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Research on Dynamic Targets Tracking Based on Color Cues Under Complicated Scene

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Abstract

Compared with DST, DSmT can be good evidence of contradictions to resolve the issue of evidence portfolios, In view of the occluding in tracking dynamic targets in complex background, a new anti-occluding target tracking algorithm based on DSmT and particle filter is proposed by color cues. The simulation results show that the proposed algorithm is effective and practicable in tracking occluded target and intersected target. Compared with the existing combination rules, the newly proposed rule is applied to both cases of conflicting and coincidence.

Keywords: DSmT; color cues; dynamic targets; tracking

1. Introduction

The visual object tracking is a key issue in many vision-based applications, such as visual surveillance, visual navigation of robots, human-computer interaction, medical diagnose and military guidance[1]. Along with the rapid growth of the information techniques in the last tens of years, the object tracking has attracted many researchers' attention and has become a very popular research topic. Although many effective visual object 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 object and non-linear deformations of shapes, and noise and dense clutters in complex background, etc. 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 dynamic targets tracking.

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In this paper, a tracking algorithm based on the DSmT theory is proposed by adapting color cues. The dynamic tracking model with the major colors cues of the targets is built so that the targets can be represented with a few of the model parameters, and its performance is superior to the histogram used widely in targets tracking. The proposed tracking algorithm can track targets robustly in complex scenarios such as appearance change and occlusions by different tracking experiments.

2. Dynamic Targets Tracking

Highly non-linear and non-Gaussian estimation problems are ubiquitous in target tracking. Particle filters (PF) is an effective tool for such problems, and the basic theory of PF can be founded in literatures [3,4]. In order to handle real-time tracking problem effectively under occlusion conditions, and degrade the uncertainty, non-integrality and indefiniteness. A key technique in information fusion and several tracking problems under occlusion condition are studied based on the framework of PF and DSmT, and the corresponding model will be established in this paper, and a general framework for dynamic targets tracking using color cues will be described. This approach uses the DSmT combinational rule to refer the information provided by the color cues into a single representation, and this latter takes into account the conflicts between the cues that might arise due to occlusion.

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. A single map function can be derived as follows based to DSmT combinational rule.

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

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 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[5].

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

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

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.

Step 1: Initialization—generate N samples $S_{t,j} = \{s_{t,j}^{(n)}, \pi_{t,j}^{(n)}\}_{n=1}^{N}$ for each target j=1, $\cdots$,τ independently, with $\pi_{t,j}^{(n)} = 1/N$, and set t =1.

Step 2: Propagation— $S_{t^*,j}^{(n)} = A \cdot S_{t-1,j}^{(n)} + w_{t-1,j}^{(n)}$

Step 3: Observation (for each particle)—Compute $\{m_{t^*,l}^{(n)}(A)\}_{l=1}^{c}$ and $\{m_{t^*,l}^{(n)}(A)\}_{l=1}^{c}$ for $A \in D^{\Theta}$, and

Calculate the particle weight $\pi_{t^*,j}^{(n)} = Bel_{t^*}^{(n)}(\theta_j)$, Normalize the weight: $\tilde{\pi}_{t^*,j}^{(n)} = \dfrac{\tilde{\pi}_{t^*,j}^{(n)}}{\sum_{n=1}^{N} \tilde{\pi}_{t^*,j}^{(n)}}$

Step 4: Estimation—Target j=1…τ is given by $E[S_{t^*,j}] = \sum_{n=1}^{N} \tilde{\pi}_{t^*,j}^{(n)} s_{t^*,j}^{(n)}$

Step 5: Resampling (for each target)—Generate $S_{t,j} = \left\{s_{t,j}^{(n)}, \pi_{t,j}^{(n)}\right\}_{n=1}^{N}$ by resampling N times, where $p\left(s_{t,j}^{(n)} = s_{t^*,j}^{(n)}\right) = \tilde{\pi}_{t^*,j}^{(n)}$

Step 6: Incrementing—when $t = t + 1$, go to step 2.

3. Color Cues for Tracking

For two targets, we can define Θ as follows

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

In (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.

