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Face Tracking Algorithm of Power Warehouse Based on Multi-Feature Fusion Particle Filter

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Abstract

In order to improve the tracking effect of video objects in power warehouse, a particle filtering target tracking algorithm based on multi-feature fusion is proposed, which combines the nonlinear and non-Gaussian characteristics of state model and observation model in video objects tracking. Firstly, an adaptive method for selecting target color histogram is proposed to obtain more accurate target color features. Then, Local Ternary Patterns (LTP) texture features are introduced into the tracking algorithm. Based on the LTP texture features, the LTP key texture model is constructed to further enhance the target key texture information. Finally, the color feature and texture feature are used to represent the target, and the two features are fused into the framework of particle filtering, and the weight of the particle is calculated by using the fused information to reduce the influence of the algorithm on the target deformation and complex environment; at the same time, the idea of weighted classification is adopted to assign different weights according to the different contributions of different features to the classification effect, and larger weights are assigned to the reliability features to improve the classification accuracy. The experimental results show that the proposed algorithm can not only track the face effectively, but also get better tracking effect when the color of the target is disturbed, which can be applied to face tracking task in power warehouse.

Keywords: *Face tracking, particle filter, multi-features fusion, local ternary patterns*

I. Introduction

Because of the high risk of national electric power material storage and the high security of the power warehouse, it is necessary to identify and predict the possible risks in the power warehouse to protect the safety of the warehouse. The biggest risk of power warehouses comes from two aspects: one is whether the staff work safely and regulate their operations; the second is whether non-workers break into the restricted area for activities [1]. Therefore, it is an important measure to protect the safety of power warehouse by using of video monitoring and face tracking technology to track the working track of staff and the movement track of non-staff breaking into the work forbidden area. Face tracking is a hot research topic in the field of computer vision. Its main task is to detect, recognize and track moving objects from image sequences, and even to understand and describe the behavior of target objects [2]. Target tracking is widely used in human motion recognition, video surveillance, video retrieval, virtual reality and human-computer interaction. The description or representation of target features is a key part of target tracking. The features commonly used include color, edge, optical flow and texture. Among them, color feature is widely used to track moving targets because of its partial occlusion, strong rotation robustness and scale invariance [3, 4].

In the process of target tracking using color features, color histogram is usually used to model the target color. The

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color histogram is robust to the target's expansion, rotation and partial occlusion. However, when the tracked target rotates or changes its pose, the overall color histogram is not effective for tracking the target due to the lack of spatial information. To solve this problem, Okuma [5] et al. adopted multi-parts color histogram as the target color model. However, the research results of Muroi [6] et al. show that when the target color is single, the spatial information of the target is not needed, and the effect of using the overall color histogram is better. According to the characteristics of the whole color histogram and the multi-block color histogram, this paper proposes an adaptive color histogram selection method. When the target color is relatively single, the overall color histogram is selected as the target color model. When the target color is complex, the multi-block color histogram is selected as the target color model.

However, when a single color feature is used to track the target, the tracking effect of the target will be affected when there is interference of objects with similar color in the background. Using a variety of features to track the target can overcome the deficiency of relying solely on color features to track the target. The texture feature describes the spatial distribution of pixel gray in the image and provides a method to describe the spatial structure of the image. In this paper, the color feature and Local Ternary Patterns (LTP) texture feature of the target are fused into the calculation of particle weight, which improves the tracking stability and accuracy of the video sequence image. The main contributions of this paper are as follows:

(1) In order to improve the robustness of target tracking, this paper adopts adaptive color histogram as the target color model, and adaptively selects the whole color histogram or multiple color histograms according to the color distribution of the target

(2) Local Ternary Patterns (LTP) texture features are introduced, and based on LTP texture features, a LTP key texture model is proposed, which not only enhances the target key texture information, but also simplifies the original LTP texture model

(3) In order to overcome the influence of background confusion on target tracking, LTP key texture features were introduced as the auxiliary features of target tracking, color features and texture features were regarded as two independent tracking clues, and the multiplicative fusion strategy was adopted in the particle filter framework to achieve target tracking

Experimental results show that the algorithm proposed in this paper can not only improve the robustness of target tracking, but also achieve good tracking results in the case of serious background confusion. It can be applied to both single target tracking and multi-target tracking occasions.

II. Multi-Feature Extraction

2.1 Color Features

2.1.1 HSV Weighted Color Histogram

Color feature is often used to track the target because it is insensitive to the rotation and attitude change of the target. In this paper, a weighted color histogram based on HSV color space is used to represent the target color distribution $\{p_y^{(u)}\}_{u=1,2,\cdots,m}$ centered on $\boldsymbol{y}$,

$$p_y^{(u)} = f\sum_{i=1}^{N} k\left(\frac{\| \boldsymbol{y} - \boldsymbol{x}_i \|}{h}\right)\delta[b(\boldsymbol{x}_i) - u] \tag{1}$$

