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# Robust infrared target tracking based on particle filter with embedded saliency detection

Fanglin Wang [a], Yi Zhen [b], Bineng Zhong [c], Rongrong Ji [a,*]

[a] School of Information Science and Engineering, Xiamen University, China
[b] Department of Electrical and Computer Engineering, Edmund T. Pratt Jr. School of Engineering, Duke University, USA
[c] School of Computer Science, Huaqiao University, China

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ABSTRACT

Infrared target tracking has attracted extensive research efforts in recent years. However, effective and efficient infrared target tracking is still a hard problem due to the low signal-to-noise ratio, difficulty of robustly describing complicated appearance variations as well as the abrupt motion of targets. In this paper, we propose a tracking method under the Particle Filtering framework by using a hierarchical sampling method, in which two complementary appearance models are used. Firstly, a saliency appearance model is proposed to suppress the cluttered background and properly guide particles to appropriate states. Then the eigen space model is employed as the other observation method to accurately estimate the target state. The hierarchical sampling process is proposed to incorporate the two complementary observation models to account for the abrupt motion efficiently. Experimental results on AMCOM FLIR sequences and comparisons with the state-of-the-art methods demonstrate that the proposed method is robust to appearance changes as well as drastic abrupt motions.



## 1. Introduction

Target tracking in forward looking infrared (FLIR) video sequences is an important but challenging topic in computer vision. Different from visible light spectrum videos, the difficulties of tracking FLIR videos lie in the low signal-to-noise ratio (SNR), poor target visibility, competing background clutter and abrupt motions incurred by high ego motion [34]. For tracking algorithms, to summarize, there are two typical challenges in FLIR video tracking: (1) how to model target appearance to adapt to the appearance changes in the case of cluttered background and (2) how to deal with the drastic abrupt motions incurred by ego motions of the sensor.

How to model the target appearance is always one challenging issue in visual tracking. The visual feature can vary from low level features [33] to high level semantic features [5,37]. In the context of FLIR tracking, the frequently used visual features for appearance modeling include intensity histogram, standard variance histogram [34], edge and shapes [25], etc. Although these features have shown their effectiveness to the scale changes and slow varying appearance, it is hard to solve and model appearance changes incurred by intensity and size variations over a long time period. To overcome these limitations, Bal et al. in [2] proposed to employ an intensity function to formulate the target intensity signature concerning

* Corresponding author at: Room 606B, Administration Building #C, Haiyun Park, Xiamen University, 361005, China.
*E-mail address:* rrji@xmu.edu.cn (R. Ji).

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the intensity variance. Venkataraman et al. in [29] proposed an appearance learning based histogram model to capture the size variance and the appearance change. For object tracking, it can be also benefited from object retrieval [15,10,17] and classification methods [16,9], which can learn or find related objects in the video tracking [32,8].

For infrared target tracking, the low SNR, poor target visibility, and background clutter easily cause tracking loss. The above mentioned works aim to enhance the description of the tracking target, however, the background clutter is enhanced as well, which will still lead to poor performance in FLIR tracking. This also happens frequently in many computer vision applications [14,7]. Recently, the visual saliency detection methods have been extensively studied in computer vision community [13,26]. These algorithms try to achieve the ability of human visual system in order to detect visual saliency [12,23]. In these works, the salient targets are enhanced and the background clutter is suppressed in the meantime. In infrared images, the objective is to emphasize the targeting objects and make them salient in the imaging results and be easily observed by human. So saliency detection presents a feasible modeling method for tackling infrared target tracking. In this paper, a saliency observation model is proposed for a robust tracking performance.

Although saliency detection is able to locate the salient targets robustly, however, it tends to only give a rough prediction of the existence of salient objects, whereas for target tracking tasks the purpose is to give an accurate state estimation. Hence the saliency detection itself is not sufficient for robust and accurate tracking. To complement with saliency detection, an observation model which can model the target accurately and adapt to the appearance changes is required. There have been a lot of works devoted to building an accurate and robust object appearance models [19,39,31,22]. The incremental learning based methods can learn the object appearance online and adapt to the changes. The eigen space model used in [3,24,27] has been demonstrated effective to deal with the size and intensity changes. Yu et al. in [36] considers the tracking problem as a semi-supervised problem and online updates a hybrid discriminative generative model. In [41], an online structured SVM algorithm is employed for spatial constraints learning.

