ADAPTIVE VISUAL TRACKING METHOD OF FUSING MULTIPLE INFORMATION

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***Abstract*— The objective is to present an adaptive tracking approach of visual objects in the framework of particle filters (PF) and conflict redistribution strategy based on Dezert-Smarandache theory (DSmT). A combination rule of conflict redistribution was introduced into the researches on visual objects tracking, position and color information of moving objects were combined by modified combination strategy information, and the objects tracking model of fusing multiple information on the condition of occluded objects was established effectively. On the basis of building the execution panel of objects tracking simulation platform, many tracking experiments in complicated scene were carried out to validate the correctness and availability of the introduced method by comparing with other tracking method. Results showed that the introduced approach had excellent adaptive ability for dealing with high conflict among evidences under different occlusion condition, and could solve partly high-level vision tracking problems efficiently.**

***Keywords*— Dezert-Smarandache theory; Particle filters; Conflict redistribution strategy; Visual tracking; Multiple information**

I. INTRODUCTION

In the decades, research on visual objects tracking has yielded an arsenal of powerful algorithms, which play important roles in many applications, such as (Lee and West, 2013) visual surveillance, robotics and human-computer interaction, etc. Although many effective visual objects tracking methods have been proposed, there are still a lot of difficulties in designing robust tracking methods due to the challenging complex scenarios such as (Eslahi and Aghagolzadeh, 2016, Bousetouane et al., 2013) significant illumination changes in natural environment, pose variations of the object and non-linear deformations of shapes, and noise and dense clutters in complicated scene. Hence, visual object tracking has become one of the research hotspots in the field of computer vision. One of urgent issues for robust tracking is to track locally or wholly occluded objects persistently in complicated scene.

In recent years, particle filters (PF) algorithms has been widely applied to visual tracking fields (Ghirmia 2016, Crisan and Obanubi, 2012). Despite the flexibility and availability of PF, there still exist many open problems facing the variation of tracking object in complicated scene. Sugandi et al (2010) adopted the color-based PF to describe multiple objects tracking algorithms in an outdoor environment, but the stability of tracking algorithms have not been improved efficiently. Papadakis and Bugeau (2011) introduced a new approach of graph cuts to track occluded objects. Although the approach could handle locally or wholly occluded dynamic objects, it had difficulties in tracking static objects. Maroulas and Stinis (2012) addressed a kind of improved PF for multiple objects tracking, the effect of tracking objects was promoted greatly, but the computational effort was also increased. Dias and Bruno (2013) discussed cooperative objects tracking method by using decentralized PF and RSS sensors, and the simulated results showed the tracking performance was partly improved. Although lots of PF algorithms have been introduced to track moving objects in different cases, these approaches have mainly improved local performances by optimizing PF algorithms, and there still exist robustness issues which need to be investigated further.

When tracking occluded objects in complicated scene, lots of conflict evidences need to be handled. Hence, how to combine these evidences efficiently is very important for enhancing the robustness of tracking algorithms. Crespo et al (2009) presented an overall approach to forecasting the future position of the moving objects of an image sequence after processing the images previous to it. Chu et al (2018) designed an improved Camshift algorithm to solve the problem of tracking failure when the target was near the background color or the target is occluded, and the results showed that the algorithm could obviously improve the tracking performance.

Recently, Dezert-Smarandache theory (DSmT) was proposed by Jean Dezert and Florentin Smarandache (Smarandache and Dezert, 2009) based on Bayesian theory and Dempster-Shafer theory (DST) come forth since 2003. The DSmT is development and prolongation of evidence theory, and it was very important method to deal with highly conflicting, uncertain and imprecise sources among evidences in the process of tracking objects. Klein et al (2010) analyzed hierarchical and conditional combination of belief functions for visual tracking. Cielniak et al (2010) presented an approach to handle data association and occlusion object for visual tracking of mobile robots, and the computational effort was decreased in the course of evidences reasoning. Airouche et al (2012) adopted color, thermal and position information to track pedestrian objects by a DSmT-based framework, and the results showed the tracking performance was improved obviously. The authors (Fang *et al*., 2011) discussed different modified algorithms for video-based objects tracking, and more details were found in literatures. The above approaches based on DSmT have mainly improved local performances for tracking objects. However, there is something illogical in dealing with multiple evidences' fusion by using DSmT, and the conflicting focal elements rise illogically and the main focal element can't converge for making decision. In order to improve combine efficiency using DSmT, a kind of new combining strategy of conflict redistribution based on DSmT will be introduced to discuss the issue of objects tracking in complicated scene.

