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Moving targets visual tracking in complex scenes based on PCR6 combine rules

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The aim of this article is to investigate multi-moving targets visual tracking in complex scenes based on PCR6 (proportional conflict redistribution 6) combine rules, and improve the poor tracking performance in complex scenes. A tracking model of multi-moving targets was established by combining the color, edge and texture features of the targets, and the corresponding tracking algorithm was designed based on the framework of PF (particle filters) and PCR6 rules. The tracking process of moving targets including different scenes of mutual occlusion, proportion or illumination change was analyzed to validate the reliability and stability of the introduced method. The results show that the number of particles is significantly reduced, which helps to decrease the computational complexity and storage cost for tracking multi-targets of complex scenes. Meanwhile, the adaptive ability of fusion high conflict evidences is improved, and the multi-targets tracking performance is greatly elevated based on bad tracking surroundings. The research will further extend the applied scopes of evidence theory for PCR6 combine rules, and will meets the practical demand of multi-targets tracking in complex scenes. Especially, it has very important engineering application value for improving the artificial intelligence algorithm of visual tracking.

Keywords: particle filters (PF), proportional conflict redistribution 6(PCR6), visual tracking, features information, complex scenes.

1. Introduction

Multi-targets tracking in complex scenes is one of the research hotspots in the field of computer vision [1,2]. Especially, how to realize the effective fusion of multi-source information under high evidence conflicts is an urgent problem [3]. PF (particle filters) or also known as sequential Monte Carlo has great advantages in dealing with nonlinear and non-Gaussian multi-targets tracking field [4]. Recently, domestic and foreign scholars have proposed many methods based on PF to settle the tracking issue of moving targets in complex scenes.

The resampling PF algorithm proposed by GORDON *et al.* has been widely used in the field of target tracking, but this kind of approach may experience particle degradation during multiple iterations and updates [5]. Hence, how to improve particle diversity is an important research question in the process of resampling, which has been the focus on the control field. SHARIATI *et al.* discussed the application of PF combined with extended Kalman filter in model identification of an autonomous underwater vehicle based on experimental data [6]. ALAM *et al*. parallelized the pre values in the weight storage with the values in the random function generator, which reduced the time required for resampling, but did not effectively suppress the phenomenon of particle sample scarcity [7]. DU *et al*. utilized the layered sampling theory to enable sampling points to sample in areas with higher probability density function values, while the filtering accuracy was decreased [8]. MACLEAN *et al*. analyzed a kind of improved PF method for data assimilation based on reduced-order data models [9]. NIU *et al*. also used particle swarm optimization to optimize the particle update method, which ensured that the algorithm realized global positioning in a short time [10]. WEN *et al*. designed a kind of filter strategy to improve the resolution of the feature map [11]. ZHAO *et al*. proposed a PF algorithm based on adaptive threshold and layered capacity in order to solve the problem that the traditional particle filter algorithm reduces the filtering accuracy due to the lack of particles in the resampling process [12]. In short, although the existing PF algorithms can restrain the filter breakdown to a certain extent, how to track the target accurately and quickly in complex scenes such as illumination change, occlusion deformation, similar target, scale change, and motion mutation has not been solved effectively.

However, good fusion results can be obtained by using multi-feature information of moving objects based on DSmT (Dezert Smarandache Theory). DSmT fusion decision theory is an extension of the classical DST (Dempster-Shafer Theory), and the evidence model can be improved by establishing an identification framework [13,14]. In fact, there are important differences for the above two theories. DST only calculates the reliability assignment between deterministic information and uncertain information. DSmT not only computes the reliability assignment of deterministic information and uncertain information, but also computes the reliability assignment of conflicting information [15]. Hence, it is suitable for multi-target visual tracking in complex environment. In recent years, FANG introduced the DSmT by fusing color and position features of moving targets to achieve multi-targets tracking in natural environment, but the tracking error of real-time targets has not been settled due to the increase of conflicting focal elements [16]. In order to improve the accuracy of fusing high conflict information, further research is necessary to address the computational efficiency issue caused by conflicting focal elements. Considering that the PCR6 (proportional conflict redistribution 6) combine rules in DSmT can fuse more than three evidence sources, and the weight of different features can be analyzed by entropy weight method. In order to improving the effect of multi-targets, multi-targets visual tracking in complex scenes will be further explored by using the PCR6 combine rules, and the introduced method is also compared with the literature [16].

