A Novel Occlusion-Adaptive Object Tracking Method

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Abstract—**In conventional object tracking methods, much attention has been paid to tracking efficiency, but they often failed in tracking an occluded object. In this paper, we present a new method to improve the occlusion adaptability and tracking robustness. This proposed algorithm covers the occlusion-adaptive particle filter (OAPF) framework, which employs the adaptive state transition model to detect occlusions by a first-order histogram difference dynamic algorithm accurately and simply. Thus, when partial or complete occlusions occur, it can detect interrupted state transition to realize persistent tracking. In addition, tracking robustness is also upgraded via adaptive Gaussian noise coefficient model in particle propagation. Finally, we emphasize that the computing complexity of OAPF is evidently decreased by reducing the particle number in execution. As a result, this simple and effective occlusion-adaptive tracking method has been demonstrated through several real-time sequences.**

Keywords-object tracking; particle filter; occlusion adaptation; adaptive noise model

I. Introduction

Object tracking is a challenging problem in various video processing and computer vision applications. Adaptability under occlusions is one of the toughest open issues in object tracking process [1].

As we know, point probability estimation is one of crucial methods in most occlusion-adaptive tracking algorithms [1]. S.K. Zhou used robust statistics in an appearance-adaptive model (AAM) for single object tracking under partial occlusions [2]. But it would fail under the case of large-scale occlusion outlier. In addition, Z.H. Duan used the sum of particle weights for one object occlusion detection and recovery in adaptive particle filter (APF) [3]. Computational burden is high in that method due to its particle number is up to 500.

Furthermore, appearance template matching method is often incorporated into particle filter framework to improve tracking performance under occlusions. Y. Zhou used Bayesian decision theory to detect object state, which could distinguish the occlusion from appearance changes by risk possibilities [6]. But the computational complexity of template matching based object tracking algorithm is increased sharply in this occlusion detection scheme.

As for multi-object tracking task, Loris has proposed an online subjective feature selection mechanism to deal with occlusion problem based on joint observation model of Hybrid Joint-Separable (HJS) filter platform [9].

In our previous work, a novel tracking algorithm, so-called CamShift guided particle filter (CAMSGPF) [4], achieved robust tracking results in complex environments with less than 30 particles compared to [5]. In this paper, we present an occlusion-adaptive particle filter (OAPF) framework to improve occlusion adaptability and tracking robustness in real-time single object tracking under occlusions. Specifically, this algorithm including three facets: (1) According to the adaptive state transition model, occlusions can be detected via a first-order histogram difference dynamic model for both partial and complete occlusions accurately and simply. (2) Velocity inference model based on previous l frames is introduced to enforce tracking continuity of OAPF to be adaptive to occlusion status in tracking process. (3) Object scale variations are regarded to establish adaptive noise coefficient model to improve the tracking robustness with low computing complexity.

The rest of the paper is organized as follows. Section 2 describes the proposed occlusion-adaptive object tracking model. Section 3 conducts tracking tasks on some video sequences with occluded objects and provides experimental analysis. Finally, section 4 concludes this paper.

II. Occlusion Adaptive Object Tracking Model

The occlusion-adaptive object tracking particle filter is inspired from the work of CAMSGPF, which is described as follows,

$$x_k = f_k\left(x_{k-1}, n'_{k-1}\right) \tag{1}$$

$$z_k = h_k\left(x_k, \theta_k\right) \tag{2}$$

Where f is nonlinear state transition model and h is observation model. x_k presents object state and z_k presents object observation at time k. n' and θ denote process and observation noise.

Particle filter is an optimal Bayesian algorithm for nonlinear and non-Gaussian object tracking and it obtains the most likely posterior estimation based on sequential Monte Carlo framework. Due to its multiple hypothesis property, it can be applied to any state-space model to estimate the trajectory of an object in frames effectively [7,8]. Fig. 1 shows the occlusion adaptive tracking results of CAMSGPF and our OAPF.

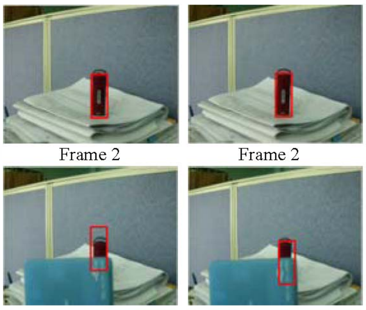


Figure 1. U-disk sequence. CAMSGPF results (Left column) and our OAPF results (Right column).