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$$k(r)=\begin{cases}1-r^2, r<1\\0, \quad r\geq 1\end{cases} \tag{2}$$

where, $u=1,2,\cdots,m$ represents the rank index of the color in the histogram; N is the number of pixels in the region; $\boldsymbol{x}_i$ represents the coordinates of each pixel in the region; $b(\boldsymbol{x}_i)$ represents the index value of the histogram corresponding to each pixel; $\delta[\cdot]$ is the Dirac delta function; $|\boldsymbol{y}-\boldsymbol{x}_i\|$ is the distance from $\boldsymbol{x}_i$ to $\boldsymbol{y}$; parameter h represents the tracking window width; $k(r)$ is the weight function, so that the pixel located in the central region of the target has a high weight; $f=1\Big/\sum_{i=1}^{N}k\left(\frac{\|y-x_i\|}{h}\right)$ is the normalization factor. The Bhattacharyya coefficient was used to describe the similarity between the target feature p_y and the candidate region q_y, that is

$$\rho(p_y,q_y)=\sum_{n=1}^{m}\sqrt{p_y^{(u)}\cdot q_y^{(u)}} \tag{3}$$

2.1.2 Adaptive Color Histogram

The particle filtering target tracking algorithm based on color histogram can track the target in complex environment and partially occluded target [7, 8]. However, when the color similar to the object being tracked appears in the background, the tracking effect will not be ideal or even miss the target. To solve this problem, Ahmed [9] and Wang [10] proposed multi-parts color histogram. Multi-block color histogram is to divide a certain area into several blocks and calculate the color histogram of each block area respectively. The comparison of experimental results in references [10, 11] demonstrates the effectiveness of using multi-block color histograms to model target colors. The multi-block color histogram uses the color and spatial information of the target to model the color distribution and is more robust than the whole color histogram. However, the research results of references [12, 13] show that when the target color is a single color, using the whole color histogram to model the target color has a better tracking effect than using the multi-block color histogram.

According to the characteristics of the whole color histogram and the multi-block color histogram, this paper proposes an adaptive color histogram selection method. First, the color histogram of each block is calculated and the degree of similarity d between them is found, known as the Bhattacharyya coefficient. When d is greater than the threshold T, it indicates that the colors of each sub-region are very similar, and then the overall color histogram is selected to model the target color; Otherwise, select the multi-block color histogramto model the target color.

The similarity between two multi-block color histograms $A'=\{p_1,p_2,\cdots,p_n\}$ and $B'=\{q_1,q_2,\cdots,q_n\}$ is calculated according to Equation (4):

$$d_{mult}(A',B')=\frac{\sum_{i=1}^{n}d(p_i,q_i)}{n} \tag{4}$$

where, p_i is the color histogram of the i-th block region of a multi-block color histogram; q_i is the color histogram of the i-th block region of another multi-block color histogram; n represents the number of block regions divided into, and n=4 in this paper.

2.2 Texture Features

2.2.1 LBP Texture Feature

LBP is a point sample texture estimation method. The texture of a point is usually obtained by subtracting the gray value of the point and the gray value of the neighboring points [6, 9]. The gray values of sampling points whose coordinates are not integer positions can be obtained by bilinear interpolation. The LBP texture feature calculation formula of the image is as follows [11],

$$\mathrm{LBP}_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{5}$$

where, $s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$ is the threshold function; R is the distance between the center pixel and its neighbors, reflecting the spatial resolution of the texture; P is the number of neighborhood pixels, and g_c is the gray value of the center point; g_p represents the gray value of the p-th equal point on the ring with a center point g_c and a radius of R. In this paper, we set $P = 8, R = 1$.

Equation (5) only has scale invariance, in order to make the texture have rotation invariance at the same time, the above binary mode can be rotated according to certain rules, so that the original 256 texture modes can be merged into 36texture modes. Among them, the 9 patterns with the highest occurrence frequency are called uniform patterns, and the corresponding pattern value is $0 \sim 8$, denized as $\mathrm{LBP}_{S,1}^{uni}$ (see Literature [14] for details). The specific definitions are as follows

$$\mathrm{LBP}_{S,1}^{uni}(x_c, y_c) = \begin{cases} \sum_{p=0}^{7} s(g_p - g_c), U(\mathrm{LBP}_{S,1}) \leq 2 \\ 9, else \end{cases} \tag{6}$$

2.2.2 LTP texture feature

Although LBP model has scale invariance and rotation invariance, it is sensitive to noise interference and has poor robustness. In order to increase its anti-noise performance, the threshold function of LBP model was modified in reference [9], and the LTP texture feature was proposed. Its threshold function $s'(x_c, y_c)$ is defined as follows

$$s'(x_c, y_c) = \begin{cases} 1, g_p \geq g_c + t \\ 0, |g_p - g_c| < t \\ -1, g_p \leq g_c - t \end{cases} \tag{7}$$

Where t is the noise threshold, and the magnitude of t directly determines the anti-noise performance of LTP algorithm. In this paper, we set $t=5$. The symmetry and noise threshold of LTP texture mode can effectively filter out the noise and improve the robustness of the algorithm. LTP texture model can be constructed by building histogram of LTP texture features.

III. Multi-Feature Fusion Based Particle Filter

3.1 Basic theory of particle filtering

Particle filtering is a method developed to deal with the problem that the posterior probability density and the observation process probability density are non-Gaussian [11]. Particle filtering is also known as Monte Carlo filtering, which is a non-parametric Monte Carlo simulation method to achieve recursive Bayesian filtering. Its basic principle is as follows: suppose the dynamic system can be represented by the following state space model

$$\boldsymbol{X}_k = g_k(\boldsymbol{X}_{k-1}, \boldsymbol{r}_{k-1}) \tag{8}$$

$$\boldsymbol{Y}_k = h_k(\boldsymbol{X}_k, \boldsymbol{\lambda}_k) \tag{9}$$

Where, $\boldsymbol{X}_k$ represents the system state vector, $\boldsymbol{Y}_k$ represents the quantity and direction finding quantity, and $\boldsymbol{r}_{k-1}$ is the independent identically distributed system noise and $\boldsymbol{\lambda}_k$ is the observation noise.

