Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 16 (2011) 54 – 58

Procedia Engineering

www.elsevier.com/locate/procedia

International Workshop of Automobile, Power and Energy Engineering

Multiple Moving Targets Tracking Research in Cluttered Scenes

Yingwu Fang *, Yi Wang, Wei Jin

Telecommunication Engineering Institute, Air Force Engineering University, 1st Fenghao Road No.117, Xi'an, 710077, China

Abstract

Traditional particle filter (PF) will have bad effect when the target's color is similar to the background or the target is blocked, and an improved tracking algorithm is presented in the framework of PF and DSmT. According to the location cue, a new tracking approach is given to establish the model of multiple moving targets based on information fusion. Experimental results demonstrate that the proposed approach can accurately track the intersecting targets in cluttered scenes, and high conflicting information is dealt with effectively. So, the introduced method improves the reliability and rationality of multiple moving targets tracking, and a robust tracking result is obtained although evidences conflict another one highly.

© 2010 Published by Elsevier Ltd. Selection and/or peer-review under responsibility of Society for Automobile, Power and Energy Engineering Open access under CC BY-NC-ND license.

Keywords: DSmT; particle filter; targets tracking

1. Introduction

Video-based target tracking is one of the research hotspots in the field of computer vision. It has a wide range of applications in military guidance, visual surveillance, visual navigation of robots and human computer interaction[1], etc. Although many effective visual target tracking methods has been proposed, there are still a lot of difficulties in designing a robust tracking algorithm due to the challenging complex scenarios such as significant illumination changes in environment, pose variations of the target and non-linear deformations of shapes, and noise and dense clutters in complex background, etc.

* Corresponding author. Tel.: +86-13689246921

1877-7058 © 2011 Published by Elsevier Ltd. Open access under CC BY-NC-ND license.
doi:10.1016/j.proeng.2011.08.1051

E-mail address: fangyw72@126.com.

DSmT is a useful method for dealing with uncertainty problems[2]. It is more efficient in combining conflicting evidence; therefore it has been successfully applied in data fusion. DSmT can be good evidence of contradictions to resolve the issue of evidence portfolios, but DSmT computation quantity oversized, also fuses the result under the low conflict situation time to D-S[3]. Especially, there exist shortcomings in its combination rule when tracking multiple moving targets. Thereby, In view of the occluding in detecting moving targets in complex background, a new anti-occluding target tracking algorithm based on occlusion condition is proposed in the framework of DSmT and particle filters (PF) [4], and an efficient combination rule is given in this paper. It is valuably concluded that high reliableness can be achieved through the experiments, and the diverseness and conflict of the fusion information are managed effectively. Meanwhile, the uncertainty, non-integrality and indefiniteness are degraded greatly.

2. Multiple Targets Tracking Based on DSmT

Let's assume that the number of targets is τ, the number of cues is c, and the τ and c are known. Up to time t-1, each target is associated with a track $\{\theta_j\}_{j=1}^{\tau}$. At time t, an image frame is extracted from the video sequence and a number of measurements are obtained for each target candidate. Thus, the target given is to combine these measurements in order to determine the best track for each candidate. It is important to notice that a target candidate, in this paper, refers to a particle sample. The hyper-power set D^{Θ} defines the set of the hypotheses for which the different cues can provide confidence values. These hypotheses can correspond to: 1) individual tracks θ_j., 2) union of tracks $\theta_r \cup \ldots \cup \theta_s$,, which symbolizes ignorance, 3) intersection of tracks $\theta_r \cap \ldots \cap \theta_s$, which symbolizes conflict or 4) any tracks combination obtain 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 in 4). Given this framework, expresses the confidence with which cue l associates particle n to hypothesis A at time t. A single map function can be derived as follows based to DSmT combinational rule[5]. .

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

Since the target 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[6].

$$Bel_t^{(n)}(\theta_j) = \sum_{\substack{\theta_i \subseteq A \\ A \in D^{\Theta}}} m_t^{(n)}(A) \,. \tag{2}$$

$$Pls_t^{(n)}(\theta_j) = \sum_{\substack{\theta_i \subseteq A \\ A \in D^{\Theta}}} m_t^{(n)}(A) \,. \tag{3}$$

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 target, they are rather used to quantify the weight of the candidate as a sample of the state posterior distribution $p(X_t|Z_t)$. The particle filtering algorithm based on DSmT is implemented in this paper, and the corresponding step is given below.

3. Tracking Two Targets Using Location Cues

For two targets, we can define Θ as follows

$$\Theta = \{\theta_1, \theta_2, \overline{\theta_1 \cup \theta_2}\}. \tag{4}$$

In Eq.(4), θ_1 refers the first target, θ_2 refers to the second target and $\overline{\theta_1 \cup \theta_2}$ refers to the rest of the scene. Actually, hypothesis $\overline{\theta_1 \cup \theta_2}$ **c**an refer to the background information. However, since this latter can change during the tracking, we will refer to $\overline{\theta_1 \cup \theta_2}$ as the false alarm hypothesis. Beside, $\theta_1 \cap \theta_2 \neq \phi$ due to the possible occlusion, and $\theta_j \cap \overline{\theta_1 \cup \theta_2} = \phi$ for j=1,2.