A. System Observation Model

In the observation model, the posterior density function $p(x_k|z_{1:k})$ is approximated by a set of N samples (particles) with weights $\{x_k^i, w_k^i\}_{i=1}^N$. Given the posterior density function $p(x_{k-1}|z_{1:k-1})$, under the first order Markov assumption, regressive Bayesian theory is optimal. Firstly, the weight of particle that models posterior density is updated as

$$w_k^i \propto \frac{p(z_k|x_k^i)\,p(x_k^i|x_{0:k-1}^i)}{q(x_k^i|x_{0:k-1}^i, z_k)} \tag{3}$$

The proposal importance sampling distribution function $q(x_k^i|x_{0:k-1}^i, z_k)$ further increases computational burden. Thus, in this paper, we substitute it by prior distribution $p(x_k^i|x_{0:k-1}^i)$ in tracking model. Secondly, the likelihood distribution $p(z_k|x_k^i)$ in (3) gives

$$p(z_k|x_k) \propto e^{-\lambda D^2[h_0, h(x_k)]} \tag{4}$$

Here $D[]$ is Bhattacharyya similarity metric to compare the reference histogram h_0 and the candidate histogram $h[x_k]$.

B. Occlusion-Adaptive Dynamic State Transition Model

Occlusion-adaptive tracking model assumes that state transition can be implemented by combining with more clues, depending on the object is occluded or not. In [4], Camshift is integrated into particle filter to upgrade particle sampling and object scale adaptation. However, CAMSGPF has no measurements to handle the problem that particles will spread more widely in occlusion situations which results in regaining the exact target position unsuccessfully.

The dynamic of occlusion adaptive state transition in OAPF is updated as

$$\hat{x}_k = x_{k-1} + e_k(\nabla x) + n_k' \tag{5}$$

Where $\hat{x}_k$ is the current state estimation of target. $e_k(\nabla x)$ denotes the estimated state difference according to previous l frames [3] as (6) showing. The choice of n_k' will be discussed below.

$$e_k(\nabla x) = \frac{1}{l}\sum_{n=k-l}^{k-1} |x_n - x_{n-1}| \tag{6}$$

Specially, it turns out that histogram difference of that particle with maximal weight will change most acutely when occlusion appears. In practice of OAPF adaptive state transition, we detect occlusion state of target from the histogram difference model written as (7) and (8).

$$h_{diff} = \frac{M_{00}}{Sum_{bins}}\Big|_{Max\_weight} \tag{7}$$

$$M_{00} = \sum_{j=1}^{bins} r(a_j) \tag{8}$$

Where h_{diff} is normalized histogram difference of the maximal weighted particle to detect the occlusion status. And M_{00} is the zeroth moment of likelihood distribution. $r(a_j)$ means the ratio of histogram bin value of object current and reference histogram.

If the occlusion situation is detected through (7), considering consistency of movement, we can predict variety of velocity $\hat{v}_k$ using a first-order linear approximation [2]

$$\hat{v}_k = \hat{x}_{k-1} - \hat{x}_{k-2} + n_k' \tag{9}$$

On one hand, if occlusion status is detected, we let $e_k(\nabla x) \simeq \hat{v}_k$ to implement occlusion adaptive tracking. On the other hand, if the target is not occluded, we choose $e_k(\nabla x) = 0$ respectively.

C. Adaptive Noise Coefficient Model

From the discussion above, in order to overcome the problem of sample impoverishment in OAPF, we define new adaptive noise $n_k' = r_k \times n_k$, where r_k is a new adaptive noise coefficient and relates with object scale varieties in particle propagation. $n_k \sim N(0, \sigma^2)$, and σ^2 is covariance.

If the random noise of state transition model is small, the particle sample impoverishment will be obvious. And if the random noise is large, it will need more particles to realize exact state prediction [2]. In our algorithm, we compute state adaptive noise associating with object scale subspace to balance between sampling effectiveness and diversity.

The following adaptive noise coefficient model in (10) and (11) is the one we used, which makes particle propagation more concentrated around real object position in small particle number situation. r_{ky} and r_{kx} are vertical and horizontal coordinate noise coefficient. r_w and r_h represent object width and height variable scale. α is a constant controlling importance of two linear components.

$$r_{kx} = \alpha * r_w + (1-\alpha) * r_h \qquad (10)$$

$$r_{ky} = (1-\alpha) * r_w + \alpha * r_h \qquad (11)$$

D. *Summary of The OAPF*

The overall structure of OAPF is summarized in Fig. 2.

$\{S_i\}_{i=1..N} = OAPF\{S_{i-1}\}_{i=1..N}$
Initialize N particles states and weights.
For (i=1: N)
{
·Adaptive noise model based particle propagation
·Compute h_{diff} of maximal weighted particle by (7)
·If (Flag_Occluded == 1)
Occlusion-adaptive tracking via velocity inference
·Else
Tracking with modified CAMSGPF
}
Weights normalizing and particles resampling

Figure 2. The algorithm structure of OAPF.

