In this paper, we proposed a robust and efficient vehicles tracking algorithm. The contributions of this paper are summarized as follows.

(1) In order to deal with the tracking failure caused by large-area occlusion in the target tracking process, we propose an improved particle filter tracking algorithm based on color, which uses the symmetry of information entropy.
(2) Under the conditions of improving the operation speed based on the SIFT feature particle filtering tracking algorithm, in order to enhance the robustness of the algorithm, we use symmetry to replicate symmetric eigenvectors.
(3) Combining the color local entropy representing the global information of the target with the SIFT characteristics representing the local feature information of the target, as well as the license plate information, this paper proposed a particle filter tracking algorithm that fuses the color local entropy and the SIFT characteristics, which uses the Kalman filter to predict the motion state of the vehicle, and quickly searches and positions the accurate location of the lost target vehicle according to the vehicle SIFT and license plate characteristics. This algorithm not only ensures the real-time performance, but also improves the robustness.

Through the comparison of experiments, the improving validity of the improved particle filter tracking algorithm in section 3 and the improved SIFT feature particle filter tracking algorithm (ISIFTPF) in section 4 were verified firstly. Then the robustness and the real-time performance of the multi-feature fusion particle filter vehicle tracking algorithm were verified, under four complex situations, including the proximity to the same model interference conditions, the distance caused by the reduction of feature points, the illumination mutations, the target disappearance and reproduction. In the future, our study focus will shift to the field of multi-target tracking in the intelligent transportation system and the vehicle target tracking under the low illumination conditions at night.

REFERENCES

[1] N. Wax, "Signal-to-noise improvement and the statistics of track populations," *J. Appl. Phys.*, vol. 26, no. 5, p. 586, 1955.
[2] R. W. Sittler, "An optimal data association problem in surveillance theory," *IEEE Trans. Military Electron.*, vol. 8, no. 2, pp. 125–139, Apr. 1964.
[3] Y. Bar-Shalom, "Tracking methods in a multi target environment," *IEEE Trans. Autom. Control*, vol. AC-23, no. 4, pp. 618–626, Aug. 1978.
[4] R. A. Singer, "Estimating optimal tracking filter performance for manned maneuvering targets," *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-6, no. 4, pp. 473–483, Jul. 1970.
[5] Y. Cheng, "Mean shift, mode seeking, and clustering," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 17, no. 8, pp. 790–799, Aug. 1995.
[6] X.-R. Li and Y. Bar-Shalom, "Multiple-model estimation with variable structure," *IEEE Trans. Autom. Control*, vol. 41, no. 4, pp. 478–493, Apr. 1996.
[7] T. Kirubarajan and Y. Bar-Shalom, "Low observable target motion analysis using amplitude information," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 32, no. 4, pp. 1367–1384, Oct. 1996.
[8] S. Mori, B. J. Crain, V. P. Chacko, and P. C. M. Van Zijl, "Three-dimensional tracking of axonal projections in the brain by magnetic resonance imaging," *Ann. Neurol.*, vol. 45, no. 2, pp. 265–269, Feb. 1999.
[9] H.-N. Dai, R. C.-W. Wong, and H. Wang, "On capacity and delay of multichannel wireless networks with infrastructure support," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1589–1604, Feb. 2017.
[10] H.-N. Dai, R. C.-W. Wong, H. Wang, Z. Zheng, and V. A. Vasilakos, "Big data analytics for large-scale wireless networks: Challenges and opportunities," *ACM Comput. Surv.*, vol. 52, no. 5, p. 99, Sep. 2019.
[11] H.-N. Dai, H. Wang, G. Xu, J. Wan, and M. Imran, "Big data analytics for manufacturing Internet of Things: Opportunities, challenges and enabling technologies," *Enterprise Inf. Syst.*, vol. 13, pp. 1–25, Jun. 2019.
[12] A. Doucet, S. Godsill, and C. Andrieu, "On sequential Monte Carlo sampling methods for Bayesian filtering," *Statist. Comput.*, vol. 10, no. 3, pp. 197–208, Jul. 2000.