At present, it is still a challenging task to improve the robustness of multi-targets tracking algorithm in complex scenes. Some improved evidence fusion rules have been proposed in previous research work so as to enhance the rationality of information fusion results. Although these approaches greatly reduce the influence of unreliable evidence on fusion results, there is still lack of good solution on how to fast combine multiple feature information to achieve excellent convergence effect under bad tracking conditions. Especially, in complicated scene such complete knowledge is difficult to obtain due to occlusion objects locally or wholly, how to develop robust real-time visual objects tracking algorithm is very important in complicated scene. In order to realize reliably fusion of multi-source information, the color, edge and texture features of moving targets will be combined to investigate multi-targets visual tracking based on PCR6 combine rules in DSmT. In this article, the main purpose is to achieve effectively multi-targets tracking method in complex scenes by improving computational efficiency of bad tracking conditions. The research results have significant practical value for improving artificial intelligence algorithms of visual tracking.

2. Tracking model

DSmT is the development and extension of the traditional DST, which can better solve the integration problem of uncertain and high conflict evidence, and DSmT includes different combine rules of PCR. In these evidence rules, PCR5 and PCR6 are efficient fusion methods by assigning confidence conflicts to non-empty sets in a proportional relationship. PCR5 assigns a partial conflict to all the elements involved in the conflict, which mainly aims at the fusion of two evidence sources. However, PCR6 combines the conflicting information according to the confidence level of different evidences, which simplifies the calculation of DSmT. Therefore, PCR6 is a relatively efficient conflict redistribution rule in the mathematical sense, which mainly aims at the fusion of three or more evidence sources [17].

On this foundation, multi-feature information of moving objects is introduced to explore visual tracking of multi-feature fusion PF, and the basic tracking step of PF includes selection of samples, propagation of samples, observation of samples and calculation and estimation of the mean state, and the detailed content can be found in literatures [18,19]. Although many PF targets tracking methods are proposed, there are still some difficulties in designing a successful tracking platform in complex scenes. For purpose of establishing a robust PF framework, the color, edge and texture features of moving targets it is combined with PCR6 rules, and the adaptive filtering process is executed to analyze moving targets visual tracking in complex scenes. Furthermore, PCR6 is implemented to the specific combined method of PF, which also can be seen in literature [20,21].

In the framework of generalized identification, when a map $m(\cdot)$:DV $\rightarrow [0,1]$ meet the following conditions:

$$m(\varphi) = 0 \tag{1a}$$

$$\sum_{A \in D^V} m(A) = 1 \tag{1b}$$

According to Eq. (1), $m(A)$ is the reliability assignment function for event A based on the identification frame V. Assuming $m_i(\cdot)$ represents generalized basic belief assignment functions provided by independent reliable information sources. Then, the PCR6 combination rules for multiple sources of evidence are expressed as [22,23]:

$$\begin{cases} \forall A \in D^V/\Phi \\ m_{\mathrm{PCR6}}(\Phi) = 0 \\ m_{\mathrm{PCR6}}(A) = m_{1,2,\ldots,k}(A) + \ldots \\ \sum_{i=1}^{k} m_i^2(A) \sum_{\substack{\bigcap_{s=1}^{k-1} Y_{\sigma_i(s)} \bigcap A = \Phi \\ (Y_{\sigma_i(1)},\ldots,Y_{\sigma_i(k-1)}) \in (D^Y)^{k-1}}} \left(\frac{\prod_{j=1}^{k-1} m_{\sigma_i(j)}(Y_{\sigma_i(j)})}{m_i(A) + \sum_{j=1}^{k-1} m_{\sigma_i(j)}(Y_{\sigma_i(j)})} \right) \end{cases} \tag{2}$$

where k represents the number of sources of evidence, $Y_{\sigma_i}(j)$ represents a subset of categories in frame V, $\neq 0$, $m_i(A) + \sum_{j=1}^{k-1} m_{\sigma_i(j)}(Y_{\sigma_i(j)}) \neq 0$, and $m(\cdot)$ represents the belief assignment function.