At present, lots of strategies have been developed for addressing the object identification based on DSmT, and the related studies of visual object tracking based on DSmT are very less. In complicated scene such complete knowledge is difficult to obtain due to occlusion objects locally or wholly, and PF algorithm can't solve conflict among evidences efficiently. Hence, how to develop robust real-time visual objects tracking approach is very important in complicated scene. The aim of this article is to present an adaptive tracking approach of visual objects in the framework of PF and conflict redistribution based on DSmT, and the introduced approach will deal with the conflict evidences among occlusion objects locally or wholly in order to attain an excellent information fusion.

II. CONFLICT REDISTRIBUTION RULE BASED ON DSMT

A. Problem Description

DSmT is a generalization of the classical Dempster-Shafer theory (DST). The DSmT framework can easily handle not only exclusivity constraints, but also non existential constraints or mixed constraints as well, which is very useful in some dynamic fusion problems where the DST usually fails, DSmT differs from DST because it is based on the free Dedekind's lattice, and the detailed examples of the types of constraints can be found (Airouche *et al*., 2012). In the framework of DSmT, one considers$\Theta=\{\theta_1,\cdots,\theta_n\}$ as a finite set of n exhaustive elements only. Eventually some integrity constraints can be introduced in this free model depending on the nature of problem we have to cope with. The hyper-power set of Θ denoted D^Θ is defined as:

(1) φ, $\theta_1,\cdots,\theta_n\in D^\Theta$; (2) If A, $B\in D^\Theta$, then $A\cap B$ and $A\cup B$ belong to D^Θ; (3) No other elements belong to D^Θ, except those obtained by using rules (1) or (2).

From the frame of discernment Θ, a map $m(\cdot):D^\Theta\rightarrow[0,1]$ is defined as:

$$m(\phi)=0,\ \sum_{A\subseteq D^\Theta} m(A)=1, \tag{1}$$

The quantity $m(A)$ is called the generalized basic belief assignment/mass of A. The generalized belief and plausibility functions are defined respectively in almost the same manner as within the DST, i.e.

$$Bel(A)=\sum_{\substack{B\subseteq A\\ B\in D^\Theta}} m(B)\cdot Pl(A)=\sum_{\substack{B\cap A\neq\phi\\ B\in D^\Theta}} m(B), \tag{2}$$

ın in closed frame of discernment, the DSmT rule of combination is defined as:

$$\forall A\neq\phi\in D^\Theta,\ m(A)=\sum_{\substack{X_1,X_2,\cdots,X_n\in D^\Theta\\ X_1\cap X_2\cap\cdots\cap X_n=A}}\prod_{i=1}^{n} m_i(X_i), \tag{3}$$

The following example is given to point out the existent problem when DSmT fusing conflict among evidences. Let $m(A)$=0.9, $m(B)$=0.05, $m(\Theta)$=0.05($m(\Theta)$). The combined results of focal element A based on DSmT is gotten by numerical simulation, as shown in Table 1, and it can be seen that the evidence sustains obviously focal element A. According to the natural logic, the same evidences are combined, and the conflict focal elements and basic belief assignments of uncertain information are decreased continually after the evidence of sustaining focal element A is combined. At the same time, the basic belief assignment of focal element A is increased gradually and astringed. But the computed result is different from the above analysis, the conflict focal element presents an illogical increase, and the value of conflict focal element is 0.9135 by fusing 40 times. However, the basic belief assignment of focal element A is decreased slowly, and it is tended to 0 finally. Hence, it is difficult to make any decision according to the combined results in Table 1.