Let's assume that both target models are known and given by normalized color histograms $\{q_j(u)\}_{u=1}^{m}$, where u is a discrete color index and m is the number of histogram bins. At time t, the normalized color histogram of particle $s_{t,j}^{(n)}$ is given by $\left\{h_{t,j}^{(n)}(u)\right\}_{u=1}^{m}$. The probability that particle $s_{t,j}^{(n)}$ belongs to target j=1,2 according to the color histogram is derived from the following Gaussian pdf.

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

where σ is a color bandwidth parameter, $d_{t,j}^{(n)}$ is the Bhattacharyya distance between $h_{t,j}^{(n)}(u)$ and $q_j(u)$ at time t.

$$d_{t,j}^{(n)} = \sqrt{1 - \sum_{u=1}^{m} h_{t,j}^{(n)}(u) q_j(u)}. \tag{6}$$

Let's define $\{q_{FA}(u)\}_{u=1}^{m}$ as the histogram of the scene from which we subtract the histogram of targets 1 and 2.

$$q_{FA}(u) = \max\{q_{scene}(u) - q_1(u) - q_2(u), 0\}. \tag{7}$$

The probability that $s_{t,j}^{(n)}$ belongs to the false alarm hypothesis will be given by

$$p_{t,FA}^{(n)} = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{\left(d_{t,FA}^{(n)}\right)^2}{2\sigma^2}}. \tag{8}$$

Where $d_{t,FA}^{(n)} = \sqrt{1-\sum_{u=1}^{m} h_{t,j}^{(n)}(u)\, q_{FA}(u)}$

The mass functions of particle n according to color can be evaluated as follows

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

$$m_{t,2}^{(n)}(\theta_j) = \frac{p_{t,j}^{(n)}}{p_{t,1}^{(n)} + p_{t,2}^{(n)} + p_{t,FA}^{(n)}}, \; j = 1,2. \tag{10}$$

4. Tracking Experiment and Analysis

In order to test tracking efficiency and correctness, two different videos with the same scene are selected to compare the introduced method, as shown in figure 1 and figure 2. There are only two people in the first video, and there are many people in the second video, and two intersecting targets will be marked.

Fig.1 Two targets of the first video

Fig.2 Two targets of the second video

Owing to the increased number of particles will increase the processing time, 20 particles are using to dynamic targets tracking in the first video by the above analysis, and 30 particles are given to meet the accuracy of dynamic tracking in the second video. The dynamic tracking process of main frame is given, and figure 3 is the first video and figure 4 is the second video, respectively.

Fig.3 The tracking process of main frames in the first video

Fig.4 The tracking process of main frames in the second video

At last, the dynamic tracking result of intersecting targets in cluttered scenes is gotten, and figure 5 is the first scene and figure 6 is the second scene, respectively.

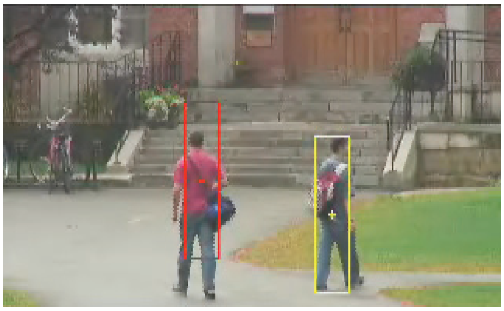

Fig.5 The result of intersecting targets in the first video Fig.6 The result of intersecting targets in the second video

It can be seen from the above tracking process, 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 color cues based on the DSmT.

5. Conclusion

Highly non-linear and non-Gaussian estimation problems are ubiquitous in dynamic target tracking, and it is a tough job to select the characteristics of targets in target tracking system. If targets have more features, tracking accuracy could be improved effectively. However, computing quantity and calculation time would also be increased. It is imperative for us to take compromise of real-time and accuracy. As high stability and low computation al characteristics, color cues are become main information, and it can be used to establish dynamic targets tracking model based on DSmT with the DSmT is very effective evidence theory for such problems. The experimental results have been demonstrated that this method ameliorated the interference immunity of the traditional model for tracking targets. The introduced method improved the tracking accuracy and robustness while not affecting the real-time characteristics, and it have better dynamic tracking effect for different scenes.

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