

Face Tracking Based on Particle Filter with Multi-feature Fusion

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Abstract

Traditional particle filter cannot accommodate to the environment of background interferences, illumination variations and occlusions. This paper presents a face tracking method with fusion of color histogram, contour features and grey model based on particle filter. First, it brought in contour features as the main cue of multiple features when tracking the face without stable color histogram. Then, as prior information was neglected in traditional particle filter, this paper employed GM(1,1) model to yield proposal distribution, such that the proposal distribution would bear a higher approximation to posterior probability. Finally, in the importance sampling step, sampling was corresponded to the particle weight in case of the particle degradation. The experiments show that our method outperformed the previous with more accuracy and flexibility, particularly under the condition of color background interferences, drastic illumination variations and complete occlusions.

Keywords: Face tracking, color histogram, contour features, particle filter, GM(1,1) model

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1. Introduction

Particle filter [1-3] is widely used recently, having solved dozens of tracking issues. To overcome the impacts of face rotation, complexion interference and partial occlusion, Jianpo G [4] proposed a face tracking method with the cues of color and shape based on particle filter. Hui T [5] put forth a particle filtering method with the fusion of color and texture features, describing the face features with the distinctive environmental adaptability of weighted color histogram and rotated composite wavelets. To cope with interferences of illumination and pose variations, Juan W [6] presented a new face tracking method with the cues of color and contour. All these methods hold some robust performance, nevertheless, yet they never handled the condition of complete occlusions. As the traditional particle filter ignored the guidance effect of prior information upon the proposal distribution, simulating the posterior probability distribution would be very difficult. Haitao Y [7] exploited the searching ability of particle swarm optimization through a nonliner and non-Gauss multimode distribution. Mingqing Z [8] employed history state estimation as the prior information to yield the proposal distribution. Yet all the methods above failed to solve the interference issues in a poor color environment.

In order to boost the reliability of face tracking, this paper treats color information as the first cue and contour as the second cue, in addition with an improved GM(1,1) model to yield the proposal distribution. In the importance sampling process, sampling is according to the particle weights to alleviate the particle degradation, thus the accuracy will be enhanced further more.

2. Particle Filter with Multi-Feature Fusion

Traditional particle filter merely employs the color as the single feature, which possesses a fairly poor accuracy. In this paper, color features, contour features as well as GM(1,1) model will be melting all together. And then an adaptive procedure will be proceeding by snatching a dominated value each time in fluctuated weights. Following are major distinctive features used in this paper, they will fuse together to perform an adaptive face tracking.

2.1. Color Features

The color space of HSV drawing clear bounds between brightness and color, it is invulnerable to illumination variations. In this paper, to minimize the impacts of luminance component V, a quantization process will be performed with model 8X8X4. When calculating the color histogram, weights imposed by discrepant influence factor of particles, which have alleviated the influence of background information onto the pixels located in edges. This article selects Epanechnikov Kernel function as the weight, which could improve the reliability of color distribution. Suppose the color histogram in candidate area is $\hat{p}(y)$, weighted color histogram of face model is $\hat{q} = \{\hat{q}_u\}_{u=1, \dots, m}$, and then the similarity function $\rho(y)$ between face model and candidate model will be defined as:

$$\rho(y) = \rho[\hat{p}(y), \hat{q}] = \sum_{u=1}^m \sqrt{\hat{p}(y) \hat{q}_u} \quad (1)$$

2.2. Contour Features

Face contours are the very discriminative features as well, it's reasonable to choose the contours as the second cue. This paper employs a method of shape context to extract the contour features, initially proposed by Belongiel S et al. [9]. Firstly, Canny operator is applied to acquire the face edge, and a uniform sampling will be processed after it. For each feature in the sampling contours, to build polar coordinate system in their center position. Suppose one coordinate of selected feature is (x_0, y_0) , another feature's coordinate in identical contours is (x, y) , then the polar coordinate (r, θ) is calculated. The coordinate of one single feature in contours is about the vector length and angle histogram with relation to another feature. A statistic number of total features located in each cell of relevant polar coordinate will then be counted up. After a normalization transition, the face histogram H_F^s and the candidate object histogram H_O^s will be known. Then, Chi-square measure will be used to describe the similarity d_s :

$$d_s = 0.5 * \sum_{i=1}^n \sum_{k=1}^K \frac{[h_o^i(k) - h_F^j(k)]^2}{h_o^i(k) + h_F^j(k)} \quad (2)$$

Where $h_o^i(k)$ is the candidate contours histogram, $h_F^j(k)$ denotes face model histogram.