[13] N. J. Gordon, D. J. Salmond, and A. F. M. Smith, ''Novel approach to nonlinear/non-Gaussian Bayesian state estimation,'' *IEEE Proc. Radar Signal Process.*, vol. 140, no. 2, pp. 107–113, Apr. 1993.
[14] S. J. Godsill, J. Vermaak, W. Ng, and J. F. Li, ''Models and algorithms for tracking of maneuvering objects using variable rate particle filters,'' *Proc. IEEE*, vol. 95, no. 5, pp. 925–952, May 2007.
[15] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, ''A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking,'' *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Feb. 2002.
[16] M. Isard and A. Blake, ''CONDENSATION—Conditional density propagation for visual tracking,'' *Int. J. Comput. Vis.*, vol. 29, no. 1, pp. 5–28, Aug. 1998.
[17] Y. Kang, W. Xie, and B. Hu, ''A scale adaptive mean-shift tracking algorithm for robot vision,'' *Adv. Mech. Eng.*, vol. 5, Jan. 2015, Art. no. 601612.
[18] P. Perez, C. Hue, J. Vermaak, and M. Gangnet, ''Color-based probabilistic tracking,'' in *Proc. Eur. Conf. Comput. Vis.*, 2002, pp. 661–675.
[19] K. Nummiaro, E. Koller-Meier, and L. Van Gool, ''An adaptive color-based particle filter,'' *Image Vis. Comput.*, vol. 21, no. 1, pp. 99–110, Jan. 2003.
[20] S. T. Birchfield and S. Rangarajan, ''Spatiograms versus histograms for region-based tracking,'' in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2, Jun. 2005, pp. 1158–1163.
[21] S. T. Birchfield and S. Rangarajan, ''Spatial histograms for region-based tracking,'' *ETRI J.*, vol. 29, no. 5, pp. 697–699, Oct. 2007.
[22] C. R. Del-Blanco, N. Garcia, L. Salgado, and F. Jaureguizar, ''Object tracking from unstabilized platforms by particle filtering with embedded camera ego motion,'' in *Proc. IEEE Int. Conf. Adv. Video Signal Based Surveill.*, Sep. 2009, pp. 400–405.
[23] I. Leichter, M. Lindenbaum, and E. Rivlin, ''Mean shift tracking with multiple reference color histograms,'' *Comput. Vis. Image Understand.*, vol. 114, no. 3, pp. 400–408, Mar. 2010.
[24] P. Li-Zhi and W. Run-Sheng, ''Particle filter tracker based on multiple color distribution models,'' *J. Circuits Syst.*, vol. 16, no. 1, pp. 92–96, 2011.
[25] J. Wang and Y. Yagi, ''Integrating color and shape-texture features for adaptive real-time object tracking,'' *IEEE Trans. Image Process.*, vol. 17, no. 2, pp. 235–240, Feb. 2008.
[26] J. Ning, L. Zhang, D. Zhang, and C. Wu, ''Robust object tracking using joint color-texture histogram,'' *Int. J. Pattern Recognit. Artif. Intell.*, vol. 23, pp. 1245–1263, Nov. 2009.
[27] I. Leichter, M. Lindenbaum, and E. Rivlin, ''Tracking by affine kernel transformations using color and boundary cues,'' *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 1, pp. 164–171, Jan. 2009.
[28] H. Zhou, Y. Yuan, and C. Shi, ''Object tracking using SIFT features and mean shift,'' *Comput. Vis. Image Understand.*, vol. 113, no. 3, pp. 345–352, Mar. 2009.
[29] M. Kristan, J. Perš, S. Kovačič, and A. Leonardis, ''A local-motion-based probabilistic model for visual tracking,'' *Pattern Recognit.*, vol. 42, no. 9, pp. 2160–2168, Sep. 2009.
[30] Z. Jiang, ''Object modelling and tracking in videos via multidimensional features,'' *ISRN Signal Process.*, vol. 2011, Feb. 2011, Art. no. 173176.
[31] X. Qiu, S. Liu, and F. Liu, ''An adaptive kernel-based target tracking method based on multiple features fusion,'' *IEEE Trans. Electr. Electron. Eng.*, vol. 7, no. 1, pp. 91–97, Jan. 2012.
[32] M. Zhan, M. Xin, and J. Yang, ''Adaptive multi-feature tracking in particle swarm optimization based particle filter framework,'' *J. Syst. Eng. Electron.*, vol. 23, no. 5, pp. 775–783, Oct. 2012.
[33] H. Wang, Q. Wang, W. Meng, and D. Yaping, ''A particle filter algorithm for real-time multiple objects tracking based on color local entropy,'' in *Proc. 3rd Int. Conf. Instrum., Meas., Comput., Commun. Control*, Sep. 2014, pp. 114–119.
[34] Y. Wang, X. Ban, J. Chen, B. Hu, and X. Yang, ''License plate recognition based on SIFT feature,'' *Optik*, vol. 126, no. 21, pp. 2895–2901, Nov. 2015.
[35] D. G. Lowe, ''Distinctive image features from scale-invariant keypoints,'' *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, Nov. 2004.
[36] W. Meng, W. Li, and X. Wang, ''Transferring a generic pedestrian detector towards specific scenes,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2012, pp. 3274–3281.
[37] C. Ma, J.-B. Huang, X. Yang, and M.-H. Yang, ''Hierarchical convolutional features for visual tracking,'' in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2015, pp. 3074–3082.
[38] M. Danelljan, A. Robinson, F. S. Khan, and M. Felsberg, ''Beyond correlation filters: Learning continuous convolution operators for visual tracking,'' in *Proc. Eur. Conf. Comput. Vis.*, vol. 9909. Springer, 2016, pp. 472–488.
[39] C. Ma, X. Yang, C. Zhang, and M.-H. Yang, ''Long-term correlation tracking,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2015, pp. 5388–5396.
[40] J. F. Henriques, R. Caseiro, P. Martins, and J. Batista, ''High-speed tracking with kernelized correlation filters,'' *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 3, pp. 583–596, Mar. 2015.
[41] S. Hong, T. You, S. Kwak, and B. Han, ''Online tracking by learning discriminative saliency map with convolutional neural network,'' in *Proc. Int. Conf. Mach. Learn.*, Jun. 2015, pp. 597–606.
[42] Y. Li and J. Zhu, ''A scale adaptive kernel correlation filter tracker with feature integration,'' in *Proc. Eur. Conf. Comput. Vis.*, Cham, Switzerland: Springer, 2014, pp. 254–265.
[43] J. Zhang, S. Ma, and S. Sclaroff, ''MEEM: Robust tracking via multiple experts using entropy minimization,'' in *Proc. Eur. Conf. Comput. Vis.*, Cham, Switzerland: Springer, 2014, pp. 188–203.
[44] L. Bertinetto, J. Valmadre, S. Golodetz, O. Miksik, and P. H. S. Torr, ''Staple: Complementary learners for real-time tracking,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 1401–1409.
[45] Y. Wu, J. Lim, and M.-H. Yang, ''Online object tracking: A benchmark,'' in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2013, pp. 2411–2418.

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