The targets locations at time t-1 are known and given by $(x_{t-1,1}, y_{t-1,1})$ and $(x_{t-1,2}, y_{t-1,2})$. At time t, the probability that a particle $s_{t,j}^{(n)}$ located at $\left(x_{t,j}^{(n)}, y_{t,j}^{(n)}\right)$ belongs to target j=1,2 according to the location information is defined from a Gaussian pdf as follows

$$p_{t,j}^{(n)} = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{\left(x_{t,j}^{(n)} - x_{t-1,j}\right)^2 + \left(y_{t,j}^{(n)} - y_{t-1,j}\right)^2}{2\sigma^2}} . \tag{5}$$

where σ is a bandwidth parameter. Similarly, the probability that given particle does not belong to θ_1 and θ_2 is inversely proportional to the distance between the particle and both targets. Since Θ is exhaustive, a particle that does not belong to θ_1 and θ_2 do belong to $\overline{\theta_1 \cup \theta_2}$. This leads us to the definition of a new pdf, $p_{t,FA}^{(n)}$, which measures the membership of a particle $n = 1,\cdots,N$ to the false alarm hypothesis

$$p_{t,FA}^{(n)} = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{\left(d_{\max} - d_{1-2}^{(n)}\right)^2}{2\sigma^2}} . \tag{6}$$

$$d_{1-2}^{n} = \sqrt{\left(x_{t-1}^{(n)} - \frac{x_{t-1,1} - x_{t-1,2}}{2}\right)^2 + \left(y_{t-1}^{(n)} - \frac{y_{t-1,1} - y_{t-1,2}}{2}\right)^2} . \tag{7}$$

where d_{max} is the radius of a circle centered on the mid-point of targets 1 and 2, and which contains all the particles used for tracking at the time t-1, $d_{1\text{-}2}^{(n)}$ is the distance separating particle n and the mid-point.

The mass function of particle n according to its location is given by

$$m_{t,1}^{(n)}(\theta_j) = \frac{p_{t,j}^{(n)}}{p_{t,1}^{(n)} + p_{t,2}^{(n)} + p_{t,FA}^{(n)}}, \ j = 1,2 \cdot \tag{8}$$

$$m_{t,1}^{(n)}(\overline{\theta_1 \cup \theta_2}) = \frac{p_{t,FA}^{(n)}}{p_{t,1}^{(n)} + p_{t,2}^{(n)} + p_{t,FA}^{(n)}} . \tag{9}$$

The weight of $s_{t,j}^{(n)}$ particle within the posterior $p(X_t|Z_t)$ distribution, for target j, is calculated using belief (or the plausibility) function, so that

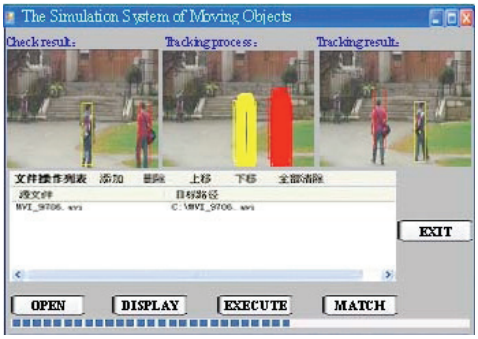
$$\pi_{t,j}^{(n)} = Bel_t^{(n)}(\theta_j) = m_t^{(n)}(\theta_j) + m_t^{(n)}(\theta_1 \cap \theta_2) \qquad j = 1,2 \cdot \tag{10}$$

The generalization of the tracking scheme described in this section to τ targets can be carried out by defining a frame of discernment $\Theta = \{\theta_1, \cdots, \theta_\tau, \theta_1 \cup \cdots \cup \theta_\tau\}$, where θ_j are individual targets and $\overline{\theta_1 \cup \cdots \cup \theta_\tau}$ is the false alarm hypothesis.

4. Experiment Analysis and Discussion

4.1 Tracking Analysis

On the basis of the above analysis, the corresponding program is given by Visual C++ 2005. In order to check the correctness and efficiency of the algorithm, there will select a part of movie video in a cluttered scene, as shown in Fig.1a, and two intersecting targets will be selected to track. Since the purpose of this paper is tracking and not the target detection, both targets are selected manually. Each target is tracked using 30 particles only. An increased number of particles will result in a smoother tracking, while increasing the processing time. For the sake of clarity, the person on the right is denoted target 1 and the person on the left is denoted target 2. The interface of simulation system and the tracking process of main frame are given in this paper, as shown in Fig.1 and Fig.2b-2e. At last, the tracking result of intersecting targets in cluttered scenes is gotten as shown in figure 2f.