The ego motion of the sensor is frequently encountered in FLIR target tracking. A strong ego motion may lead to large displacements in two consecutive frames [20]. Under these circumstances, the number of samples for a naive particle filter-based tracker has to be increased, which leads to high computational cost. To solve this strong ego motion problem, Shaik et al. [25] integrated two separate global motion compensation modules with two separate tracking modules. In [34], the global motion was compensated with the optical flow computed from a Gabor filter. Venkataraman et al. [28] incorporated two dynamic models in the target's kinematics.

In this work, we propose an infrared target tracking algorithm under the particle filtering framework by using hierarchical sampling under which two observation models are used. To address the frequent tracking loss due to low SNR problem, a saliency model is proposed to enhance the target and in the meantime suppress the background clutter and give a rough estimation of target state. To complement with the saliency model, the incremental eigen space model is employed in order to give an accurate and robust target state estimation. To address the abrupt motion in infrared tracking, the two observation models are embedded in a two stage hierarchical sampling process. In the first stage, samples are widely drawn to cover the possible states the target might possess. The saliency model is employed in this stage to estimate the target state roughly. In the second stage, a further sampling process is conducted and the incremental eigen space model is employed for accurate state estimation. To evaluate the effectiveness of the proposed method, we have conducted experiments on the AMCOM FLIR videos. Comparisons with the state-of-the-art methods indicate that the proposed method delivers more accurate tracking performance and is robust drastic abrupt motion, low SNR, and appearance changes.

The remainder of this paper is organized as follows. Section 2 briefly reviews the particle filter tracking framework. The proposed hierarchical tracking algorithm is introduced in Section 3. Experimental results are provided in Section 4. Section 5 concludes the paper.

## 2. Particle filtering based tracking

Particle filtering is a sequential Monte Carlo method [1] which recursively approximates the state $\mathbf{X}_t$ of a system based on Bayesian model using finite samples [21,35]. It can be seen as a graphical model method [38]. The objective in a tracking task can be regarded as to estimate the posterior distribution $p(\mathbf{X}_t|\mathbf{Y}_{1:t})$, where $\mathbf{Y}_{1:t} = (\mathbf{Y}_1, \ldots, \mathbf{Y}_t)$ denotes the observations up to current time step. In the Bayesian filtering framework, the posterior distribution is obtained in two steps: prediction and update. In the prediction step, by using the dynamic mode $p(\mathbf{X}_t|\mathbf{X}_{t-1})$ the posterior is predicted as

$$p(\mathbf{X}_t|\mathbf{Y}_{1:t-1}) = \int p(\mathbf{X}_t|\mathbf{X}_{t-1})p(\mathbf{X}_{t-1}|\mathbf{Y}_{1:t-1})d\mathbf{X}_{t-1}. \quad (1)$$

In the update step, the posterior is calculated according to Bayesian rule:

$$p(\mathbf{X}_t|\mathbf{Y}_{1:t}) = \frac{p(\mathbf{Y}_t|\mathbf{X}_t)p(\mathbf{X}_t|\mathbf{Y}_{1:t-1})}{p(\mathbf{Y}_t|\mathbf{Y}_{1:t-1})}. \quad (2)$$

Particle filtering aims to approximate the posterior $p(\mathbf{X}_t|\mathbf{Y}_{1:t})$ by using a set of $N$ samples (also named particles) $\left\{\mathbf{X}_t^{(i)}\right\}_{i=1}^N$ with importance weights $\{w_t^{(i)}\}_{i=1}^N$. These samples are drawn from a proposal distribution $q(\mathbf{X}_t|\mathbf{X}_{1:t-1}, \mathbf{Y}_{1:t})$ which may depend on the old states and the new measurements. To maintain a consistent sample the weight is recursively updated as