According to Eq. (2), $\sigma_i = 1, 2, \ldots, i, \ldots, k$, then σ_i meets the following conditions:

$$\begin{cases} \sigma_i(j) = j, & j < 1 \\ \sigma_i(j) = j + 1, & j \geq 1 \end{cases} \tag{3}$$

When high conflict evidences are combined in the process of multi-targets tracking, PCR6 rules also require a large amount of combing computation. In order to reflect the importance of each evidence and obtain accurately combing results, the weight can be determined by entropy weight method. The entropy weight method is an approach of objective evaluation index weight based on the principle of information entropy [24]. In fact, the smaller the information entropy of the evaluation index, the greater the information provided by the index. In general, the entropy weight method is used to solve the weight, which reflects the information amount of each index by calculating the information entropy of the index. Finally, the weight of the index entropy can be determined, and the mainly solving process includes the dimensionless processing of raw data, normalization processing of data and calculation of index entropy value.

Assuming there is an index system to be evaluated includes m objects to be evaluated and n evaluation indicators. Then, the original data can be denoted by the matrix $R_{m \times n}$. Further, the original data is represented as matrix $A = (A_{ij})_{m \times n}$ after dimensionless process. At the same time, the data is denoted as matrix $A' = (A'_{ij})_{m \times n}$ by normalization processing for matrix A.

According to the definition of entropy, the following formula for calculating entropy of each evaluation index is expressed as [25]:

$$\begin{cases} t_{ij} = \dfrac{A'_{ij}}{\sum_{i=1}^{m} A'_{ij}}, & (j = 1, 2, \dots, n) \\ H_j = -\dfrac{1}{\ln m} \sum_{i=1}^{m} t_{ij} \ln t_{ij} \end{cases} \tag{4}$$

where A'_{ij} represents normalized matrix coefficients, m represents the number of objects to be evaluated, n represents the number of evaluation indicators, t_{ij} represents the relative value of normalized matrix coefficients for evaluated objects.

For the j-th evaluation index, the formula of calculating the entropy weight of each index is given as

$$\eta_j = \frac{1 - H_j}{\sum_{j=1}^{n} (1 - H_j)} \tag{5}$$

An improved evidence rules are obtained by combining Eq. (2) and Eq. (5). Namely, the corresponding expression is gotten by replacing $m_i(\cdot)$ of Eq. (2) with $\eta_j m_i(\cdot)$. Based on the given fusion strategies of conflicting evidences, three information sources including the color, edge and texture features are introduced to combine conflict evidences, and the tracking model of multi-targets is established in complex scenes.

Further, the color is a visual feature that is relatively intuitive and easy to observe. It has good stability for target tracking and can represent the appearance of the target robustly in most video environments. Edge feature have very good action on the segmentation of targets, objects and backgrounds in the image, and can enhance the contour details in the image and compensate for the insufficient description of spatial information by color feature. Texture feature has strong robustness to target changes in illumination, angle and size. Generally, local binary pattern (LBP) operator is used to extract texture features from images. In order to make the tracking process more accurate and stable, three types of evidence information of moving targets are integrated in this model.

For color feature information of moving targets, color values are obtained by extracting pixel values from the image. The pixel value far from the target center gets a smaller weight, and the pixel near the target center gets larger weight by comparing the similarity between each pixel value and the distance from target center. Namely, the distance between pixel values can be weighted through Gaussian kernel function.

$$k(r) = \begin{cases} 1 - r^2, & r \le 1 \\ 0, & \text{other} \end{cases} \tag{6}$$

$$r = \frac{\| p - c \|}{\sqrt{h_x^2 + h_y^2}} \tag{7}$$

where p represents the pixel value, c represents the target center position, r represents the normalized distance between the pixel value and the target center position, h_x and h_y represent the length and width of the target tracking rectangle window in the image.

By calculating the eigenvalue probability of all pixels in the target area, the color histogram of the target area is obtained as

$$\begin{cases} q_{\text{color}}(u) = e \sum_{i=1}^{l} k(r)\,\delta\left[h(y_i) - u\right] \\ e = \dfrac{1}{\sum_{i=1}^{l} k(r)} \end{cases} \tag{8}$$

where l represents total number of pixels, δ represents Kronecker delta function, e represents normalized function.

For edge feature information of moving targets, the edge histogram of the target area is given by using the gradient direction of pixels as an index and calculating the normalized edge values.

$$q_{\text{edge}}(u) = \sum_{i=1}^{l} g(x_i)\,\delta\left[h(x_i) - u\right] \tag{9}$$

where g represents edge gradient value, $h(x_i)$ represents index function.