2.3. Proposal Distribution Generated with GM(1,1) Model

The traditional GM(1,1) model selects the first value of original sequence as the initial value, which lacks of rationality as well as theoretical basis to some degree. A minimum indicator function is set to determine the initial value in [10], having improved the accuracy of GM(1,1) generally. Through a solution of first-order homogeneous equation, the time response sequence at the moment $k+1$ is:

$$\tilde{x}^{(1)}(k+1) = (\beta x^{(0)}(1) - \frac{u}{a}) e^{-ak} + \frac{u}{a} \quad (3)$$

Where β is the adjustment coefficient. Then through a recovery of first-order regressive, the prediction value of GM(1,1) model will be updated as:

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \quad (4)$$

And the covariance of particle filter is:

$$\hat{\sigma}_k = \sum_{i=1}^N w_k^{(i)} (x_k^i - \hat{x}^{(0)}(k))(x_k^i - \hat{x}^{(0)}(k))^T \quad (5)$$

Finally, the grey prediction model generates the proposal distribution, which is:

$$q(x_k^i | x_{k-1}^i, z_k) = N(\hat{x}^{(0)}(k), \hat{\sigma}_k) \quad (6)$$

2.4. Face Tracking Method

Here are the major stages of computation in our method:

- 1) To calculate the histograms H_F^s from front, side and back part in human face. The generated outputs will be preserved in the related vector.
- 2) To select a rectangle window and compute the weighted color histogram of face in that window as the matching template. Then the threshold of color similarity T_1 will be calculated.
- 3) To initialize N particles in the center of face area, the initial weight of each particle will be set as $1/N$. After that, configure the length of GM(1,1) model, $m=5$, and engendering the initial GM(1,1) model.
- 4) To denote the renewed position of each particle, according to proposal distribution of the GM(1,1) model. In the previous m frames, the position of particles is to be updated based on Gauss dynamic model.
- 5) To count the color histograms in the center window of each renewed particles. Each feature is to be compared to the face template, following with a criterion of similarity between them.
- 6) To update the weight of each particle on the ground of similarity value. To sort the particles judging by each weight value.
- 7) To pick up the maximum weight, deciding whether its value within the given threshold T_2 . The value of threshold T_2 rests with similarity of contours histogram d, $T_2=0.3*d$. After capturing the new position, GM(1,1) model will be updated.
- 8) In the following stage of resampling, 1/3 of the sorted particles will be duplicated twice, while the remainders will duplicate only once. The duplicating process will never cease until the sum of particles approaches N.

3. Experimental Result and Analysis

The first experiment proceeds by a face tracking sequence provided by Stanford University. In this task, 100 particles are selected to conduct the contrast work. The contrast results of reference [6], [8] and our method are shown in Figure 1. In the traditional particle filter, particles degeneration occurs frequently, thus targets will lose focus easily with the similarity interferences of color. The contours cue is incorporated into the particles in reference [6], ameliorating robustness when encountering the complexion interference in the background. The objects in reference [8] will get lost easily when encountering the similarity interference of complexion. With a merge of contours as the second cue in our method, plus with storage of side and back face information in advance. Our method maintains a robust tracking, even when the color features are not evident and a drastic rotation of face occurs now and then. In addition with grey information to yield the proposal distribution, the trouble of particle degradation will be alleviated. The error contrast diagram of four methods mentioned above in x and y direction is shown as Figure 2, the definition of error is:

$$e = \frac{|p_r - p_o|}{\nabla p_r} \times 100\% \quad (7)$$

Where p_r denotes the real position of human face, and p_o is the observed value of face position with related tracking methods, ∇p_r denotes the authentic displacement of two adjacent frames.