Table 1 The combined results of focal element A

Fusion times	$m(A)$	$m(B)$	$m(A\cup B)$	$m(A\cap B)$
0 time	0.9000	0.0500	0.0500	0.0000
10 times	0.5987	9.9e-11	9.8e-14	0.4013
20 times	0.3253	7.6e-20	5.3e-25	0.6267
30 times	0.1943	e-30	7.3e-33	0.8516
40 times	0.0955	e-40	8.6e-41	0.9135

According to the above analysis of fusion results, DSmT handling illogically the conflict is mainly manifested in the following respects: (1) the conflict information not only come from the single focal element between clear information, but also may be come from the different conflict. (2) the conflict may be produced between conflict and unknown information. (3) the conflict focal element can't be distributed if it is produced. For example, the conflict focal element $A\cap B\cap C$ may be produced after the focal elements $A\cap B$ and $B\cap C$ are combined, but the conflict focal element $[(A\cap B)\cup C]\cap(A\cup B)$ can be produced after the focal elements $(A\cap B)\cup C$ and $A\cup B$ are combined. In order to enhance fusion purpose, an improved combination method based on DSmT is addressed to enhance fusion efficiency.

B. Combining Rule of Conflict Redistribution

According to the above discussion, an improved combination rule of conflict redistribution is introduced by improving the disposal way for the conflict focal elements. The basic idea of conflict redistribution rule based on DSmT is described as follows: (1) the conflict information is only produced by the conflicts between certain focal element information, and the uncertain information is dropped out produce the conflict. (2) when the conflict information and uncertain information or conflict information between are combined, the uncertainty of combining rule is increased greatly. (3) when the conflict information and single focal element of producing the conflict are combined, the conflict information is redistributed to the single focal element according to combination results.

In order to describe the total level of conflicts between evidences efficiently, an influence coefficient R is introduced to address the conflict level. Based on the mass function, the conflict level can be corrected by R, and the corresponding expression of R is given by (Fan and Zou, 2006).

$$R=\left(\sum_{A\subseteq U} m_1(A)m_2(A)+\sum_{B_i\cap C_j=\varnothing} m_1(B_i)m_2(C_j)\right)^{-1}\left(\sum_{B_i\cap C_j=\varnothing} m_1(B_i)m_2(C_j)\right), \quad (4)$$

where A denotes the single focal element of identification framework, m_1, m_2 denotes the basic probability assignment function of two evidences source, respectively.

According to Eq.(4), when the influence coefficient R tends to 1, the conflict between evidences is strenuous, and conflicts are partly transferred to a union of conflict focal elements. When the influence coefficient R tends to 0, the conflicts between evidences are very weak, and they are partly transferred to the conflict focal elements. As a result, the corresponding combining rule of conflict redistribution between evidences is defined as follows.

$$m(A)=\sum_{\substack{B_i\cap C_j=A\\ B_i,C_j\subseteq\Theta}} m_1(B_i)m_2(C_j)+(1-R)\sum\frac{r_1 m_1(A)}{r_1 m_1(A)+r_2 m_2(X)}m_1(A)m_2(X), \quad (5)$$

$$r_i=\frac{S_i}{\sum_{j=1}^{n} S_j}\max\left\{\frac{\sum_{j=1}^{n} S_j}{S_j}\right\}, \quad (6)$$

where r denotes the absolute reliability of evidence, S denotes the degree of support based on D-S evidence theory (Sugandi *et al*., 2010).

III. EXPERIMENT EXAMPLES ANALYSIS

Based on the above analysis, an objects tracking algorithm of multi-source information fusion was designed based on the improved combination rule. By using Visual studio 2005 C++.net environment and open source computer vision library (OPENCV 1.0), the objects tracking simulation platform was established to execute the tracking algorithm. At last, the simulated platform of objects tracking could be operated based on window XP system, and the basic configuration environment included Pentium(R)D CPU 3.00GHz, 4GB memory and 300G hard disk. As a result, the tracking procedure can be performed when based-video image frames come by the tracking platform, and the execution panel of objects tracking simulation platform is shown in Fig.1. In order to reduce computation complexity of the tracking method, the number of particles can be adjusted adaptively with the change of conflict evidences in the process of tracking test.