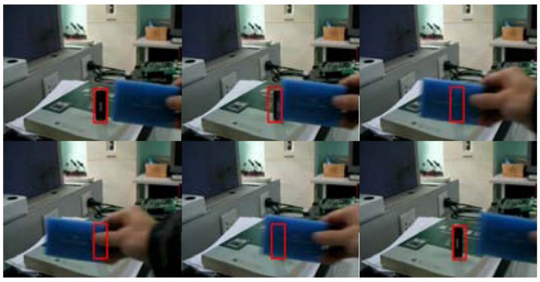
In above structure, occlusion detection and adaptation are realized in particle filter framework, and these adaptive mechanisms make use of characteristics of particle filter skillfully. Hence, it is simple, fast and effective in real-time object tracking process. We define the judgment that if h_{diff} is less than λ, we declare validness of 'Flag_Occluded', which is an indication of occlusion state.

III. Experimental Results

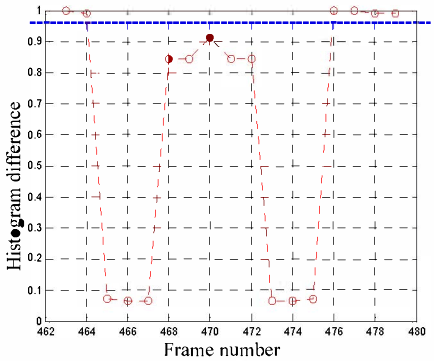
In this section, the performance of OAPF is compared with CAMSGPF and other algorithms. We initialize the OAPF manually in first frame: N=20, λ=0.97, α=0.7, l=1. In following experiments, the target finally estimated is shown with a red rectangle. And occlusion detection, occlusion adaptation, tracking robustness and computing complexity have been tested for our proposed tracking algorithm.

A. *Occlusion Detection*

We first test our algorithm to detect the occlusion state by (7). In this experiment, target is featured with similar color as around complicated environment and very few particles (N=20) are used. Target is not moving, but the camera is mobile and un-calibrated. The tracking result of occluded U-disk is represented in fig. 3(a). More specifically, fig. 3(b) plots the corresponding h_{diff} curve recovered by OAPF, and we can see that h_{diff} is tiny in occlusion frame situation. Although the hand brings some increase to h_{diff} in this sequence, it is still smaller than 0.92 in all the occluded process. So it is easy to set a λ (we set λ =0.97 as blue dashed shown.) to distinguish the occlusion state by this algorithm.



(a)



(b)

Figure 3. (a) U-disk sequence tracking result (frame 464, 465, 467, 472, 475, 477). (b) The curve of h_{diff} from frame 463 to 479.

B. *Occlusion Adaptation for Object Tracking*

We illustrate the effectiveness of our occlusion adaptive approach by comparing with CAMSGPF as fig. 4 demonstrated. In this U-disk sequence, featured with similar color as around complicated environment and very few particles (N=20), the target is partial or complete occluded. Our proposed algorithm can estimate object current state correctly based on occlusion detection mechanism and velocity inference model. While conversely, CAMSGPF will lose target in partial, especially in complete occlusion situations.

C. *Algorithm Complexity Comparison*

Table I presents particle number comparison results of OAPF and other three tracking algorithms. According to the particle filter algorithm framework, we know that the computing complexity of these algorithms mainly lies on the particle number. OAPF can remarkably decrease the particle number to 20 to reduce the cycle computing. And its occlusion adaptability is quite well due to the novel occlusion detecting and adaptive tracking mechanisms.

Figure 4. Occlusion adaptation of U-disk tracking results from OAPF (odd row) and CAMSGPF (even row). (frame 1, 106, 205, 216, 241, 248)

TABLE I. PARTICLE NUMBER COMPARISION

Algorithm Name	Particle Number	Occlusion Adaptability
OAPF	20	Tracking in partial or complete occlusion
AAM [2]	40 (Average)	Tracking lost in large-scale occlusion
APF [3]	500 (In occlusion)	Tracking lost but can recover
CAMSGPF [4]	20	Tracking lost in occlusions

IV. CONCLUSIONS

A particle filter based occlusion-adaptive algorithm called OAPF for robust real-time object tracking has been proposed by histogram difference analyzer and velocity inference in adaptive state transition model. Simultaneously, the new Gaussian noise coefficient adaptive model enhances the tracking robustness in object state estimation with nearly same computing complexity as CAMSGPF. Many tracking experiments demonstrate that OAPF is simple and effective in both tracking robustness and occlusion adaptation.

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