Local binary patterns (LBP) operator is used to extract texture feature information from images. The LBP operator is indexed by the pixel value in the region, the texture histogram of the target area is gotten by counting the number of pixel occurrences.

$$q_{\text{texture}}(u) = \frac{1}{N} \sum_{i=1}^{N} \delta\left[b(x_i) - u\right] \tag{10}$$

where N represents neighboring pixels around the central pixel, $b(x_i)$ represents index function.

Further, a Bhattacharyya distance is used to measure the similarity between target template and candidate template.

$$\begin{cases} d_{k,f}^{i} = \sqrt{1 - \sum_{i=1}^{l} \sqrt{q_f(u)\, p_{k,f}^{i}(u)}} \\ f \in \{\text{color, edge, texture}\} \end{cases} \tag{11}$$

After the information obtained by the observation model is used to measure the similarity between the predicted target template and the observed candidate template, the obtained Bhattacharyya distance is usually further modified by using the kernel function. As a result, it is converted to the observed probability density function that determines the degree of updating of particle weights.

$$\begin{cases} p(z_k^i | x_k) = k_k(q(u), p(u)) \propto \exp\left\{ \dfrac{-\left[d_{k,f}^i(q(u), p(u))\right]^2}{2\sigma_f^2} \right\} \\ f \in \{\text{color, edge, texture}\} \end{cases} \tag{12}$$

where σ_f represents the noise variance of each histogram.

In order to enhance the accuracy of tracking targets, the weighted method is selected to update the template. Namely, according to the previous and current target template histograms, the merged target template can be obtained based on the below expression:

$$q(u) = (1-\zeta)\, q_n(u) + \zeta q_0(u) \tag{13}$$

where $q_0(u)$ represents the histogram of previous target template, $q_n(u)$ represents the histogram of current target template, ζ represents the previous target template coefficient.

Furthermore, in order to estimate the robustness of the tracking approach when handling high conflict among evidences, the root-mean-square-error (RMSE) of estimated position is given to evaluate the performance of different tracking methods, and the corresponding expression is given by

$$\text{RMSE} = \sqrt{\frac{1}{z} \sum_{i=1}^{z} \left\{ \left[x_j(t) - \hat{x}_j(t)\right]^2 + \left[y_j(t) - \hat{y}_j(t)\right]^2 \right\}} \tag{14}$$

where z denotes the number of tracking targets, $(x_j(t), y_j(t))$ denotes the real position at time t in j-th experiment, $(\hat{x}_j(t), \hat{y}_j(t))$ denotes the estimated position at time t in j-th experiment.

Based on the color, edge and texture histograms of moving objects, the object description is introduced into the PF framework. In order to improve the stability of the tracking algorithm, by using the conflict evidence merging strategy proposed in this article, the weight of color, edge and texture features are adaptively adjusted according to the similarity of feature information in the tracking process. At the same time, according to the degree of conflict, the number of particles is appropriately reduced at the next time if the conflict is small in current time. On the other hand, if the target is obscured or the background changes and other conflicts lead to large tracking errors, the number of particles should be appropriately increased to search the possible position of the target. Finally, accurate and stable multi-target tracking can be achieved in complex scenes.

In a word, based on the similarity of the feature information, the PCR6 rules can fuse the membership vector of each index by calculating entropy weight values. After adaptive adjustment different cues, the influence of information conflict and unreliable information on fusion results is effectively reduced. In order to improve fusion efficiency under poor tracking conditions, the introduced method not only considers the weight between membership vectors, but also overcomes the limitation of traditional methods in integrating highly conflicting evidence. The main step of tracking algorithm is described as follows.

Step 1: The first frame of video stream is read, and the tracking target in the first frame of video sequence is manually selected and the initial state is set. The color, edge and texture feature of the target are extracted, and the combination relationship of conflicting evidences in different time series is determined based on the PCR6 rules.

Step 2: The histograms of color, edge and texture need to be calculated. The selected target parameter is copied so as to produce N particles. The histogram of the target area determined by each sample in the sample set is calculated, and the Bayesian distance between the histograms of candidate targets and the selected tracking targets also needs to be processed and calculated.

Step 3: The next frame is read sequentially, and the previous particle is transferred to produce a new particle. The fusion observed likelihood function value for each particle and weight are calculated and normalized in the model.

