Research on Moving Object Tracking Under Occlusion Conditions

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Abstract—**With the development of information fusion, a new theory based on Dezert-Smarandache Theory (DSmT) was widely applied to lots of aspects. Owing to the difficulty of handling conflict evidence combination when tracking multiple moving objects under occlusion conditions, a DSmT method with anti-occluding objects tracking in complex background is proposed based on occlusion judgment prediction, and the corresponding computing examples of generating hyper-power sets and tracking under different occluding conditions are analyzed and discussed in this paper. Calculation results show that the method is proven to be correct and effective in tracking occluded objects. When analyzing multi-objects tracking under very complex environment, it will lay a firm foundation for further solving information fusion of conflict evidences.**

Keywords-Information fusion; DSmT; conflict evidence; objects tracking; occluding conditions

I. INTRODUCTION

Moving object tracking is one of core technology in computer vision, and it is an important element of surveillance, guidance, obstacle avoidance system[1-3]. Moving object tracking includes advanced knowledge and research results of image processing, pattern recognition, artificial intelligence, automatic control and computer applications, etc. With a knowledge of a priori distributions and conditional probabilities, the probabilistic methods, and especially the Bayesian inference, offer the most complete, scalable and theoretically justifiable approach for data fusion. However, in real complex scenes such complete knowledge is difficult to obtain due to high occlusion, background clutter, illumination and camera calibration problems. An alternative approach is proposed for data fusion; namely the Dempster-Shafer (DST) theory[4]. DST theory does not require the knowledge of prior probabilities. The uncertainty and imprecision of a body of knowledge are represented via the notion of confidence values that are committed to a single or a union of hypotheses. The orthogonal sum rule of DST theory allows the integration of information from different sources into a single and overall representation[5,6]. Unfortunately, Bayesian inference and Dempster-Shafer theories lack to provide an interesting manner of modeling conflicts and paradoxical interpretation arising between the difference information sources[7]. The Bayesian inference assumes that all sources provide bodies of evidences using the same objective and universal interpretation of the phenomena under consideration; therefore, it cannot handle conflicts. In most practical fusion applications based on DST theory, ad-hoc or heuristic techniques must always be added to the fusion process to manage or reduce the possibility of high degree conflict between the sources. Otherwise, the fusion result leads to false conclusions or cannot provide a reliable result at all. To overcome these limitations, a recent theory of plausible and paradoxical reasoning has been developed. The Dezert-Smarandache theory (DSmT) can be considered as a generalization of the DST theory in [8]. In this paper, a sequential particles filter approach for multiple targets tracking using multiple cues will be proposed, and the different cues are combined based on the DSmT. If the targets are partially or completely occluded, the conflicts and paradoxes that arise between the measured cues are assessed and used in the tracking process. The proposed scheme is simple and provides an effective tracking in cluttered scenes. By the simulation computing and discussion, result shows that the tracking method proposed is excellent and effective for objects tracking in some complex environment.

II. OCCLUDING PROBLEM AND DSMT

When tracking object is part or whole occluded, object tracking system must have good robust to anti-occluding, and the system can capture object over again and maintain tracking. Therefore, the system is asked for the below ability. Firstly, moving object can be stable tracked under the order condition. Secondly, object can be judged under occlusion condition. Thirdly, object can be effective identified and tracked newly after object is occluded.

It is very different to be divided up object from some background when moving object is in the complex environment by PF. Considering DSmT is more desirable in the case of solving conflicting evidence, it is more efficient in combining conflict evidence especially when the evidences conflict highly, and the occlusion problem can be solved effectively when moving object is tracked. So, the DSmT will be used to the object tracking.

While the DST considers Θ as a set of exclusive elements, the DSmT relaxes this condition and allows for overlapping and intersecting hypotheses. This allows for quantifying the conflict that might arise between the different sources throughout the assignment of non-null confidence values to the intersection of distinct hypotheses.

Let $\Theta = \{\theta_1, \theta_2,\ldots, \theta_k\}$ be a set of k elements which can potentially overlap. The hyper-power set D^{Θ} is defined as the set of all composite hypotheses obtained from Θ with $\cup$ and $\cap$ operators such that.

1). $\varphi, \theta_1, \theta_2,\ldots, \theta_k \in D^{\Theta}$.

