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Particle filter initialization in non-linear non-Gaussian radar target tracking

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Abstract: When particle filter is applied in radar target tracking, the accuracy of the initial particles greatly effects the results of filtering. For acquiring more accurate initial particles, a new method called "competition strategy algorithm" is presented. In this method, initial measurements give birth to several particle groups around them, regularly. Each of the groups is tested several times, separately, in the beginning periods, and the group that has the most number of efficient particles is selected as the initial particles. For this method, sample initial particles selected are on the basis of several measurements instead of only one first measurement, which surely improves the accuracy of initial particles. The method sacrifices initialization time and computation cost for accuracy of initial particles. Results of simulation show that it greatly improves the accuracy of initial particles, which makes the effect of filtering much better.

Keywords: radar target tracking, particle filter, initialization.

1. Introduction

In the domain of radar tracking, when the moving model is linear, the system error and measurement error are both Gaussian white noise and the Kalman filter can get the optimal estimation. In most practical situations, the moving models are non-linear and the measurement noise is non-Gaussian, then the extended Kalman filter (EKF) comes into use. EKF gives reasonable results in some cases that are only mildly non-linear, but in many examples (such as big angle measurement noises) the filtering results are unsatisfactory.

To avoid these difficulties and to gain a better appreciation of the non-linear estimation problem, a more direct Bayesian approach to obtain the target probability density function (PDF) is adopted [1–4], with its name as PF(PF for short). The essence of PF is to seek for a group of random samples, an approximation of the PDF of the state of the target so that it can handle any functional non-linearity and systems of measurement noise with any distribution[5–7]. The PDF of the state of the target is based on all the available information. Research in this field has gained many results[5–8]. On particle initialization, the general method is to sample particles in the case of a known initialized state, however, in reality, a known state is not easy to obtain. It seems that the measurement is the only source on which the initial samples can be based on.

If the first measurement is not accurate, the samples will not be reasonable, either, so a weak filtering results, even divergence, is unavoidable.

2. Radar target tracking

2.1 Motion model

Constant velocity model is defined as

$$s_{k+1} = F * s_k + w_k \tag{1}$$

where s_k means the state information of the target, and $F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}$ (T is sampling strength), w_k is white Gaussian noise with mean zero and covariance matrix. $Q = q\begin{bmatrix} Q_1 & 0 \\ 0 & Q_1 \end{bmatrix}, Q_1 = \begin{bmatrix} \frac{T^3}{3} & \frac{T^2}{2} \\ \frac{T^2}{2} & T \end{bmatrix}$,

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q is the strength of maneuvering.

2.2 Measurement model

Measurement from sensor include range (r) and azimuth angle (θ), radar location is (0, 0), standard deviations of r and θ are σ_r and σ_θ.

Measurement model is defined as

$$z_k = \begin{bmatrix} \sqrt{s_k^2[1] + s_k^2[3]} \\ \arctan(\dfrac{s_k[3]}{s_k[1]}) \end{bmatrix} + v_k \tag{2}$$

where $v_k \sim N(0, R)$, and $R = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\theta^2 \end{bmatrix}$.

2.3 Flicker noise

In the radar system, scattering properties of target may cause the measurement noise, non-Gaussian, we call this kind of noise as “flicker noise”.

In PDF, the center of Gaussian noise and flicker noise is almost the same; the difference is that the tail of flicker noise is relatively long. The PDF of flicker noise can be composed with Gaussian function and Laplace function as

$$f_t(x) = (1-\varepsilon) f_g(x) + \varepsilon f_l(x) \tag{3}$$

In which ε means a positive number less than 1, and $f_t(\cdot)$, $f_g(\cdot)$,$f_l(\cdot)$ represent PDF of flicker noise, Gaussian noise, Laplace respectively. The PDF of Gaussian noise and Laplace can be shown as, $f_g(x) = \dfrac{1}{\sqrt{2\pi}\sigma}\exp(-\dfrac{x^2}{2\sigma^2})$ and $f_l(x) = \dfrac{1}{2\eta}\exp(\dfrac{-|x|}{\eta})$.

3. Basic theory of particle filtering algorithm

3.1 Optimum Bayes estimation

Assume that a dynamical system can be described as

$$\begin{cases} x_{k+1} = f(x_k, \omega_k) \\ z_{k+1} = h(x_{k+1}, v_{k+1}) \end{cases} \tag{4}$$

If the initial PDF is $p(x_0|z_0) = p(x_0)$, then

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1}) p(x_{k-1}|z_{1:k-1}) \mathrm{d}x_{k-1} \tag{5}$$

and

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k) p(x_k|z_{1:k})}{\displaystyle\int p(z_k|x_k) p(x_k|z_{1:k}) \mathrm{d}x_k} \tag{6}$$

Eqs. (5) and (6) describe the basic idea of Bayes estimation, but Eq. (5) is not effective to non-linear system. Therefore, it is always a major problem to make it valuable in non-linear, non-Gaussian system. PF is a method based on the Bayes estimation and Monte Carlo method.

3.2 Particle filtering algorithm

The primary theory of PF is Sequential Importance Sampling (SIS). Its basic idea is to represent posterior probability density by a series of weighted sum of random samples[3]. As the number of samples tends towards infinite, SIS approximates the optimum Bayes estimation. It can be shown as

$$\hat{p}(x_{0:k}|z_{1:k}) = \frac{1}{N}\sum_{i=1}^{Ns} \delta_{x_{0:k}^i}(dx_{0:k}) \tag{7}$$

Generally, it is hard to sample from $p(x_{0:k}|z_{1:k})$ directly, and an effective way is to apply a known PDF $q(x_{0:k}|z_{1:k})$, which can be easily sampled. One principle of its election is to make the variance of importance weigh least. Sample particles with number N from $q(x_{0:k}|z_{1:k})$, update each of them with new measurement. But when this process goes on several times, distribution of importance weight is apt to concentration, which is called degeneracy. Gordon's method is to delete particles with tiny weight, and copy those with large weight. At last, the PDF is

$$p(x_k|z_{1:k}) = \sum_{i=1}^{Ns} \omega_k^i \delta(x_k - x_k^i) \tag{8}$$

The detailed process is as follows:

(1) Initialization k=0.

Sample $x_0^i \sim p(x_0)$

(2) Importance weight computation.

Set k=k+1,

Sample $x_k^i \sim q(x_k|x_{0:k-1}^i, z_{0:k})$ $\quad i$ =1, 2, $\cdots$, N

Importance weight

$$\omega_k^i = \omega_{k-1}^i \frac{p(z_k|x_k^i) p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{0:k-1}^i, z_{0:k})} \quad i = 1, 2, \cdots, N \tag{9}$$

Normalization importance weight

$$\tilde{\omega}_k^i = \omega_k^i / \sum_{j=1}^{N} \omega_k^j \tag{10}$$

(3) Resampling

Sample particles ($\tilde{x}_k^i$; i=1, 2, $\cdots$, N) from (x_k^i; i=1, 2, $\cdots$, N), and redistribute weight $\omega_k^i = \tilde{\omega}_k^i = 1/N$.