Step 4: The state estimation of the target at the current moment is detected through state prediction analysis, and the fusion weight of color, edge and texture features at the next moment is adjusted by weighted update. The initial particle at the next moment can be obtained by resampling particles.

The above steps include the main tracking process, and the targets tracking based on multi-feature information fusion can be realized through multiple cycles. The entire tracking platform consists of six modules including set parameter module, read module, processing module, detecting module, calculating module and tracking module. Figure 1 shows the tracking platform of visual tracking.

According to Fig. 1, the set parameter module is given to provide correlative parameters for every module, and to read module of video sequences applied to read video data by video collecting equipment and provide right data format for latter tracking.

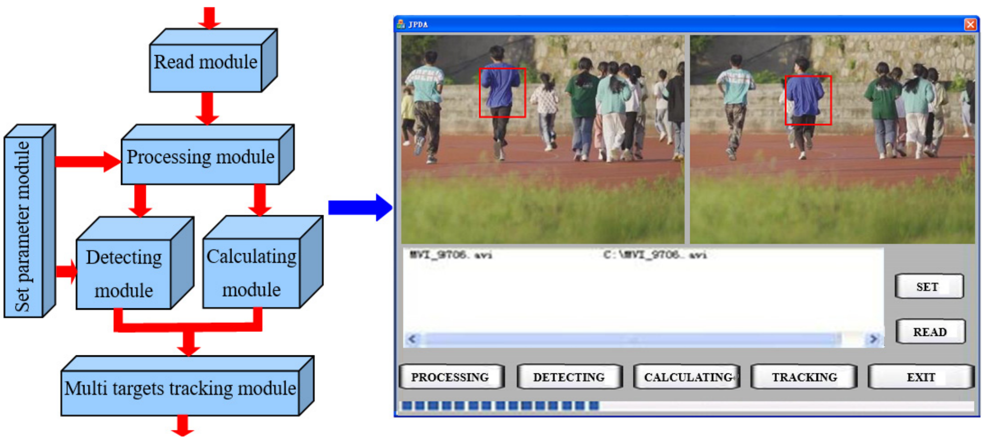

Fig. 1. The tracking platform of visual tracking.

The preprocessing module is adopted to suppress noise and pre-segment of video image. The detecting module is used to detect interested moving targets, and eliminate the influences of illumination and shadow. The calculating module is executed to analyze the state parameters of different conflicting information. Based on the operation of the above modules, the multi-targets tracking module can carry out tracking process for the tracking algorithms.

3. Cases and discussions

In the process of visual tracking experiments, a desktop computer with 8GB memory and i7-8500 processor was used to handle moving image, and MATLAB R2016b was applied to compute the processing matrix. Next, the tracking results of fusing multi-feature information in different tracking environments and conditions are analyzed.

Firstly, a sequence video of training ground from a web video was given to verify the reliability of the algorithm for fusing multi-feature information. The target in the sequence was from near to far distance, and there were jumping and accelerating movements, other moving objects and so on. The position of the target in the first frame was initialized by manually selecting a rectangular window, and the tracking process and results were represented by the red rectangular window. The conflict information in the tracking process mainly included the change of the proportion of moving target and the background environment as well as the cross of targets. By using the method proposed for tracking testing, the key frames and tracking result were given in Fig. 2.