Assuming that $\boldsymbol{X}_k$ obeys a Markov process of order 1, and for a given $\boldsymbol{X}_k$, it is independent of the direction finding quantity $\boldsymbol{Y}_k$, and the prior distribution of the initial state X_0 is $p(\boldsymbol{X}_0)$, let

$$\boldsymbol{X}_{0:k} = \{\boldsymbol{X}_j, j = 0,1,\cdots,k\}, \quad \boldsymbol{Y}_{1:k} = \{\boldsymbol{Y}_j, j = 0,1,\cdots,k\}$$

According to the basic principle of Bayesian filtering, there are

$$P(\boldsymbol{X}_k \mid Y_{1:k-1}) = \int P(\boldsymbol{X}_k \mid \boldsymbol{X}_{k-1}) P(\boldsymbol{X}_{k-1} \mid Y_{1:k-1}) d\boldsymbol{X}_{k-1} \tag{10}$$

$$P(\mathbf{Y}_k \mid Y_{1:k}) = \frac{P(\mathbf{Y}_k \mid \boldsymbol{X}_k) P(\boldsymbol{X}_k \mid Y_{1:k-1})}{P(\mathbf{Y}_k \mid Y_{1:k-1})} \tag{11}$$

$$P(\mathbf{Y}_k \mid Y_{1:k}) = \int P(\boldsymbol{X}_k \mid \boldsymbol{X}_{k-1}) P(\boldsymbol{X}_{k-1} \mid Y_{1:k}) d\boldsymbol{X}_k \tag{12}$$

Equations (10)-(12) form a recursive process. When the system satisfies the linear and Gaussian assumptions, the optimal solution of the system state can be found through continuous recursion. However, if the system cannot satisfy this assumption, the closed-state optimal solution of the system can not be obtained. To solve this problem, particle filtering method is proposed.

The main idea of particle filtering is to use Monte Carlo method to extract N independent identically distributed samples $\{\boldsymbol{X}_{0:k}^{(i)}, i = 1,2,\cdots,N\}$ from the posterior probability density function $P(\boldsymbol{X}_{0:k} \mid \boldsymbol{Y}_{1:k})$ of the state. The posterior probability density (PDF) of the state at time k can be approximated by the empirical distribution [15, 16],

$$\hat{P}(\boldsymbol{X}_{0:k} \mid \boldsymbol{Y}_{1:k}) = \frac{1}{N}\sum_{i=1}^{N} \delta(\boldsymbol{X}_{0:k} - \boldsymbol{X}_{0:k}^{(i)}) \tag{13}$$

where $\delta(\cdot)$ is the Dirac function. However, the usual state of the PDF is unknown. In this case, N samples $\{\boldsymbol{X}_{0:k}^{(i)}, i = 1, 2, \cdots, N\}$ should be independently extracted from an easily sampled importance distribution function $q(X_{0:k} \mid Z_{1:k-1})$, then the PDF approximation of the state is

$$\begin{cases} \hat{P}(X_{0:k} \mid Y_{1:k}) = \sum_{i=1}^{N} \hat{w}_k^{(i)} \cdot \delta(X_{0:k} - \boldsymbol{X}_{0:k}^{(i)}) \\ \hat{w}_k^{(i)} = w_k^{(i)} \Big/ \sum_{i=1}^{N} w_k^{(i)} \end{cases} \tag{14}$$

where, $w_k(X_{0:k}) = \dfrac{P(Y_{1:k} \mid X_{0:k})P(X_{0:k})}{q(X_{0:k} \mid Y_{1:k})}$ is the importance weight, and q is the distribution function of importance. The system state at time k is estimated to be

$$\hat{\boldsymbol{X}}_k = \sum_{i=1}^{N} w_k^{(i)} \boldsymbol{X}_k^{(i)} \tag{15}$$

This method is called sequential importance sampling (SIS). The phenomenon of particle degradation exists in sequential importance sampling: after a number of iterations, the weight of one particle may approach 1, and the weight of the rest may approach 0. To solve this problem, the reference [17] proposed the idea of resam-pling, which overcame the problem of particle degradation and made the particle filtering method widely used. The reference [18] and reference [19] introduced this approach to the field of computer vision for tracking non-rigid, multi-joined hand movements, in these researchs, the evolution of the system state with time is simulated by sampling particles with time evolution.

3.2 Visual tracking state model and observation model

3.2.1 Visual tracking state model

$\boldsymbol{x} = [x, y, \theta, \Delta x, \Delta y, \Delta\theta]$ is defined as the state variable, where (x, y) is the central position of the target, θ is the size of the target, and $\Delta x, \Delta y, \Delta\theta$ is the dynamic change between adjacent frames. The i-th particle state $\boldsymbol{x}_{k-1}^{(i)}$ at the moment $k-1$ and the i-th particle state $\boldsymbol{x}_k^{(i)}$ at the moment k can be described as [11],

$$\boldsymbol{x}_k^{(i)} = \boldsymbol{A}\boldsymbol{x}_k^{(i)} + \boldsymbol{\eta}_{k-1}^{(i)} \tag{16}$$

where, $\boldsymbol{\eta}_{k-1}^{(i)}$ represents the system noise matrix at the moment $k-1$, and A represents the state transition matrix between adjacent frames,

$$A=\begin{bmatrix} a_x & 0 & 0 & b_x & 0 & 0 \\ 0 & a_y & 0 & 0 & b_y & 0 \\ 0 & 0 & a_\theta & 0 & 0 & b_\theta \\ 0 & 0 & 0 & b_x & 0 & 0 \\ 0 & 0 & 0 & 0 & b_y & 0 \\ 0 & 0 & 0 & 0 & 0 & b_\theta \end{bmatrix}$$