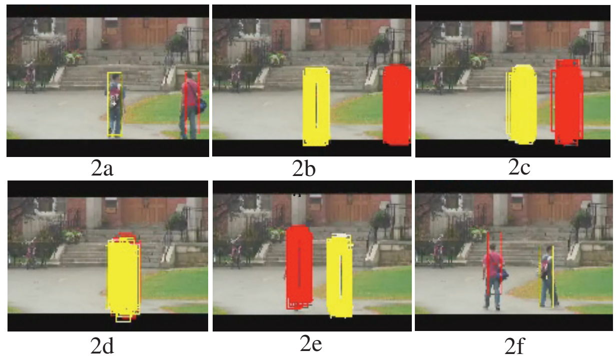


Fig.1 The tracking interface of simulation system Fig.2 The tracking process of main frames and tracking result

It can be seen from the above tracking process, the tracking sequence is divided into three phases. The first phase is the pre-occlusion sequence, the second phase corresponds to the occlusion sequence, and the third phase is the post-occlusion sequence. Tracking in the second phase is challenging due to the closeness of the targets, which perturbs the measured cues and might lead to a false identification. The location cue loses gradually its ability to separate targets 1 and 2 as they converge to the intersection point. However, the location cue remains a valid measurement because it is independent from the relative location of targets with respect to the camera (occluding or occluded). According to the above analysis, in the framework of DSmT and particle filters, the introduced method accurately identifies the targets during the three phases of the tracking. This is due to the effective handling of the conflicting information provided by the location cues based on the DSmT.

4.2 Confidence Levels of Particles Discussion

In order to discuss confidence levels during the tracking, the variation of the average value of confidence levels for all particles are calculated, and the corresponding result are shown in figure 3.

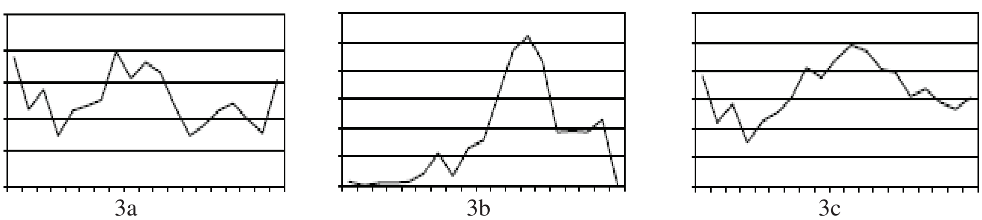


Fig.3. The variation of the average value of confidence levels

The confidence level for the occluded target, $m_{avg}(\theta_1)$, is high during phases 1 and 3, but it decreases in phase 2, Indeed, in phases 1 and 3 the location cues agree on the identity of the target. However, in phase 2 the target is occluded and this reduces the confidence value provided. Figures 3a, 3b and 3c show that the effect of the occlusion on the occluding target is small in comparison with its effect on the occluded target. The existence of such an effect can be justified by the presence of target 1 in the immediate neighborhood of target 2, which rapidly modifies the location measurement for some particles.

5. Conclusion

Aiming at the problem that PF requires many particles to approximately describe state of target, which is more time-consuming. DSmT is a useful method for dealing with uncertainty problems, and it is more efficient in combining conflicting evidence. Therefore it has been successfully applied in target tracking. In this paper, a new algorithm was studied to track fast moving target with complex scene based on DSmT and PF. Owing to use a new combination rule of evidence, the particle description became more rational, the number of particle required was reduced, and the tracking efficiency was improved greatly by the tracking experiment.

Acknowledgements

The project is supported by the Science Foundation of the Telecommunication Engineering Institute of Air Force Engineering University (No.DYCX1005), and the authors are very grateful to the foundation.

References

[1] Yilmaz A., Javed O., Shah M. Object Tracking: a Survey. *ACM Computing Surveys* 2006;**38**:1-45.

[2] Dezert J., Smarandache F. *Advances and applications of DSmT for information fusion.* Rehoboth, American Research Press; 2004.

[3] Dempster AP. Upper and Lower probabilities induced by multi valued mapping. *Annals of Mathematical Statistics* 1967;**38**,325-339.

[4] Arulampalam M., Maskell S. A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking. *IEEE Trans On Signal Process* 2002; **50**:160-188.

[5] Chen C., Lin X., and Shi Y. Moving object tracking under varying illumination conditions. *Pat. Rec. Let*. 2006;**27**:1632-1643.

[6] Dezert J., Smarandache F. *On the generation of hyper-powersets for the DSmT.* Proc. of Int. Conf. Information Fusion, Cairns, Queens land, Australia; 2003.