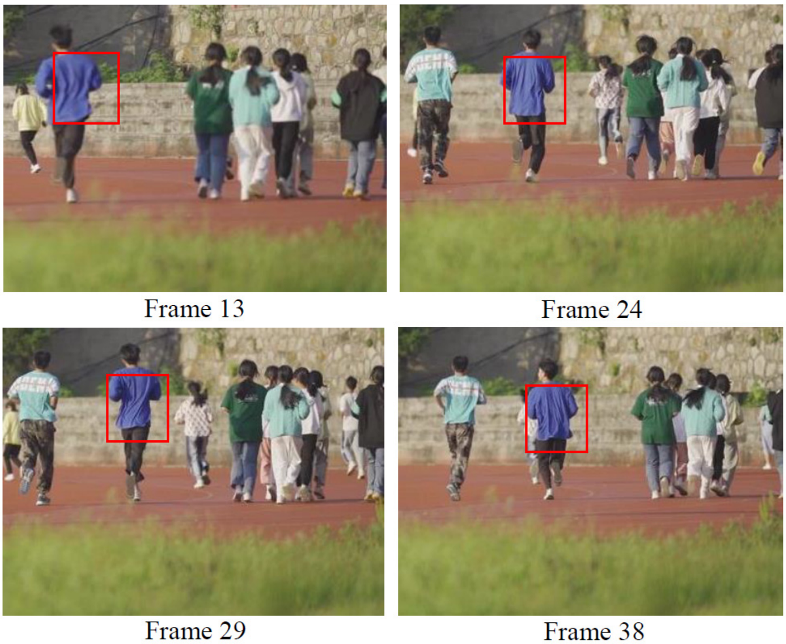

Fig. 2. The tracking process of key frames and tracking result.

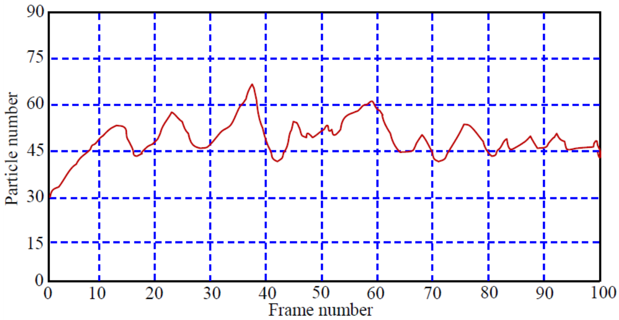

Fig. 3. The curve of particle number in different tracking stages.

The variation curve of particle number in different tracking stages were shown in Fig. 3.

By analyzing the particle number and the change of the moving target in the first 50 frames, it was found from the Figs. 2 and 3 that only the part of the target was within the tracking window at the beginning of the tracking stage, but it was gradually tracked in frame 13 for the selected target. In the whole tracking phase, the size of the tracking window did not decrease with the target becoming smaller. Subsequently, reliable tracking was achieved using up to 67 particles in frame 38. Finally, the number of tracked particles decreased with the decrease of conflicting information. The algorithm in this paper gained a good balance between tracking speed and tracking performance, and obtained a fast tracking velocity while guaranteeing the tracking performance.

Secondly, a video under different occluding conditions was tested to validate the stability by using the combination rules, and the performance of multi-targets tracking under high conflict conditions such as crossover, occlusion and background interference was further discussed. The three moving targets in the selected basketball court video were marked as targets A, B and C, respectively. In the process of visual tracking, the difficulty of tracking focused on the color conflict of A and C targets, the mutual occlusion of targets B and C, and the interference of environmental background. As a result, the algorithm test was performed for the selected three targets in the whole tracking process from frame 1 to frame 180, and the key frames of the tracking process and tracking results were shown in Fig. 4.

According to Fig. 4, the conflict information of target A did not change significantly, and the particle number fluctuated less from frames 19 and 150. When targets B and C moved to frame 46, the two targets were crossed and occluded each other, and the illumination of the targets area also changed gradually. However, when targets B and C moved to the 46th frame, there was mutual occlusion, and the illumination of the target area gradually changed. From frame 74 to frame 150, there were partial occlusion and background environment changes between targets B and C, and the tracking window became smaller. In fact, there was no significant offset when target B and target C approached each other in frames 46–138. However, the center of the tracking