When the target moves at a constant speed, the corresponding values $a_x, a_y, a_\theta, b_{\dot{x}}, b_{\dot{y}}, b_{\dot{\theta}}$ of $x, y, \theta, \Delta x, \Delta y, \Delta\theta$ in A can be set as a constant, and their values need to be obtained through appropriate debugging. The values in this paper are $a_x = 1.1, a_y = 1.1, a_\theta = 1.2, b_{\dot{x}} = 0.06, b_{\dot{y}} = 0.06, b_{\dot{\theta}} = 0.0015$ respectively.

3.2.2 Visual tracking observation model

In this paper, target tracking is based on color and texture features, and the observation quantity includes two parts: color observation quantity and texture observation quantity. The color observation equation is

$$\omega_c(y_c \mid \boldsymbol{X}_k) = \frac{1}{\sqrt{2\pi}\sigma_c} e^{-\frac{d_c^2}{2\sigma_c^2}} \tag{17}$$

Where, y_c represents the color observation, ω_c represents the observational likelihood function, and d_c represents the Bhattacharyya distance between the color histogram of the particle-centered region and the color histogram of the target region. The texture observation equation is

$$\omega_t(y_t \mid \boldsymbol{X}_k) = \frac{1}{\sqrt{2\pi}\sigma_t} e^{-\frac{d_t^2}{2\sigma_t^2}} \tag{18}$$

Where, y_t represents the texture observation value, ω_t is the observed likelihood function, and d_t represents the Bhattacharyya distance between the particle centric region texture histogram and the target region edge direction histogram.

3.3 Multiplicative information fusion strategy

Common information fusion strategies include multiplicative fusion, weighted sum fusion, election and minimum and maximum rules. Multiplicative fusion makes full use of all kinds of information, is simple, easy to understand and realize, and it is always optimal to estimate under the assumption of independence based on the principle of Bayesian filtering [16], so it is widely used in various fields of computer vision. The joint likelihood model of n cues can be expressed as

$$p(y_1, \cdots, y_n \mid x) = \prod_{i=1}^{n} p(y_i \mid x) \tag{19}$$

where y_i is the observation under the i clue and independent of each other, and x is the target state to be estimated.

In order to overcome the shortcoming that the target tracking relying solely on color features is easily affected by illumination change and background confusion, and combined with the LTP texture features that are insensitive to illumination change and less dependent on color change, a target tracking algorithm based on the multiplicative fusion of color and texture features is proposed. During tracking, it is assumed that the color histogram and the texture histogram are two independent cues, each of which generates independent observations. The multiplicative fusion strategy is adopted for color and texture features, as shown in Equation (19). Therefore, the total observation equation of state $\boldsymbol{X}_k$ at time k is

$$\omega_k(y \mid \boldsymbol{X}_k) = \omega_c(y_c \mid \boldsymbol{X}_k) \cdot \omega_t(y_t \mid \boldsymbol{X}_k) \tag{20}$$

3.4 Multi-feature fusion particle filtering algorithm

Specific steps of particle filtering target tracking algorithm based on adaptive color histogram and LTP texture histogram are as follows:

Step1 Initialization:

(1) Select the target area with the rectangle box.

(2) Calculate the weighted color histogram p_{c1}, p_{c2}, p_{c3} and p_{c4} of the subregion of the target region, then the target color histogram is selected according to the adaptive color histogram method. If the whole color histogram is selected, the target color histogram is $p_c = \{p_c^{(u)}\}_{u=1,2,\cdots,M}$; if the multi-part color histogram is selected, the target color histogram is $p_c = \{p_{c1}^{(u)}, p_{c2}^{(u)}, p_{c3}^{(u)}, p_{c4}^{(u)}\}_{u=1,2,\cdots,M}$.

(3) Calculates texture direction histogram $p_t = \{p_{LTP}^{(u)}\}_{u=1,2,\cdots,M}$ for the target area.

(4) The particle filter is initialized according to the size of the target region.

Step2 Resampling. A group of new particles $\{x_{k-1}'^{(i)}, 1/Ns\}_{i=1,\cdots,N_s}$ is generated from particle group $\{x_{k-1}^{(i)}, w_{k-1}^{(i)}\}_{i=1,\cdots,N_s}$ through resampling. The specific process is as follows:

(1) Generate a set of random numbers $r \sim U(0,1)$ that obey uniform distribution.

(2) Calculate the standard summation probability $e_{k-1}'^{(i)}$:

$$e_{k-1}'^{(0)} = 0,\ e_{k-1}'^{(i)} = e_{k-1}'^{(i-1)} + w_{i-1}^{(i)}, \quad e_{k-1}'^{(i)} = e_{k-1}^{(i)} / \sum_{i=1}^{N_s} c_{k-1}^{(i)}$$

then find the smallest j, such that $e_{k-1}'^{(j)} \geq r$.

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(3) $x'^{(i)}_{k-1} = x^{(j)}_{k-1}$

Step3 State prediction. Particle group $\{x'^{(i)}_{k-1}, 1/N_a\}_{i=1,\cdots,N_a}$ makes a one-step prediction through dynamic model (16) to obtain a new particle group $\{x'^{(i)}_{k}, 1/N_a\}_{i=1,\cdots,N_a}$, where N_a is the number of particles.