The second experiment is performed with drastic illumination variations. The illumination changes appear as a strong interference factor onto the color, the traditional particle filter fails to deal this problem reasonably, thus easily losing focus in some face tracking environment. The

RGB space is employed in reference [6], performing well in a color-stable situation. But once the illumination changes drastically, the tracking effect would be impaired badly. As a fusion of the color cue proposed in reference [8], the tracking effect would still be weakened once the color varies acutely. The tracking result of four methods mentioned above is shown in Figure 3, and the error contrast diagram in x and y direction is shown as Figure 4.

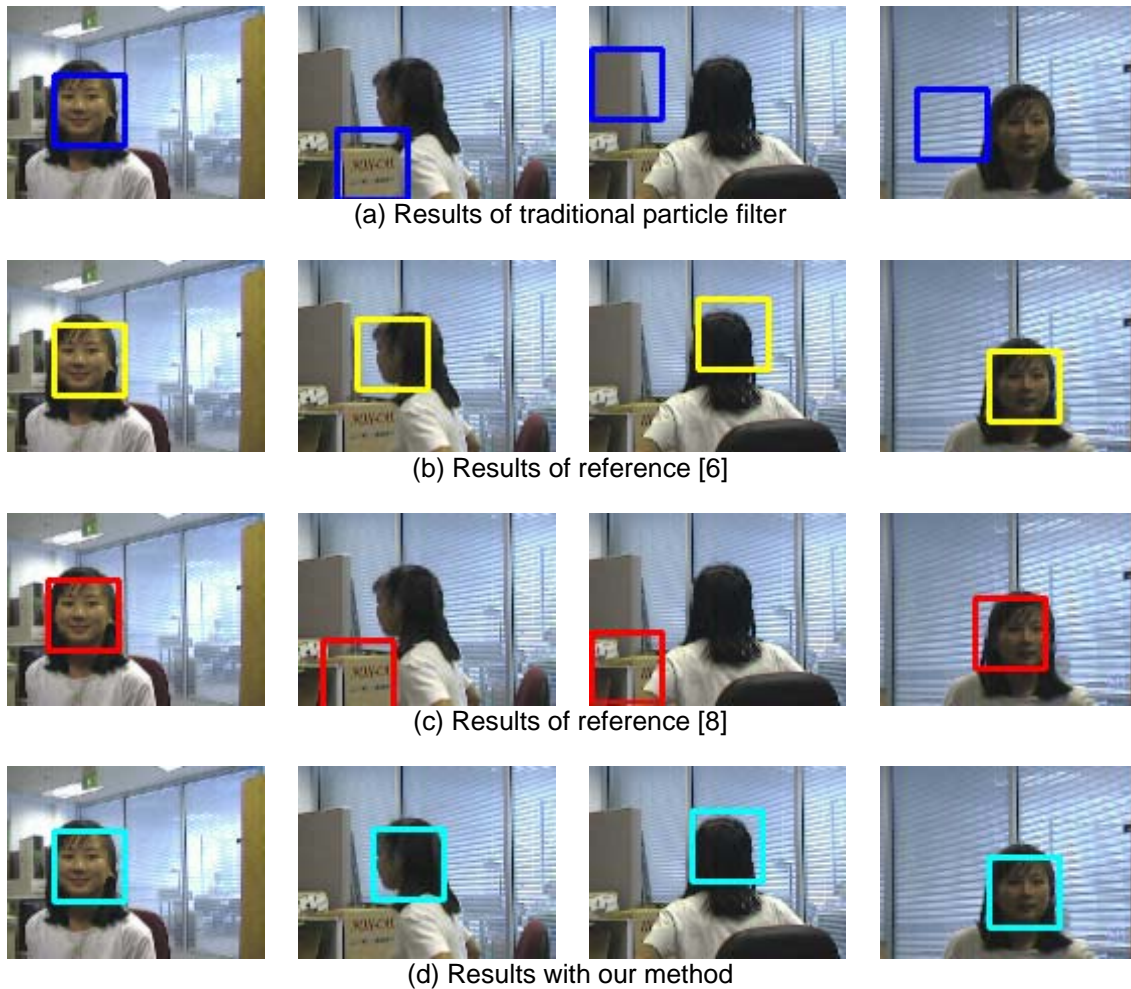


Figure 1. Contrast results of four methods (Frame 32, 86, 98, 137)