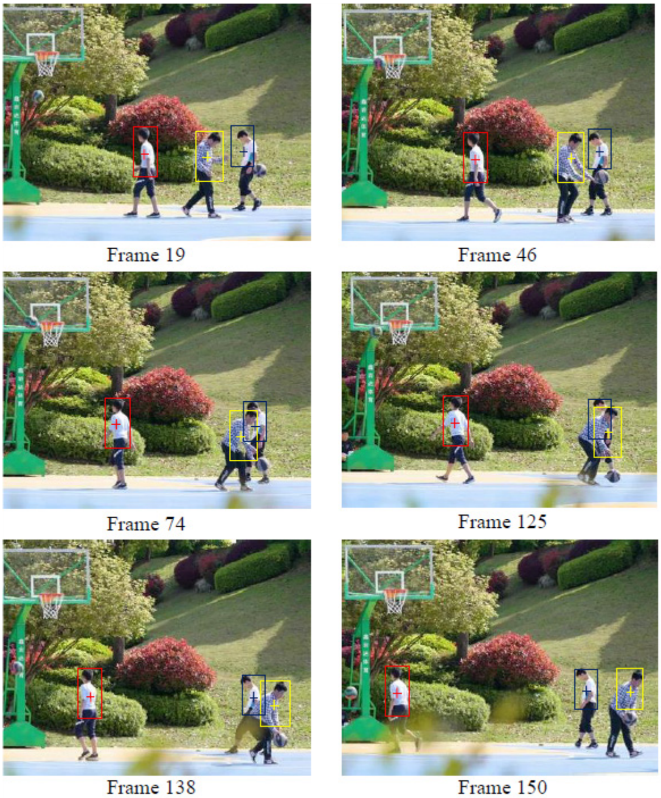

Fig. 4. The key frames and tracking result.

window changed at frame 150, but the tracking window did not deviate from the target center through adaptive adjustment during the whole tracking process.

At the same time, Fig. 5 shows the change curves of particle number in different tracking stages for three moving targets. It was noticed from Fig. 5 that particle number in different tracking stages for three moving targets exhibited different change level with the increase of conflict evidence. For target A, only a maximum of 38 particles was used to achieve stable tracking. However, the consumption of algorithm time was obviously increased when processing the conflict information of target B and C. Finally, the whole tracking process adopted a maximum of 112 and 116 particles to respond the tracking error caused by occlusion and illumination change. The result illustrated that the tracking model was not affected by other factors, and the rectangular window was stabilized around the center of the targets. The corresponding algorithm utilized local features of the targets to complete visual tracking in complex scenes by combining color, texture, and edge information. Therefore, PF tracking based on PCR6 combine rules has strong robustness, and could meet the requirements of multi-targets tracking in complex scenes.

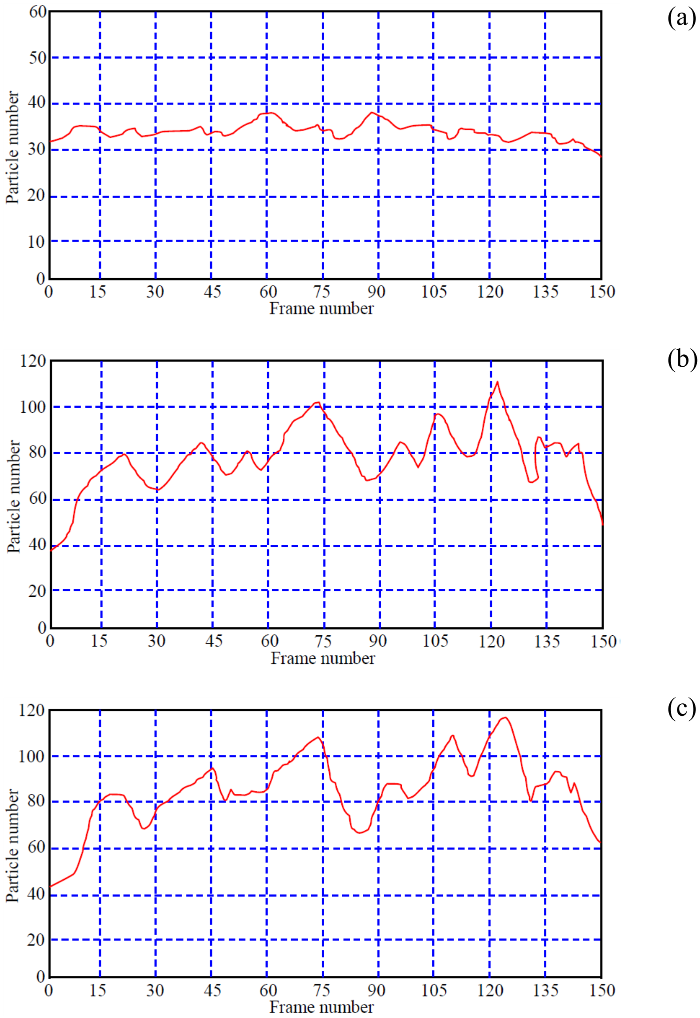

Fig. 5. The curve of particle number in different tracking stages. (a) Target A, (b) target B, and (c) target C.

Further, in order to test the influence of tracking bias, the RMSE of the particle set during propagation iteration was analyzed. At the same time, the PF approach [16] was also used to calculate the RMSE. Figure 6 shows the change curve of RMSE with frame number in the whole tracking stages. In Fig. 6, the red line indicated the PF approach, and the blue line indicated the introduced approach.