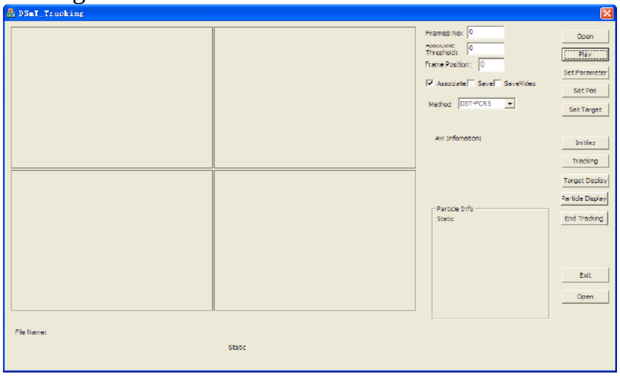

Fig.1. The execution panel of tracking platform.

In order to validate the fusion efficiency of combination rule introduced, the previous numerical example in section 2.1 was computed by using the improved rule of conflict redistribution. Let m(A)=0.9, m(B)=0.05, m(Θ)=0.05(m(Θ)), the comparison of the combined results with different combination rule were obtained, as shown in Table 2.

Table 2 The comparison of combined results of focal element A

Fusion method		$m(A)$	$m(B)$	$m(A\cup B)$	$m(A\cap B)$
DSmT rule	0 time	0.9000	0.0500	0.0500	0.0000
	10 times	0.5987	9.9e-11	9.8e-14	0.4013
	20 times	0.3253	7.6e-20	5.3e-25	0.6267
	30 times	0.1943	e-30	7.3e-33	0.8516
	40 times	0.0955	e-40	8.6e-41	0.9135
Improved rule	0 time	0.9000	0.0500	0.0500	0.0000
	4 times	0.9314	0.0051	0.0047	0.0519
	8 times	0.9433	0.0036	0.0033	0.0507
	10 times	0.9475	0.0027	0.0024	0.0498
	15 times	0.9475	0.0027	0.0024	0.0498

According to the results in Table 2, the basic belief assignment of main focal element A was increased efficiently, and the value of focal element A was stably converged to 0.9475 by fusing of 10 times. Both conflict focal elements and basic belief assignment of uncertain information were confined reasonably, and the efficient decision was executed based on the combined results. Hence, the introduced combination rule could settle fluctuation problem tempestuously of focal element basic belief assignment in the process of fusion information. The rule could deal with multiple evidences' fusion. Finally, the basic belief assignment of main focal element could converge for making track decision.

Further, three testing videos under different occluding conditions were tested to validate the correctness and availability of the method by using the improved combination rule. These videos data included different scene factors such as the change of moving target proportion, the complicated background, the illumination variation and the objects occlusion locally or wholly, etc. In order to handle conflict evidences efficiently, the number of particles was selected using adaptive adjustment strategies based on the degree of conflict.

The first image scene came from the football training scene of a network video, the size of the image was 320×240, and the feature of this image sequence included the change of moving target proportion and the complicated background. The first frame position of moving target was selected manually using rectangular tracking window, and the tracking process and results were shown in the white rectangular window. According to the given combination rules of conflict redistribution, the number of original particles was 40 or so in order to reduce the computational complexity of the tracking algorithm, and the number of particles was adaptively adjusted to the change of conflict evidences in the whole tracking process. The high conflict information included the change of moving target proportion and the varied background in the process of tracking. Finally, stably tracking was realized by using about 42 particles for the selected target, and the tracking process and results for single target were showed in Fig.2.

Fig.2. The tracking process and result for single target.

According to Fig.2, the size of the moving object slowly became smaller with the change background, and the tracking window could make the corresponding change with the decrease of the target dimension. In frame 20, it was very difficult to discern the change of target dimension by the color cue. In order to achieve the robust tracking, the position cue was adaptively combined in frame 35, and the color cue had a secondary role in the process of tracking. By analyzing the variation level of particle number of different tracking stages, the position cue could make up the deficiency, and the search scope was reduced. As a result, the operation speed and tracking accuracy were improved greatly. The maximum number of particles was 65 in the whole tracking process, which was used to response the tracking error. The efficiency was greatly increased by using these particles, and the stable tracking was finally realized in complex scenes. It was seen that a satisfactory tracking result was obtained by using the model including color and position information of moving targets.