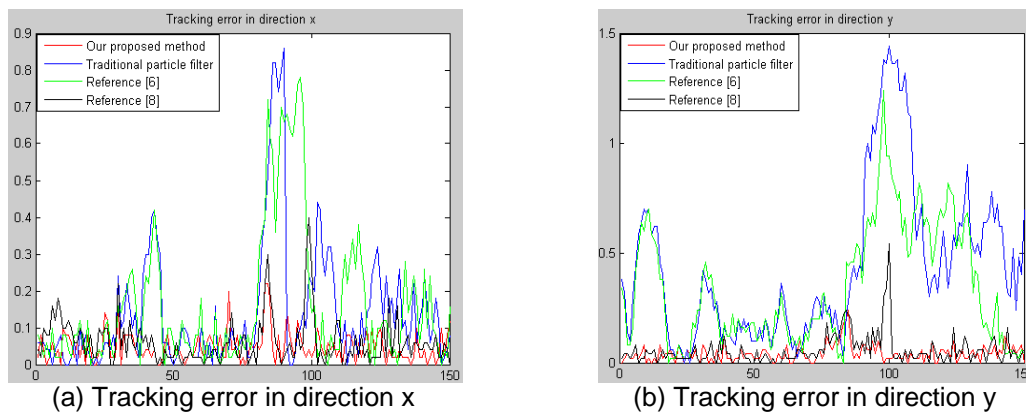


Figure 2. Error contrast diagram of four methods

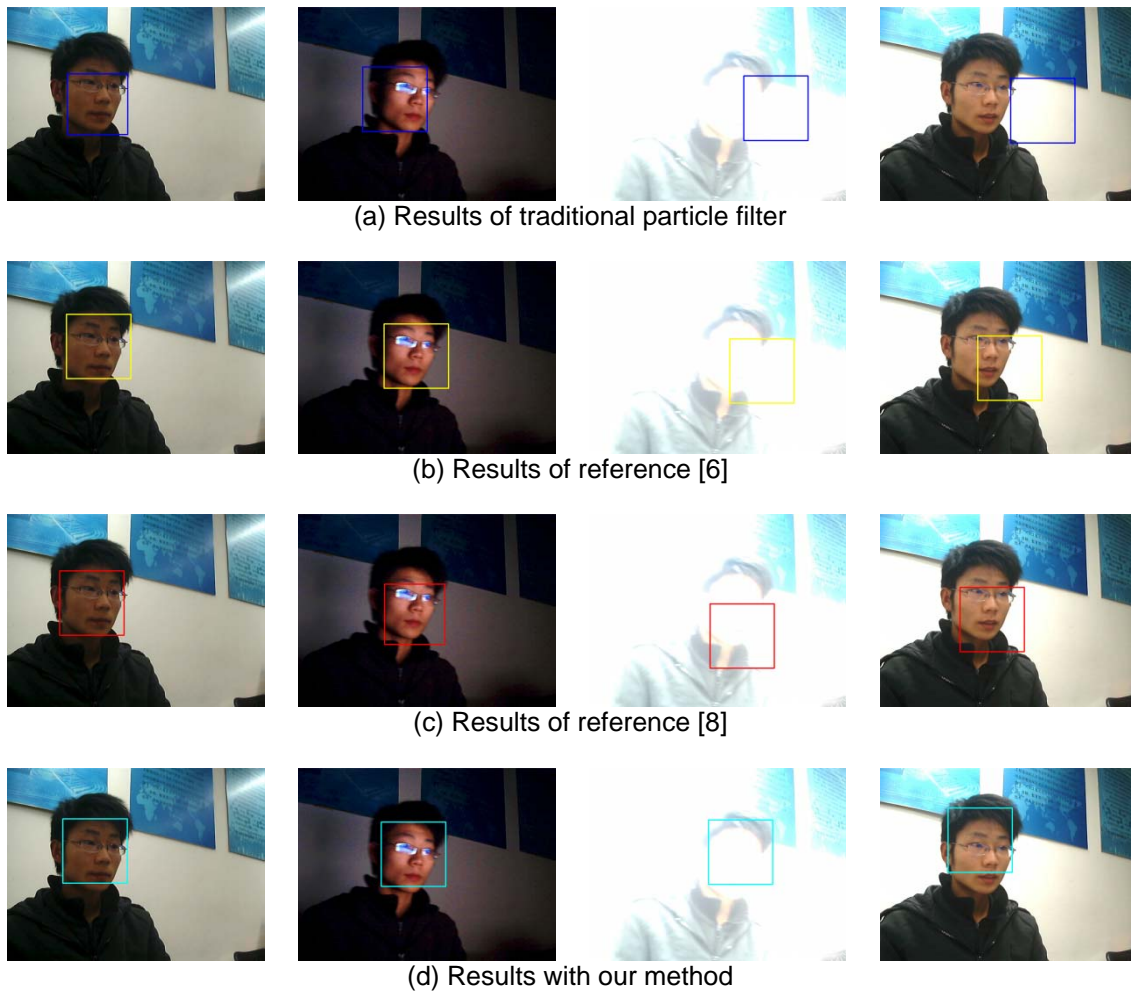


Figure 3. Tracking results with drastic illumination variations (Frame 27, 30, 46, 49)

