Multi-target Particle Filter Tracking Algorithm Based on Wireless Sensor Networks

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Abstract: In order to improve the multi-target tracking efficiency for wireless sensor networks and solve the problem of data transmission, analyzed existing particle filter tracking algorithm, ensure that one of the core technology for wireless sensor network performance. In this paper, from the basic theory of target tracking, in-depth analysis on the basis of the principle of particles filter, based on dynamic clustering, proposed the multi-target Kalman particle filter (MEPF) algorithm, through the expansion of Kalman filter (EKF) to generate the proposal distribution, a reduction in the required number of particles to improve the particle filter accuracy at the same time, reduce the computational complexity of target tracking algorithm, thus reducing the energy consumption. Application results show that the MEPF in the proposed algorithm can achieve better tracking of target tracking and forecasting, in a small number of particles still has good tracking accuracy. Copyright © 2014 IFSA Publishing, S. L.

Keywords: Particle filter, Wireless wireless sensor, Target tracking, Automatic control, Localization algorithm.

1. Introduction

Target tracking is one of the typical applications of wireless sensor networks, both in the military or civilian areas; target tracking technology has important application value. In the military field, target tracking can be used for missile guidance and defense, sea and air defense, battlefield target tracking and monitoring enemy and so on. In civilian areas, target tracking can be used to track goods warehouse logistics, road transport planning, monitoring wildlife and intruder monitoring. Since the sensor nodes with small size, low price, ease of deployment, and other communications and computing capabilities, while the network self-organization, invisibility and robustness characteristics, compared with the traditional tracking methods, wireless sensor networks for its good features make up for the shortcomings of traditional tracking methods, making more suitable for wireless sensor networks to locate and track moving targets. Therefore, research on target tracking based on WSN has great theoretical and practical significance [1].

Wireless sensor network target tracking system includes the following three stages: 1) target detection; 2) targeting; 3) target prediction and pass [2, 3]. The activated near the target node is composed of a dynamic tracking area, through the detection and localization of the target sound [4], vibration information, image information such as node, and then the target position information is sent to the dynamic tracking region data processing center, complete the update and prediction of target position.
and status in the data processing center. According to the data processing mode, target tracking can be divided into centralized and distributed in two ways [5].

In wireless sensor networks, in order to realize the multiple target tracking, first needs to solve the multiple moving targets at the same time found in multiple sensor, target tracking and data association problem of value, which is not only the core problem of multi target tracking, but also a difficult problem for wireless sensor networks, because of the sensor capacity constraints, cannot be fully observed on the target parameters, but also in the target trajectory intersection, cross, convergent phenomenon, amount at this time of sensor nodes measured value will be more target signal superposition, the signal level is very difficult to distinguish that makes the problem more difficult.

In this paper, combining with the application of the wireless sensor networks, information obtained from the measurement point of view, according to the local characteristics of the proposed target tracking, particle filter algorithm for multi target tracking based on prediction. The algorithm according to the historical track of the target, make full use of the prediction results time to update the particle filter process, the acoustic signal aliasing separation, in order to solve the tracking problem in wireless sensor networks target. Finally, the simulation of the algorithm to do the simulation analysis, confirmed the algorithm can in the condition of small calculation cost lower, multiple target tracking.

2. Target Tracking Filter Algorithm

2.1. Bayesian Filtering

Bayesian filtering is the use of a priori probability density function of the system and the state observer system state variables to construct the posterior probability density, which is a priori probability density model, predicts the state of the system, using the most recent correction system combining observations, thus obtained after posterior probability density [6, 7].

Variable system problems in the analysis and reasoning, such as target tracking, dynamic characteristics of commonly used state space model to describe the time-varying system [8]. State-space model can well describe the relationship between dynamic or tense and observed signals and unknown unknowns, it is suitable to solve the multi-variable data and nonlinear, non-Gaussian process. Typically includes a description of the state space model state variables change with time system model and observation model with measurement noise associated with the state variables. State variable contains information describing the system, for target tracking, the state variable represents the position of the target, speed and other sport properties. Measurement vector typically represents the state vector associated with noise in the observations. Bayesian framework based on discrete state-space model is to obtain the probability density distribution of recurrence. Control input is ignored; the discrete state space model of the system is described as follows:

State-space model: 
\[ x_k = f_k(x_{k-1}, w_{k-1}), \]

Observation model: 
\[ z_k = h_k(x_k, v_k), \]

where \( f_k(x_{k-1}, w_{k-1}) \) and \( h_k(x_k, v_k) \) is bounded nonlinear function, \( x_k \in \mathbb{R}^n \) is the system state vector at time \( k \), \( z_k \in \mathbb{R}^n \) is the system state vector of observations \( x_k, w_{k-1}, v_k \) respectively the process noise and observation noise, process noise, the probability density distribution of the noise measurement is generally known.