Step4 Updating the weights. According to the observed value, the weight is updated. Equation (20) is used to calculate the weight of the particle, and then the particle weight $\boldsymbol{w}_k^{(i)}$ is obtained by normalization.

Step5 The average value of the output target state is estimated as $\hat{\boldsymbol{X}}_k = \sum_{i=1}^{Ns} \boldsymbol{w}_k^{(i)} \boldsymbol{X}_k^{(i)}$.

IV. Experimental Results and Analysis

In order to verify the performance of the proposed algorithm, the proposed algorithm was compared with the K-LBP algorithm [20] based on texture features and the PF-Color algorithm [15] based on Color features in some standard test sequences. The test equipment is configured with a 2.4GHz main frequency I5 dual-core processor, 4GB memory, Windows 10 operating system, and the development environment is a hybrid compilation environment of MATLAB and C++, the version of which is MATLAB 2019A. All the experimental results in this paper are the simulation results of the above experimental equipment. Data sets and parameter Settings: in the experiments, standard test sequences and videos recorded on the laboratory platform were selected to evaluate the algorithm in this paper; let's take the number of particles N_a=80; Both σ_c and σ_t of Equations (17) and (18) are set to 0.03; the threshold value in the adaptive color histogram method is set as the empirical threshold of 0.4. The tracking effect of the proposed algorithm, k-LBP algorithm and PF-Color algorithm on the standard video test sequence is shown in Figure 1 and 2. The center position error curve and precision curve of each video sequence are shown in Figure3 and 4.

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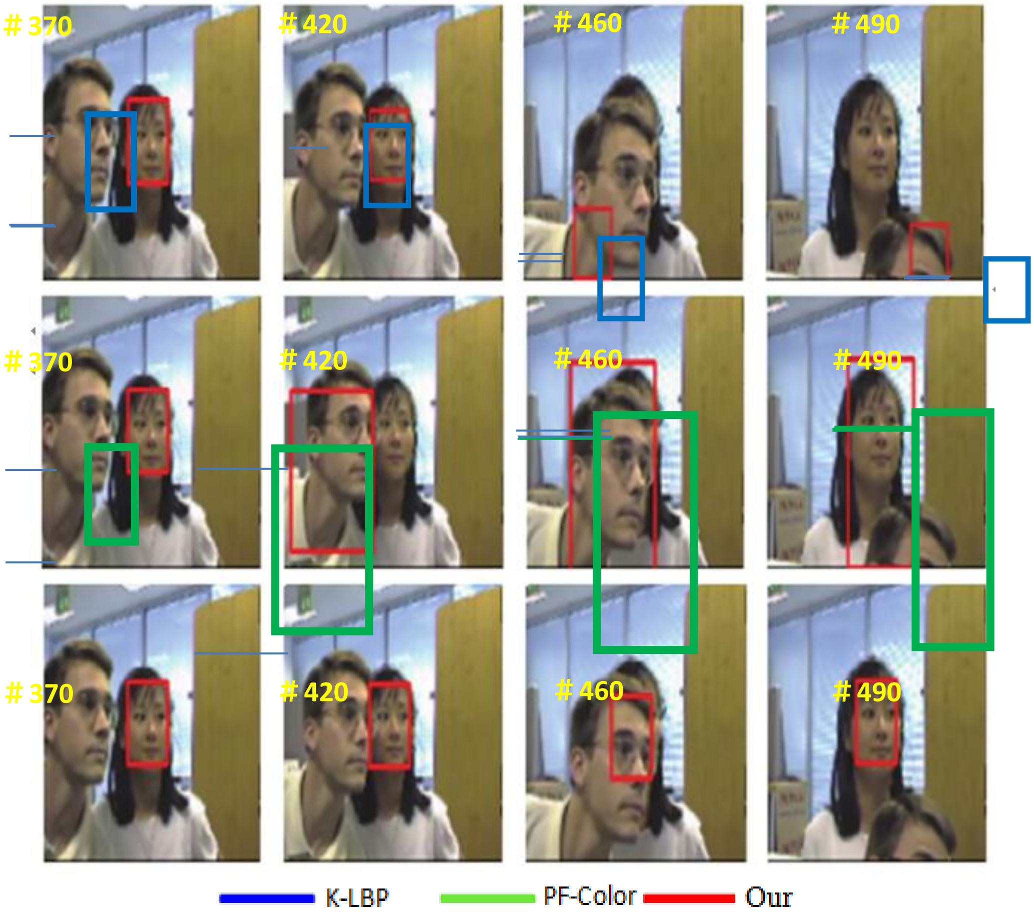


Fig 1: Tracking results of video sequence Girl

In the Girl video sequence, the main distractions are occlusion, scaling, and rotation in and out of the plane. Before 450 frames, K-LBP algorithm and the proposed algorithm have similar tracking effect and can basically track the face target stablly. The PF-Color algorithm always has some deviation, mainly because the PF-Color algorithm only considers the Color information, when the girl's head rotates in the video, part of the background information is taken as the target of the face, leading to the deviation of the tracking results. The algorithm in this paper increases the weight of the features of the unchanged areas, integrates the color histogram and texture features, and responds to the changes of the target more flexibly, making the tracking results relatively stable.