The second image came from a mall region, and there were only two crosses and closely spaced objects in the region. For the sake of clarity, the girl was denoted object 1, and the boy was denoted object 2. Let the two persons in a video scene keep uniform motion along the moving direction of the cross and occlusion. The tracking sequence was divided into three phases. Phase 1 was the pre-occlusion sequence, phase 2 corresponded to the occlusion sequence, and phase 3 was the post-occlusion sequence. Tracking in phase 2 was challenged due to the closeness of the object, which perturbs the measured information and might lead to a false identification. In the process of objects occlusion locally or wholly, there were high conflict problems including scale variations, cross and closely spaced objects. As a result, the tracking experiment was achieved based on the improved combination rule, and each object was tracked using 25 particles averagely. Fig.3 showed the tracking process of main frames and tracking results for two targets.

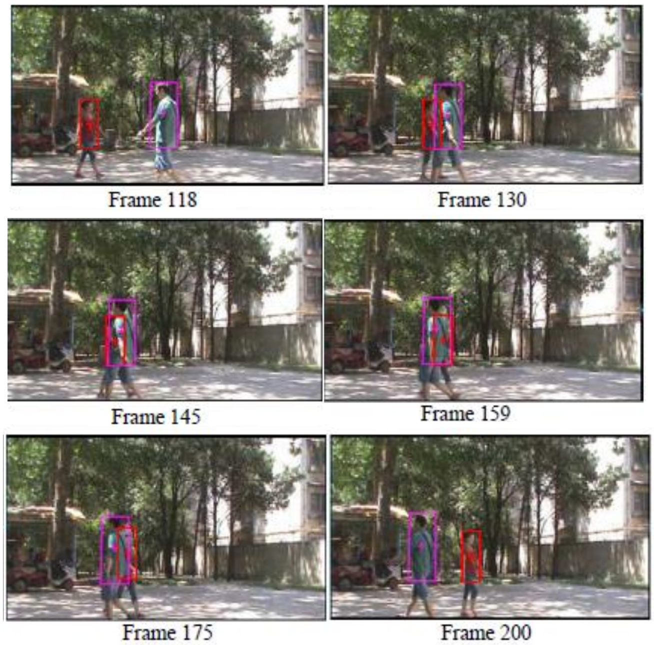

Fig.3. The tracking process and results for two targets.

According to Fig.3, it could be seen from frame 130 to frame 175 that the tracking accuracy was maintained even when the target was blocked locally or wholly. Especially, the position cue lost gradually its ability to separate objects 1 and 2 as they converged to the intersection point in frame 145. However, the position cue remained a valid measurement because it was independent from the relative position of objects with respect to the camera (occluding or occluded). The color cue was extremely sensitive to the occlusion. In order to analyze the efficiency of the introduced method when the target was blocked locally or wholly, the ratio between the number of objects detected accurately and the number of reality was also discussed. Fig.4 showed the detected results of occluded objects in natural scene by comparing with the other approach in (Sugandi *et al.*, 2010).

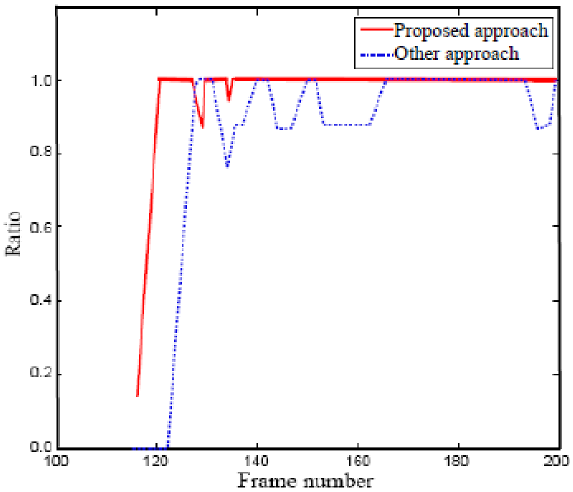

Fig.4. The detected results of occluded objects.