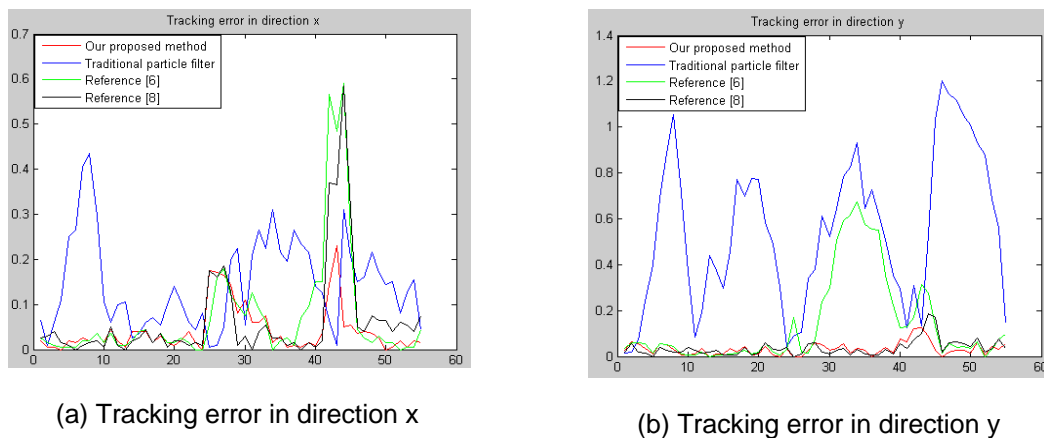


Figure 4. Error contrast diagram with drastic illumination variations

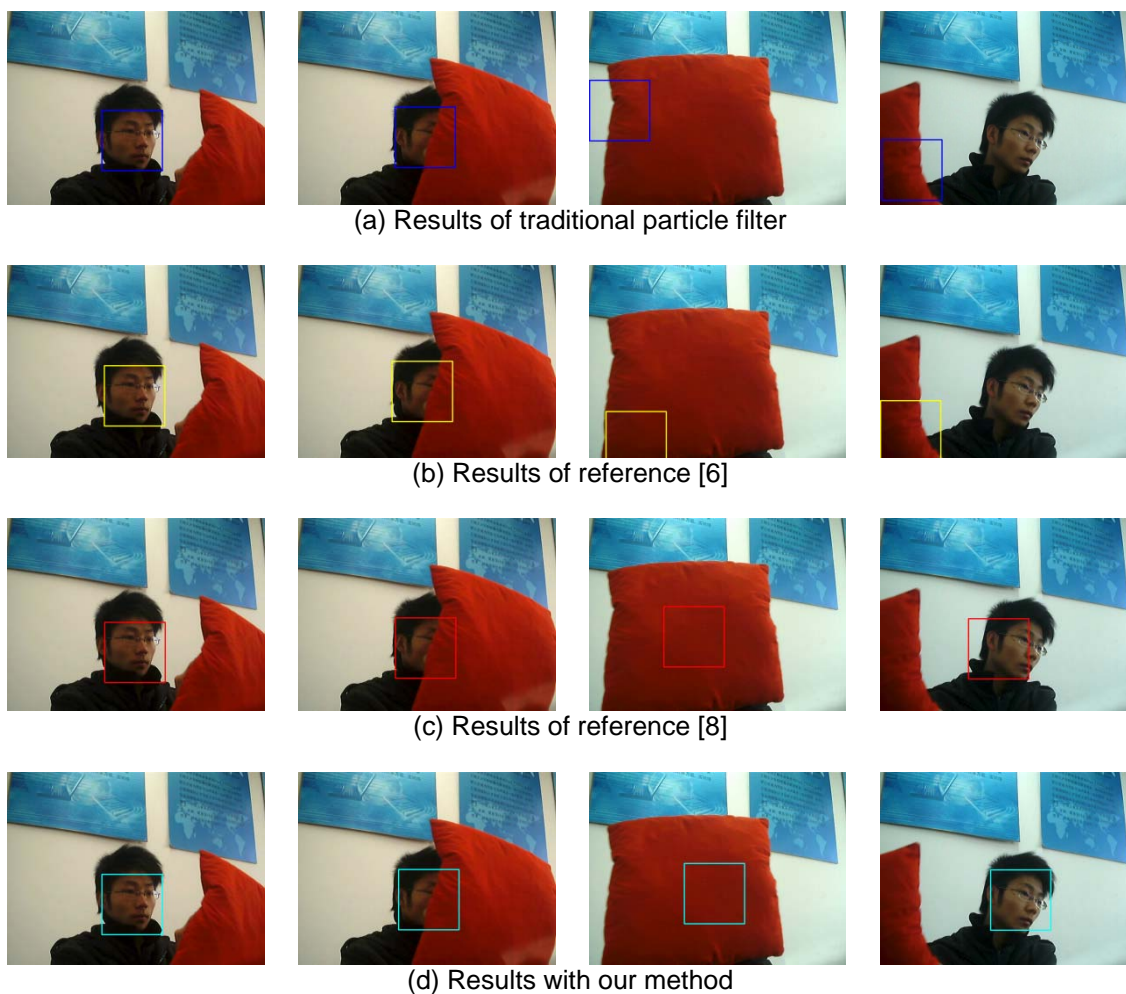


Figure 5. Tracking results with occlusions (Frame 40, 43, 46, 48)

The third experiment tracks the face with complete occlusions. The traditional particle filter performs a barely satisfactory face tracking. As is proposed in reference [6], complexion and contours information are just too barren to focus the targets. Traditional GM(1,1) model is applied in reference [8] to yield proposal distribution, enjoying certain robustness in several cases of occlusions. This paper presents an improved GM(1,1) model, which updates the prediction to alleviate the particle degradation. The experimental outputs have proved our methods with a higher robustness and efficiency. Figure 5 shows the results of face tracking with occlusions.

4. Conclusion

This paper presents a particle filter face tracking with data fusion of color histogram, contour histogram. And a merge of GM(1,1) model is attached to yield proposal distribution, approximating the results to authentic posterior probability distribution more closely. It is demonstrated through several tracking tasks that the new method could solve the problems of strong color interferences, drastic illumination variations and complete occlusions, and it outperforms the previous with better tracking robustness and higher computational efficiency.

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