The scaling and rotation of the left and right video occurred at 460 frames, and a large offset appeared in the K-LBP algorithm; due to the occlusion of the target, the PF-Color algorithm also has a certain offset; however, at about 460 frames, the tracking results of the proposed algorithm are still relatively stable. At around frame 490, because the face is blocked for a long time and the scale changes are large, the PF-Color algorithm appears a large offset when tracking the face, and the K-LBP algorithm finally fails to track the face. At this time, the method in this paper still tracks the face target well. In general, compared with the previous two algorithms for the Girl video sequence, the tracking results of the proposed algorithm are more stable.

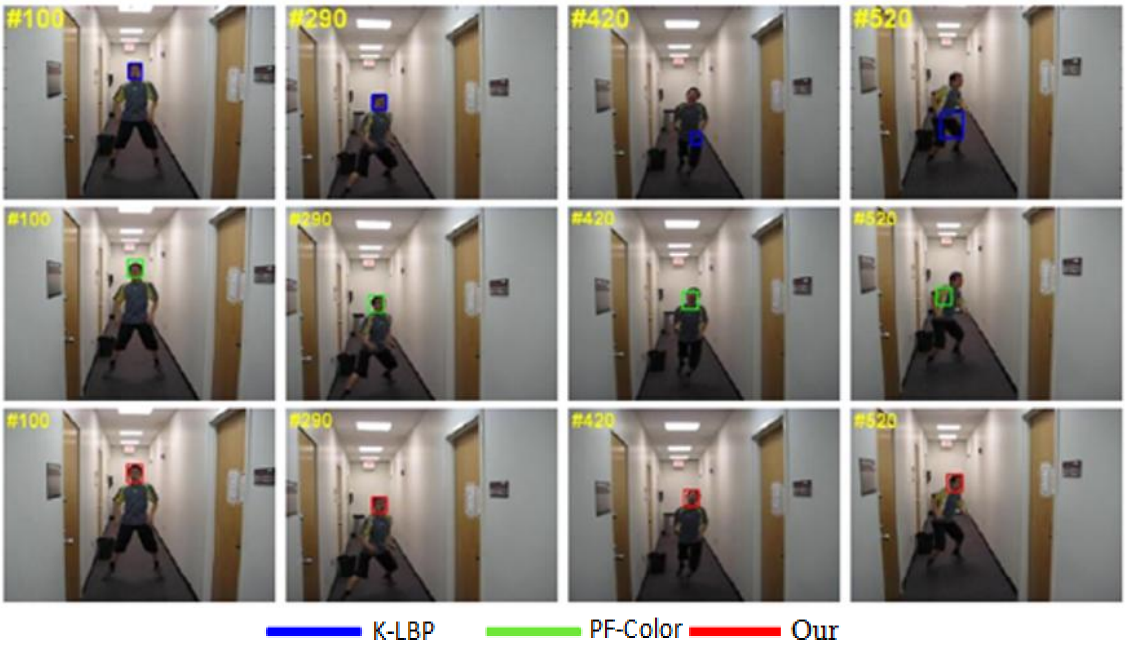
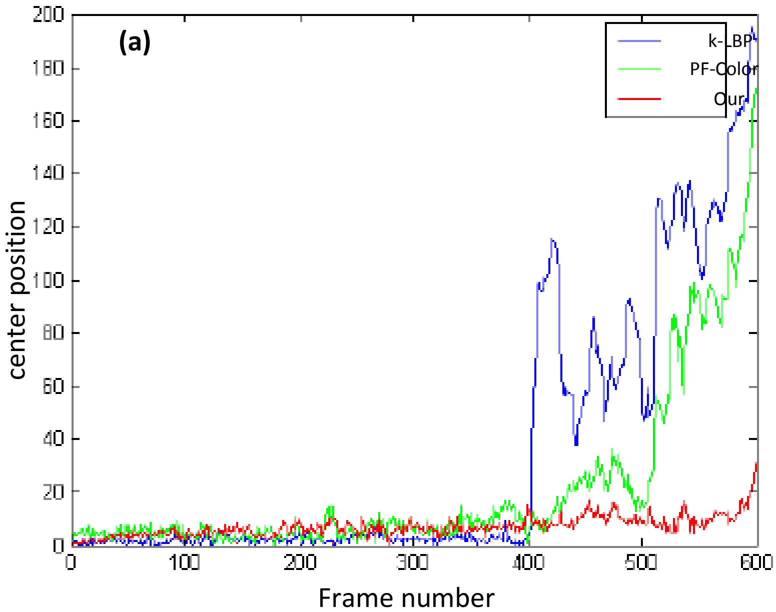


Fig 2: Tracking results of video sequence Boy

In the Boy video sequence, the target is always in fast motion, which also produces large scale transformation, motion blur and rotation in and out of the plane. Based on the reliability of the features, the algorithm in this paper updates the weight of different features in time, which makes the classification result of the classifier more accurate. At the same time, when the target is judged to be offset, the predicted position of particle wave is used to correct the sampling area, and the face target is tracked effectively in the whole video sequence, and the tracking effect is stable. After 400 frames, due to the rotation and fast movement of the target, the K-LBP algorithm gradually loses the target. Although the method is conducting real-time scaling adjustment, it cannot track the target again. After 500 frames, due to the rapid movement of the target and the deformation and rotation, the fixed update of the target template in the PF-Color algorithm can no longer meet the requirements, resulting in background errors introduced into the tracking template, and eventually gradually deviate from the real position of the target.