2). If $A, B \in D^{\Theta}$, then $(A\cup B) \in D^{\Theta}$ and $(A\cap B) \in D^{\Theta}$.

3). No other elements belong to D^{Θ}, except those defined in 1) and 2). As in the DST, the DSmT defines a map $m(.)$: $D^{\Theta} \rightarrow [0,1]$. This map defines the confidence level that each sensor associates with the element of D^{Θ}. This map supports paradoxical information, and $\sum_{A\in D^{\Theta}} m(A) = 1$.

The belief and plausibility functions are defined in the same way as for the DST. The DSmT rule of combination of conflicting and on uncertain sources is given by.

$$\sum_{A\in D^{\Theta}} m(A) = 1 \quad (1)$$

$$m(A) = \sum_{\substack{A_1, A_2,\ldots A_f \in D^{\Theta} \\ A_1\cap A_2\cap\ldots A_f = A}} \prod_{j=1}^{D} m_j(A_j) \quad (2)$$

III. OBJECT TRACKING BASED ON DSMT

Let us consider $X_t = (x_1, x_2,\ldots,x_t)$ as the state vector (location, size, etc.) describing the object and $Z_t = (z_1, z_2,\ldots,z_t)$ as the vector of measurements (color, texture, etc.) up to time t. The tracking is based on the estimation of the posterior state distribution $p(x_t|Z_t)$ at each time step. The estimation is performed using a two step Bayesian recursion. The first step is prediction.

$$p(x_t|Z_{t-1}) \infty \int p(x_t|x_{t-1}) p(x_{t-1}|Z_{t-1}) dx_{t-1} \quad (3)$$

The second step is filtering.

$$p(x_t|Z_t) \infty \int p(z_t|x_t) p(x_t|Z_{t-1}) \quad (4)$$

This recursion requires the specification of the state evolution $p(x_t|x_{t-1})$ and a measurement model linking the state and the current measurement $p(z_t|X_t)$. The basic idea behind the particle filter is very simple, and starting with a weighted set of samples.

$$S_{t-1} = \left\{ s_{t-1}^{(j)}, \pi_{t-1}^{(j)} \middle| \sum_{j=1}^{k} \pi_{t-1}^{(j)} = 1 \right\} \quad (5)$$

Which describe object candidates and distributed according to $p(x_{t-1}|z_{t-1})$, new samples are obtained by propagating each sample according to the object's state model, $p(x_t|x_{t-1})$. In the filtering step, each sample is weighted given the observation and k samples are drawn with replacement according to $\pi_t = p(z_t|x_t)$. The value is given by the below expression.

$$E[S_t] = \sum_{j=1}^{k} \pi_t^{(j)} s_t^{(j)} \quad (6)$$

Let's assume that the number of object τ and the number of cues c are known. Up to time t-1, each object is associated with a track. At time t, an image frame is extracted from the video sequence and a number of measurements are obtained for each object candidate. Thus, the objective is to combine these measurements in order to determine the best track for each candidate. It is important to notice that a object candidate, in this paper, refers to a particle sample. The hyper-power set $\{\theta_j\}_{j=1}^{\tau}$ defines the set of the hypotheses for which the different cues can provide confidence values.

These hypotheses can correspond to:

Step1: individual tracks θ_j.

Step2: union of tracks $\theta_r \cup \ldots \cup \theta_s$, which symbolizes ignorance.

Step3: intersection of tracks $\theta_r \cap \ldots \cap \theta_s$, which symbolizes conflict.

Step4: track combination by $\cup$ and $\cap$ operators. The confidence level is expressed in terms of mass function that is committed to each hypothesis and which satisfies the condition.

Given this framework, expresses the confidence with which cue l associates particle n to hypothesis A at time t. According to DSmT combinational rule, a single map function can be derived as follows.

$$m_t^{(n)}(A) = m_{t,1}^{(n)}(\cdot) \oplus m_{t,2}^{(n)}(\cdot) \oplus \cdots \oplus m_{t,c}^{(n)}(\cdot) \quad (7)$$

Where $m_t^{(n)}(A)$ is the overall confidence level with, which all cues associate particle n to hypothesis A at time t.