By comparing the RMSE with two approaches in Fig. 6, the results show that the tracking performance of introduced approach was better than that of the PF approach [16]. For the selected target A, the change of RMSE with two approaches was relatively small due to the weak conflict information. However, the RMSE fluctuation range of the PF approach was significantly higher than that of the introduced approach when tracking targets B and C with strong conflicting information. That is, the RMSE was

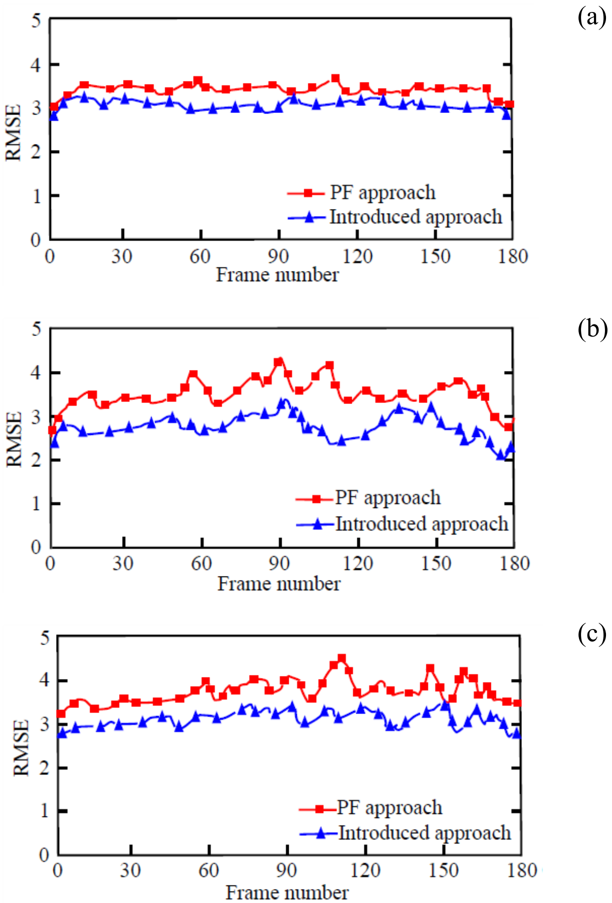

Fig. 6. The RMSE in different tracking stages. (a) Target A, (b) target B, and (c) target C.

further reduced, and the fluctuation was also smaller, and the RMSE basically varied around 2.6 by the introduced approach. Based on the above discussion, the introduced approach of combined color, edge and texture features information of moving targets to improve the tracking performance under high conflict evidences to a certain extent, and the robustness was advanced efficiently.

4. Conclusions

Visual tracking of multi-targets is the core and hot issue in the field of computer vision. How to implement robust multi-targets tracking in complex scenes is still a challenging task. In this article, an improved tracking approach by combining multi-feature information was proposed in the framework of PF and PCR6. Based on the color, edge and texture features of moving target, the corresponding tracking model and algorithm were established. The results show that the proposed method effectively enhanced the robustness of tracking multi-targets in complex scenes. The main conclusions were as follows.

1) The combination strategy of conflict evidences based on PCR6 effectively solved the computational bottleneck of conflict evidences at different levels, which had moderate computing efficiency and high trust. By establishing the tracking model of combining color, edge and texture features of moving targets, the tracking process of moving targets in different environments was explored under the conditions of mutual occlusion, proportion or illumination change. Two sets of tracking experiments indicated that the tracking effect in the whole stage was better than that of the PF approach, and the RMSE of estimate position of moving targets and computational efficiency were significantly improved. Hence, the introduced approach has high accuracy and fast convergence speed in handling high conflict evidences, and enhance the tracking stability of multi-targets tracking in complex scenes.

2) However, there still exist many open problems facing the complex scenes including many objects crosses and high occlusions full, background clutter, intense change of illumination and camera calibration, *etc*. In order to solve these problems, more efficiently tracking models are necessary to solve the matching relationship between target features and conflicting information. In addition, the increase in the particle number when dealing with high conflict information will result in a significant amount of computation, and the computational complexity of the algorithm will also be increased. In a word, further exploration is very necessary on how to achieve advanced visual tracking in complex scenes, and the results have excellent theoretical significance and practical value for promoting the application of visual tracking technology in complex scenes.

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