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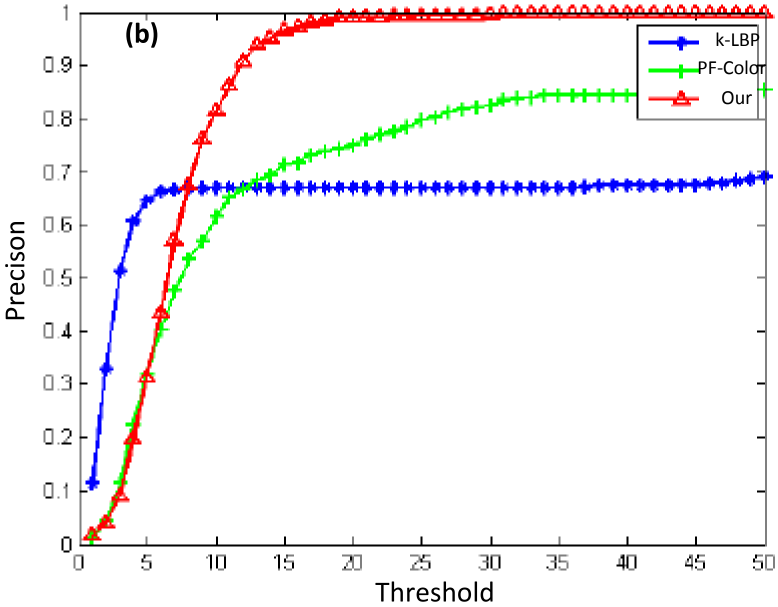
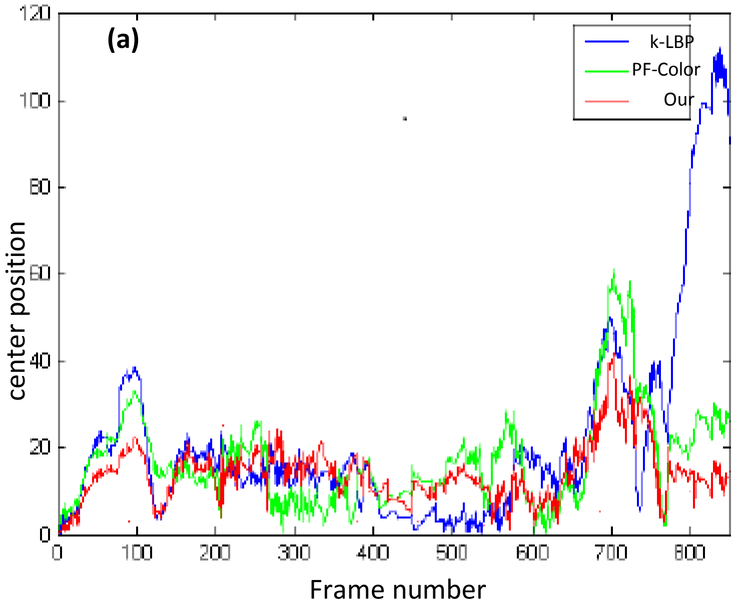


Fig 3: Girl video sequence tracking center position error and accuracy diagram (a) tracking center position error, (b) tracking accuracy



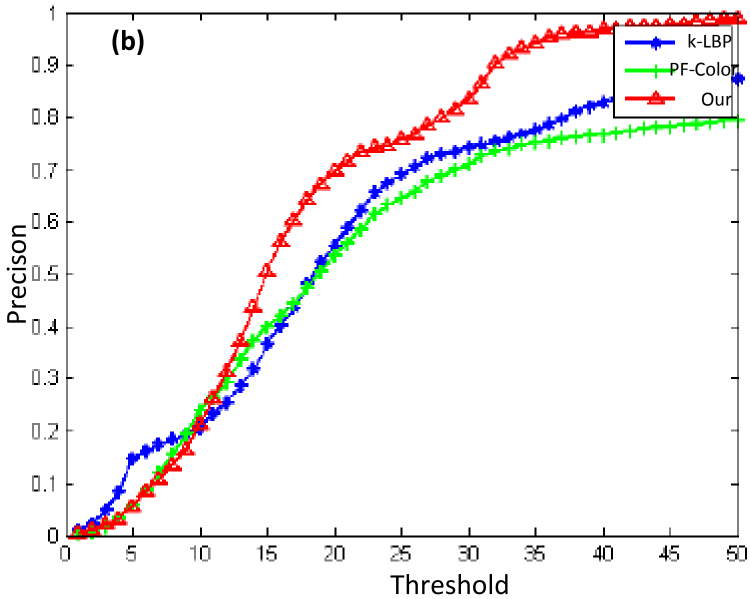


Fig 4: Boy video sequence tracking center position error and accuracy diagram (a) tracking center position error, (b) tracking accuracy

As can be seen from the error diagram and precision diagram of the center position shown in Figure 3 and 4, feature weighting and particle wave prediction were adopted in this paper, which improved the classification effect of the classifier and the tracking performance. The method presented in this paper has low center position error and high tracking accuracy, and the overall tracking result is relatively stable, which improves the robustness of tracking. Of course, when the target is interfered by large area occlusion and fast movement, the appearance of the target changes greatly, leading to the tracking effect of the three methods to different degrees of drift. As can be seen from the precision diagrams of the above several sequences, compared with the other two methods, the method presented in this paper has relatively high tracking accuracy, with low center position error and high accuracy, and can stably track the face region in the video.