Since the object candidates must be associated to individual tracks, the information contained in compound hypotheses is transferred into single hypotheses through the notions of the belief or plausibility functions.

$$Bel_t^{(n)}(\theta_j) = \sum_{\substack{\theta_i \subseteq A \\ A\in D^{\Theta}}} m_t^{(n)}(A) \quad (8)$$

$$Pls_t^{(n)}(\theta_j) = \sum_{\substack{\theta_i \subseteq A \\ A\in D^{\Theta}}} m_t^{(n)}(A) \quad (9)$$

Where $Bel_t^{(n)}(\theta_j)$ (resp. $Pls_t^{(n)}(\theta_j)$) quantifies the confidence with which particle n is associated to θ_j at time t using the notion of belief (resp. plausibility). The confidence levels are not used to determine whether a given a candidate is the best estimate or not of the object, they are rather used to quantify the weight of the candidate as a sample of the state posterior distribution $p(z_t|X_t)$.

IV. COMPUTING ANALYSIS AND DISCUSSION

Example 1 In this section, generating hyper-power sets D^{Θ} will be analyzed firstly, because it is important to estimate the memory size for storing the elements of D^{Θ} for $|\Theta| = n$. In most fusion applications only a small subset of elements of D^{Θ} have a non-null basic belief mass, because all the commitments are just usually impossible to assess precisely when the dimension of the problem increases. Thus, it is not necessary to generate and keep in memory all elements of D^{Θ}, but only those which have a positive belief mass. However, it is very important how to manage efficiently all elements of the hyper-power sets D^{Θ}. So, the part computing program of generating hyper-power sets D^{Θ} is given as follows.

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n=input ('0<n<7');
u_n =[1];
for nn=2:n
u_n=[u_n nn ( u_n*10+nn*ones (1,size ( u_n*10,2 ) ))];
end
D_n1 =[0;1];
for nn=1:n , D_n =[];
    for i =1:size (D_n1,1 ),Li=D_n1 (i,:);
       for j=i:size (D_n1,1)
         Lj=D_n1 (j,:) ; Li_inter_Lj=and (Li,Lj);
         Li_union_Lj=or(Li,Lj);
         if((Li_inter_Lj==Li)&(Li_union_Lj==Lj))
               D_n=[D_n;Li Lj];
         end
       end
   end
   D_n1=D_n ;
end
DD=D_n;DD(:,1)=[];DD(size (DD,1),:)=[]; D_n=DD;
disp (['|Theta|=n=' ,num2str(n)])
disp (['|D^Theta|= ',num2str( size (D_n ,1))])
disp (['with u_n=[',num2str(u_n ),']''and'])
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According to the above program given, an example is given to discuss the generating of hyper-power sets D^{Θ} in this paper. We hypotheses n=2, generation of D^{Θ} is equivalent to generate u_n and matrix D_n, which can be easily obtained by the procedure given. At last, the corresponding transpose matrix $\boldsymbol{D}'_3$ of $\boldsymbol{D}_3$ is gotten by matrix computing as follows.

$$D_3'=\begin{bmatrix} 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&1&1\\ 0&0&0&0&0&0&0&0&0&0&0&1&1&1&0&0&0&1&1\\ 0&0&0&0&0&0&1&1&1&1&1&1&1&1&1&1&1&1&1\\ 0&0&0&0&0&1&0&0&0&0&1&0&0&1&0&0&1&0&1\\ 0&0&0&1&1&1&0&0&1&1&1&0&1&1&1&1&1&1&1\\ 0&0&1&0&1&1&0&1&0&1&1&1&1&1&0&1&1&1&1\\ 0&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1 \end{bmatrix}_{7\times 19}$$

Example 2 Based on the DSmT method, a tracking under occluding conditions is simulated with crossing objects and closely spaced objects in the process of tracking. Two objects are selected in order to analyze conveniently. Each object is tracked using 20 particles only. An increased number of particles will result in a smoother tracking, while increasing the processing time. The tracking sequence is divided into three phases. Phase 1 is the pre-occlusion sequence, phase 2 corresponds to the occlusion sequence, and phase 3 is the post-occlusion sequence. Tracking in phase 2 is challenging due to the closeness of the object, which perturbs the measured cues and might lead to a false identification. The simulation scenario consists of two objects, and a stationary sensor at the origin with T=5second, measurement standard deviations 0.4^{0} and 70m for azimuth and range, respectively.

