Improved Particle Filter for Target Tracking

DENG Xiao-long[1], XIE Jian-ying[1], NI Hong-wei[2]
(1. Department of Automation, Shanghai Jiaotong University, Shanghai 200030, China)
(2. First Research Institute of Corps of Engineers, General Armaments Department, PLA, Wuxi 214035, China)

Abstract: A new improved particle filter algorithm with the simplified UT (unscented transformation) and the modified unscented Kalman filter (UKF) proposal distribution is presented. The scaling factor is added to adaptively estimate on line and to improve the filtering performance. An adaptive algorithm is developed. In the bearings-only tracking experiments, the results confirm the improved particle filter algorithm outperforms others.

Key words: particle filter; bearings-only tracking; UKF; proposal distribution

一个用于目标跟踪的改进粒子滤波算法. 邓小龙, 谢剑英, 倪宏伟. 中国航空学报(英文版), 2005, 18(2): 166-170.

摘 要: 简化UT(unscented transformation)转化参数, 修改UKF(unscented Kalman filter)提议分布, 提出了改进的粒子滤波算法。调节因子的增加使得能在线自适应估计, 滤波性能提高, 并形成一个自适应的算法。仅有角测量的目标跟踪仿真试验证实了改进的粒子滤波算法要优于其它滤波方式。

关键词: 粒子滤波; 仅有角测量跟踪; UKF; 提议分布

文章编号: 1000-9361(2005)02-0166-05 中图分类号: V243 文献标识码: A

In the fields of the target tracking, *etc*, the extended Kalman filter (EKF) is one of the most common suboptimal filtering approaches. However, it simply linearizes all nonlinear functions to the first order by using the Taylor series expansions. To reduce the approximate errors, Julier, *et al* put forward the unscented Kalman filter (UKF)[1]. The UKF uses the deterministic sample points to completely capture the statistics of the Gaussian random variable accurately to the second order (Taylor expansions) for any nonlinear systems, but it does not apply to general non-Gaussian cases. Particle filter (PF) has been studied by many researchers for its being not affected by the nonlinear and non-Gaussian limitations[2]. One of the key issues for PF is the proposal distribution. Now there exists the prior proposal[2], the fixed proposal, the EKF proposal[3], the UKF proposal[4], *etc*. The fixed proposal is rarely applied and the prior proposal has no consideration of the latest measurements. The EKF proposal has the shortcomings of the EKF. In Ref. [4], main parameters in the UKF proposal need to be previously set before the running and cannot be changed on line.

Bearings-only passive tracking is often regarded as a nonlinear filtering problem and has weak observability[5]. The researchers put forward some solutions, including the EKF in the Cartesian coordinates, pseudo-linear filtering, the EKF in the modified polar coordinates, *etc*. PF with the prior proposal distribution is also applied to the bearings-only tracking[2].

In this paper, the UKF proposal is modified and the improved PF is applied to the bearings-only passive tracking. The improved algorithm simplifies the parameters in UT (unscented transformation) and adds the scaling factor. The scaling factor may be tuned on line to improve the filtering performance, which develops an adaptive algorithm easy to be implemented. Moreover, the algorithm

Received date: 2004-08-30; Revision received date: 2005-01-15
Foundation item: National Natural Science Foundation of China (50405017)

also incorporates the residual resampling step and Markov Chain Monte Carlo method, *etc*. The results of the bearings-only experiments demonstrate the superiority of the improved algorithm.

1 Improved Particle Filter

1.1 Particle filter

Based on Bayesian filtering theory, the posterior density function (PDF) constitutes the complete solution to the sequential estimation problem. PF represents the required PDF by a set of random sampled particles with associated weights. Bayesian recursive filtering includes time update and measurement update

$$p(x_k \mid y_{k-1}) = \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid y_{k-1}) \mathrm{d}x_{k-1} \quad (1)$$

$$p(x_k \mid y_k) = p(y_k \mid x_k) p(x_k \mid y_{k-1}) / p(y_k \mid y_{k-1}) \quad (2)$$

where y_k, x_k represents the measurement sequences and state up to time k respectively. The analytical solutions to above integrals are often hard to be acquired. If the samples can be randomly drawn from the PDF, the PDF can be approximately represented by the set of particles. It is often not possible to sample directly from the PDF. One can circumvent by drawing from a known easy to sample proposal distribution (function), $q(\cdot)$. The associated weight is defined as

$$w_k(x_k) = p(x_k \mid y_k) p(y_k) / q(x_k \mid y_k) \quad (3)$$

As the states follow a first order Markov process, a recursive estimate of the importance weights can be obtained[3],

$$w_k = w_{k-1} \frac{p(y_k \mid x_k) p(x_k \mid x_{k-1})}{q(x_k \mid x_{k-1}, y_k)} \quad (4)$$

where $q(\cdot)$ represents the proposal distribution.

After a few iterations of estimation, it may leads to the degeneracy, that is, all but one particle would probably have the negligible weights. To reduce the effect of the degeneracy, Gordon introduces the resampling step[2], which evaluates the weights of the particles and resamples the particles to eliminate particles with small weights and multiply particles with large weights. Time update, measurement update, evaluation and resampling constitute PF.

PF relies on the importance sampling and thus requires the design of proposal distributions to approximate to the PDF as well as possible. The optimal proposal distribution is often hard to be implemented in practice. In this paper, the UKF proposal is modified and firstly applied to the bearings-only tracking.

1.2 Improved particle filter

In the UKF proposal[4], the parameters $\{\alpha, \beta, \kappa\}$ are used to control the sigma points and they need to be previously set before running and cannot be tuned on line. From the innovation theory[6], when the target suddenly maneuvers in the tracking, the innovation and the innovation distance are becoming larger. At this time, the filtering gain should be accordingly boosted to cover target maneuvering. Zhou Donghua *et al*[7] present an orthogonal theory and develop the adaptive and robust strong tracking filter by selecting a time-varied filtering gain matrix on line. Enlightened by the ideas in Ref. [7], for the cases where the process and measurement noises are additive respectively, the parameters may be simplified and the scaling factor may be added. The scaling factor may be accordingly tuned on line with the innovation distance in calculating the covariance.

Shown from the Appendix, at any time step, by selecting the suitable scaling factor, the covariance after adding the scaling factor may be the same as the one before simplification. Thus, the parameters $\{\alpha, \beta, \kappa\}$ can be reduced to $\{\alpha, \kappa\}$ and the tuning performance can be made by the scaling factor in this paper instead of by the parameter β in Ref. [4]. Moreover, the scaling factor is tuned on line with the innovation distance, which equals to that the filtering gain is accordingly adjusted. It can make the algorithm adaptive. The improved PF with the modified UKF proposal is depicted as follows:

(1) Initialization

Randomly draw N particles

At each time step, update every particle with