V. Conclusion

In order to improve the accuracy of face tracking in power warehouse, an adaptive color histogram selection method is constructed to obtain the accurate color model of the tracking target in this paper, and LTP texture histogram is introduced as the auxiliary feature of the target tracking. On this basis, a particle filtering target tracking algorithm based on multi-feature fusion is proposed in this paper. The adaptive color feature and LTP texture feature of the tracking target are integrated into the particle filtering algorithm framework, and the weight of the particle is calculated by using the fused feature information. The proposed method overcomes the problem of low robustness when using a single image feature for tracking, improves the accuracy of face tracking in power warehouse, and achieves effective tracking under illumination changes. The experimental results show that the particle filter tracking algorithm which integrates color and TFB texture features can overcome the shortcoming of single target tracking depending on color or texture, and can effectively track the target in complex scenes of power warehouse. When the target is disturbed by similar color, it can also realize the effective tracking of the target. However, how to overcome the problems caused by the increase of computation and the deterioration of real-time performance caused by the addition of features, and how to use fewer particles to effectively estimate the real state of the target, both need further research.

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References

[1] B. Chen, Y.J. Sun, L.F. Zhang, P. Liang, "Real time tracking based on weighted compressive tracking and a cognitive memory model," Signal Processing, no. 139, pp. 173-181, 2017.

[2] Z. Lian, S. Shao, C.A. Huang, "Real time face tracking system based on multiple information fusion," Multimedia Tools and Applications, vol. 79, no. 23-24, pp. 16751-16769, 2020.

[3] H. Kim, S. Kwon, S. Lee, "NRA-Net-Neg-Region attention network for salient object detection with gaze tracking," Sensors, vol. 21, no. 5, pp. 1753, 2021.

[4] S. Xuan, S. Li, Z. Zhao, Z. Zhou, W. Zhang, H. Tan, G. Xia, Y. Gu, "Rotation adaptive correlation filter for moving object tracking in satellite videos," Neurocomputing, vol. 438, no. 10, 2021.

[5] K. Okuma, A. Taleghani, N.D. Freitas, "A boosted particle filter: Multi-target detection and tracking. Proceedings of the European Conference on Computer Vision," Berlin, Germany, no. 1, pp. 28-39, 2004.

[6] M. Muroi, H. Zen, "Human tracking based on particle filter in out-door scene," Proceedings of IAPR Conference on MachineVision Application, no. 1, pp. 461-464, 2007.

[7] Y. Zhang, K. Zhang, Z. Lu, "Face tracking based on convolutional neural network and kernel correlation filter,"Journal of Network Intelligence, vol. 6, no. 2, pp. 247-254, 2021.

[8] F. Xiao, Q. Wu, H. Huang, "Single-scale siamese network based RGB-D object tracking with adaptive bounding boxes," Neurocomputing, no. 451, pp. 192-204, 2021.

[9] I. Ahmed, S. Din, G. Jeon, F. Piccialli, G. Fortino, "Towards collaborative robotics in top view surveillance: A framework for multiple object tracking by detection using deep learning," IEEE/CAA Journal of Automatica Sinica, vol. 8, no. 7, pp. 1253-1270, 2021.

[10] H. Wang, W. Ma, S. Zhang, G. Chen, H. Ge, Y. Du, "Robust visual object tracking with multiple features and reliable re-detection ccheme," IEEE Access, no. 8, pp. 98810-98826, 2020.

[11] K. Huang, Y. Shi, F. Zhao, Z. Zhang, S. Tu, "Multiple instance deep learning forweakly- supervised visual object tracking," Signal Processing: Image Communication, vol. 84, no. 115807, 2020.

[12] J.F. Ning, C.K. Wu, "A mean shift tracking algorithm basedon texture model," Pattern Recognition and Artificial Intelligence, vol. 20, no. 5, pp. 612-618, 2007.

[13] X.Y. Tan, T. Bill, "Enhanced local texture feature sets forface recognition under difficult lighting conditions," Analysis and Modeling of Faces and Gestures, no. 1, pp. 168-182, 2007.

[14] W. Song, Z. Wang, J. Wang, J. Shan, "Particle filtering for a class of cyber-physical systems under Round-Robin protocol subject to randomly occurring deception attacks," Information Sciences, no. 544, pp. 298-307, 2021.

[15] N. Zhou, L. Lau, R. Bai, T. Moore, "A genetic optimization resampling based particle filtering algorithm for indoor target tracking," Remote Sensing, vol. 13,no. 1, pp. 1-22, 2021.

[16] W. Song, Z. Wang, J. Wang, F.E. Alsaadi, J. Shan, "Particle filtering for nonlinear/non-Gaussian systems with energy harvesting sensors subject to randomly occurring sensor saturations," IEEE Transactions on Signal Processing, no. 69, pp. 15-27, 2021.

[17] R. Beeson, N.N. Sri, "Particle filtering for chaotic dynamical systems using future right-singular vectors," Nonlinear Dynamics, vol. 102, no. 2, pp. 679-696, 2020.

[18] H. Guo, A. Xu, K. Wang, Y. Sun, X. Han, S.H. Hong, M. Yu, "Particle filtering based remaining useful life prediction for electromagnetic coil insulation," Sensors, vol. 21, no. 2, pp. 1-14, 2021.

[19] J. Wang, W. Liu, W. Xing, "A framework of tracking by multi-trackers withmulti-features in a hybrid cascade way," Signal Processing-image Communication, 7no. 8, pp. 306-321, 2019.

[20] J. Lim, H. Kim, H. Park, "Minimax particle filtering for tracking a highly maneuvering target," International Journal of Robust and Nonlinear Control, vol. 30, no. 2, pp. 158-184, 2019.