Firstly, two crossing moving object will be analyzed. For two crossing moving object, the tracking method based on DSmT-PF is applied to produce the attribute probability term in generalized assignment matrix, and the corresponding computing results of tracks' purity in case of generalized data association is gotten as shown in table 1. Where missing is used for the case when in the track's gate there is no observation, and wrong is used for the case when the track is associated with the false alarm. It is very obvious that the tracks' purity is increases from the result in table Ⅰ.

TABLE Ⅰ. TWO CROSSING OBJECTS VALUES OF DATA ASSOCIATION BASED ON DSMT

Object tracking	tracking 1	tracking 2	missing	wrong
Object 1	0.774	0.120	0.014	0.007
Object 2	0.135	0.768	0.014	0.003

Secondly, two closely spaced objects will be analyzed. For two closely spaced objects, and one can easily see that the two closely spaced moving in parallel objects lose the proper directions and the tracks switch. At last, the tracking method based on DSmT is applied to discuss the data association problem, and the corresponding results based on DSmT are given in table Ⅱ. Results show the proper data associations in condition of two closely spaced objects.

TABLE Ⅱ. TWO CLOSELY SPACED OBJECTS VALUES OF DATA ASSOCIATION BASED ON DSMT

Object tracking	tracking 1	tracking 2	missing	wrong
Object 1	0.665	0.235	0.002	0.0004
Object 2	0.203	0.450	0.001	0.0000

After discussing the above two tracking processes of data association, the confidence levels for all particles during the tracking will be simulated analysis. The DSmT model is effective handled for the conflicting information provided based on DSmT method. At last, the variation of the average value of the confidence levels for all particles during the tracking are gotten by simulating, and the corresponding results are shown in figure 1.

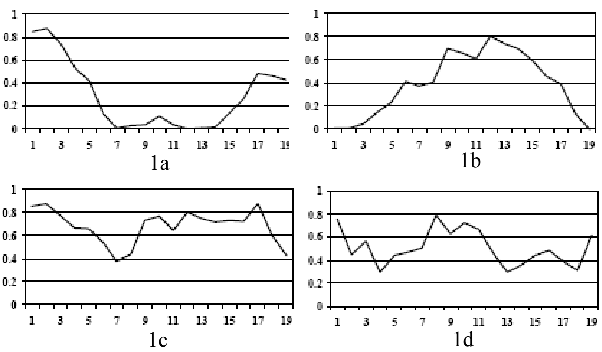

Figure 1. Confidence levels variation for all particles

According to the figure 1, the confidence level for the occluded object $m_{\text{avg}}(\theta_1)$ is high during phases 1 and 3, but it decreases in phase 2 (see figure 1a). However, in phase 2 the object is occluded and this reduces the confidence value provided. During the same phase, the confidence remains high, which explains the increase in the conflict $m_{\text{avg}}(\theta_1\cap\theta_2)$ as shown in figure 1b. The belief function $Bel_{\text{avg}}(\theta_1)$ is given in figure 1c, and this curve shows the high confidence with which the object is located despite the occlusion. This is mainly due to the introduction of the conflict information through the DSmT model. Figures 1d shows that the effect of the occlusion on the occluding object is small in comparison with its effect on the occluded object. The existence of such an effect can be justified by the presence of object 1 in the immediate neighborhood of object 2, which rapidly modifies the corresponding measurement for some particles.

CONCLUSION

The introduced method is given to analyze moving objects tracking under occluding conditions, and the below conclusions can be obtained by the computing simulation and discussion.

1). The DSmT is more desirable in the case of solving some occluding problems, and it is more efficient in combining conflict evidence especially when the evidences conflict highly.

2). In view of the occluding in detecting moving objects in complex background, a new object tracking method of DSmT is proposed to track occluded objects and interference objects, and the result show that method is effective and practicable.

3). Calculation of observation likelihood is a difficult problem under the circumstance of occlusion based on DSmT, and its difficulty lies in the use unreliable information to obtain the reliable track effect in very complex environment. Therefore, how to more improve tracking stability and robustness is very important task, too.

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