Enhancing Particle Swarm Optimization Based Particle Filter Tracker

Qicong Wang, Li Xie, Jilin Liu, and Zhiyu Xiang

Departmant of Information and Electronics Engineering, Zhejiang University, Hangzhou, Zhejiang 310013, P.R. China
{wang_qi_cong, xiehan, liujl, xiangzy}@zju.edu.cn

Abstract. A novel particle filter, enhancing particle swarm optimization based particle filter (EPSOPF), is proposed for visual tracking. Particle filter (PF) is sequential Monte Carlo simulation based on particle set representations of probability densities, which can be applied to visual tracking. However, PF has the impoverishment phenomenon which limits its application. To improve the performance of PF, particle swarm optimization with mutation operator is introduced to form new filtering, in which mutation operator maintain multiple modes of particle set and optimization-seeking procedure drives particles to their neighboring maximum of the posterior. When applied to visual tracking, the proposed approach can realize more efficient function than PF.

1 Introduction

Visual tracking is required by many vision applications, but especially in video technology [1]. Particle filters are sequential Monte Carlo methods based on point mass representations of probability densities, which can be applied to any state-space model and has proven very successful for solving non-linear and non-Gaussian state estimation problems [4]. So PF is widely applied in visual tracking. In general, uniform re-sampling is employed in particle filtering, which produces the particle impoverishment problem. To tackle this problem, a large number of particles are used in the filtering at the cost of extra computational costs.

Some algorithms employ complex sampling strategies or specific prior knowledge about the objects to reduce the impoverishment, such as partitioned sampling [5], layered sampling [6], and annealed importance sampling [7]. In [9], kernel particle filter uses an inherent re-sampling approach and broader kernel to improve the performance.

In the paper we introduce a particle swarm optimization (PSO) procedure into particle filtering. PSO is similar to the Genetic Algorithm (GA) in the sense that these two evolutionary heuristics are population-based search methods, but PSO is more computationally efficient than the GA [8]. We combine PSO with mutation operator, which can guarantee enhancing particle swarm optimization (EPSO) to obtain local optima. In EPSOPF, the iterative optimization procedure of EPSO can redistribute particles to their close local modes of the posterior, and mutation operator in EPSO

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ameliorates implicitly the diversity of particle set to alleviate the impoverishment phenomenon greatly at the same time. Moreover, we use color distributions [1] to evaluate similarity measurement of the object and a candidate for visual tracking.

2 Particle Filter

PF solves non-linear and non-Gaussian state estimation problems in Monte Carlo simulation using importance sampling, in which the posterior density is approximated by the relative density of particles in a neighborhood of state space. In [2], particle filter solves tracking problem based on the system model

$$\mathbf{x}_t = f\left(\mathbf{x}_{t-1}, \mathbf{w}_t\right) \tag{1}$$

and on the observation model

$$\mathbf{y}_t = h\left(\mathbf{x}_t, \mathbf{v}_t\right) \tag{2}$$

where $\mathbf{w}_t$ and $\mathbf{v}_t$ are only supposed to be independent white noises. $\mathbf{y}_{0:t}$ is defined as the history sequence of the random variables. Our problem consists in computing the posterior density $p\left(\mathbf{x}_t \mid \mathbf{y}_{0:t}\right)$ of the state $\mathbf{x}_t$ at each time t, which can be obtained through prediction and update recursively. By Eq. (1), we realize prediction according to the following equation

$$p(\mathbf{x}_t \mid \mathbf{y}_{0:t\text{-}1}) = \int p\left(\mathbf{x}_t \mid \mathbf{x}_{t\text{-}1}\right) p\left(\mathbf{x}_{t-1} \mid \mathbf{y}_{0:t-1}\right) d\mathbf{x} \tag{3}$$

To obtain the posterior density, we update this prediction with the observation $\mathbf{y}_t$ in terms of the Bayes rule.

In Monte Carlo methods, the posterior is approximated by the set of particles. For particle set $\left\{\left(\mathbf{s}_t^{(n)}, q_t^{(n)}\right)_{n=1,2,\ldots,N}\right\}$, where $\mathbf{s}_t$ is the particle state and q_t is the weight associated to the particle, we approximate the posterior with the following weighted sum on the discrete grids.

$$p\left(\mathbf{x}_t \mid \mathbf{y}_{0:t}\right) \approx \sum_{n=1}^{N} q_t^{(n)} \delta\left(\mathbf{x}_t - \mathbf{s}_t^{(n)}\right) \tag{4}$$

where $\delta(\bullet)$ is Dirac's delta function. And the weight q_t can be calculated through the importance density function.

The re-sampling step is crucial in the implementation of particle filtering because without it, the variance of the particle weights quickly increases [12]. In PF, uniform re-sampling is used, which is difficulty in maintain multiple modes of particle set after several updates and can result in the particle impoverishment problem.