According to Fig.4, the two objects in natural scene were detected in frame 118 by the proposed approach. But the detected time was greatly delayed by the other approach (Sugandi *et al.*, 2010), the two objects were detected in frame 123, and the detecting efficiency for the occluded object was not good. Hence, it could be seen that the introduced method had better real-time performance when detecting occluded objects. Based on the above experiment result, the corresponding error analysis of tracking objects in the direction of level and vertical was discussed. The value of object tracking minus the value of real object was defined as the mean error. Fig.5 shows the tracking error for the two objects by comparing with the conventional PF approach.

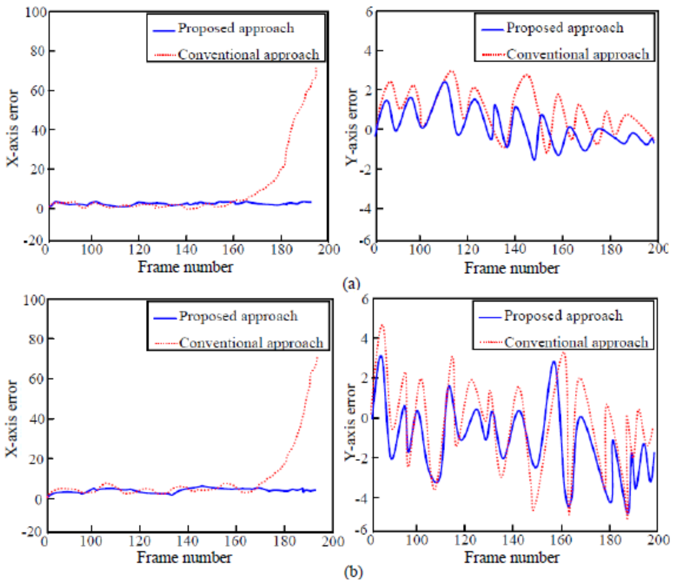

Fig.5. The mean error curves of estimated position. (a) Target 1; (b) Target 2.

It was very obvious that the introduced method had a small tracking error when the object was locally or wholly occluded, but the error change was very visible from frame 130 to frame 200 by using the conventional PF. The tracking mean error was increased greatly when high conflict evidences were handled by using the conventional approach. Especially, the tracking was almost failed from frame 145 to frame 175 owing to the occluded objects full based on the conventional PF. Hence, the correctness of introduced method was unsuspecting according to the tracking results and error analysis.

Ⅳ. CONCLUSIONS

Information processing technology is applied in computer vision for settling the occlusion problem of tracking objects in this article, and the following conclusions can be drawn:

(1) The study demonstrated that DSmT fusing high conflict among evidences information had lots of difficulties in analyzing conflict focal element. An improved combination rule of conflict redistribution based on DSmT was introduced to settle high conflict among evidences. Simulation results shown that the basic belief assignment of main focal element A was increased efficiently by the suggested combination rule, and the value of focal element A could be converged stably by fusing of 10 times. At the same time, tempestuous fluctuation problem and computational effort of the main focal element were handled for making track decision.

(2) Due to the availability of the suggested combination rule in handling high conflict among evidences, the corresponding conflict strategy and combination model in the course of tracking objects were described in detail. The execution panel of objects tracking simulation platform was established. Two sets of tracking examples in complicated scene were executed to validate the correctness and robustness of the introduced method. The results showed that the approach had excellent self-adaptive ability for dealing with high conflict among evidences. By comparison with the conventional PF under different occlusion condition, the introduced method had small tracking error when the object was locally or wholly occluded, and the tracking accuracy was maintained even by using 25 particles averagely from frame 130 to frame 175. Obviously, the introduced method had better real-time detecting performance and little tracking error when objects was locally or wholly occluded.

Acknowledgements

This study was funded by the National Natural Science Foundation of China, China (Grant No. 61875231), key Research and Development Program of Shaanxi Province (Grant No. 2020GY-190) and Scientific Research Initiation Funds for the Doctoral Program of Xi'an International University (Grant No. XAIU2018070101). The authors fully appreciate their financial support.

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Received: May 5, 2019
Sent to Subject Editor September 7, 2019
Accepted November 7, 2019
Recommended by Subject Editor Jose Guivant