Definition:
\[
Z_k = \{z_1, z_2, ..., z_k\}, X_k = \{x_1, x_2, ..., x_k\} \quad \text{VI} \text{ is a collection of } k \text{ moment all observations, state variable values. Assume that the system state probability distribution is known, that is } \\
\rho(x_0 | z_0) = \rho(x_0), \rho(x_0 | Z_1) \text{ filtering distribution can be obtained by predicting and updating the two steps.}
\]

1) Prediction: Assuming the probability density \( \rho(x_{k-1} | Z_{k-1}) \) at time \( k-1 \) is known, so we can write
\[
\rho(x_{k-1} | Z_{k-1}) = \int \rho(x_{k-1} | x_k, Z_{k-1}) \rho(x_k | Z_{k-1}) dx_k \\
= \int \rho(x_{k-1} | x_k) \rho(x_k | Z_{k-1}) dx_k, \quad (1)
\]
where \( \rho(x_k | x_{k-1}) \) is the first order Markov process, is no a priori probability state variables \( z_k \) latest observations when the density distribution, the system equations can be obtained.

2) Update: when getting observation information of \( z_k \) at the \( k \) time, according to the Bayesian principle of measurement update, to obtain the posterior probability density function:
\[
\rho(x_k | Z_k) = \frac{\rho(z_k | x_k) \rho(x_k | Z_{k-1})}{\rho(z_k | Z_{k-1})}, \quad (2)
\]
where \( \rho(z_k | x_k) = \int \delta(z_k - h_k(x_k, n_k)) \rho(n_k) dn_k \) is the likelihood function, \( \rho(z_k | Z_{k-1}) \) is the normalization constant,
\[
\rho(z_k | Z_{k-1}) = \int \rho(z_k | x_k) \rho(x_k | Z_{k-1}) dx_k
\]
So we can write

\[ \rho(x_k | Z_k) = \frac{\rho(z_k | x_k) \rho(x_k | Z_{k-1})}{\int \rho(z_k | x_k) \rho(x_k | Z_{k-1}) \, dx_k} \quad (3) \]

As can be seen from the filter update Equations (3), the posterior probability distribution status by observing \( z_k \) is corrected prior probability is obtained. And updating the prediction process carried out in an iterative manner, constitute the Bayesian filter. However, this recursive formula to calculate the posterior density of the introduction of the integral equation is usually not obtained analytic solutions, there are also computationally intensive problems in the actual application process. Therefore, Bayesian filtering is only theoretical estimates given target state solution, it is difficult practical application, but to solve the problem of target tracking indicates the theoretical orientation is the basis for a lot of filtering algorithm.

### 2.2. Particle Filter Algorithm Based on Multi-objective

Particle filter is a method of Monte Carlo simulation based on recursive Bayesian filtering [9], the key idea is to use a set of weighted sum of the weights associated with a random sample to represent posterior probabilities. When the sample size is very large, this probability is estimated to be equivalent to the posterior probability density. Can assume a state independent from the posterior probability distribution \( \rho(X_k | Z_k) \) of the \( N \) independent random sample \( \{ X_{k}^{(i)} \}_{i=1, 2, \ldots, N} \), the state probability density distribution can be approximated as:

\[ \rho(X_k | Z_k) = \frac{1}{N} \sum_{i=1}^{N} \delta_{X_k}(dX_k), \quad (4) \]

where \( \delta() \) is the Dirac impulse function, the corresponding function is expected:

\[ \bar{I}_{N(g_k)} = \int g_k(X_k) \rho(X_k | Z_k) \, dX_k = \frac{1}{N} \sum_{i=1}^{N} g_k(X_{k}^{(i)}) \]

By the law of large numbers can guarantee convergence, the convergence do not depend on the state dimension, can be easily applied to higher dimensional case.

1) The importance sampling.

Because of the need to estimate the probability distribution of a sample is often very difficult or even impossible, to avoid the following direct importance sampling method of sampling difficulties, from another random sampling is easier to extract the distribution. If the density of the sample \( \rho(X_k | Z_k) \) from the posterior probability is difficult to obtain a sample directly from the particles, where the probability of an easier introduction of the sample and from the sample distribution of \( q(x_k | Z_k) \), \( q(x_k | Z_k) \) is called here the importance of the distribution. In this case the above equation becomes:

\[ I(g_k) = \int g_k(X_k) \frac{\rho(X_k | Z_k)}{q(X_k | Z_k)} \, dX_k \]

One of the important weights:

\[ \omega^*(X_k) = \omega^*(X_{k}^{(i)}) = \frac{\rho(X_k | Z_k)}{q(X_k | Z_k)} = \frac{1}{\rho(Z_k)} \times \frac{\rho(X_k | Z_k)}{q(X_k | Z_k)} = \frac{1}{\rho(Z_k)} \times \frac{\rho(X_k | Z_k) \rho(X_k)}{q(X_k | Z_k)} \]

According to Bayesian theory, normalization constants \( \rho(Z_k) \) denominator in the formula can be expressed as:

\[ \rho(Z_k) = \int \rho(Z_k | X_k) \rho(X_k) \, dX_k = \int \omega_k(X_k) q(X_k | Z_k) \, dX_k \]

\[ E_{\omega_k} \left[ \omega_k(X_k) \right] \]

Take the proposal from a group of independent and identically distributed \( q(X_k | Z_k) \) distributed particle swarm \( \{ X_{k}^{(i)} \}_{i=1, 2, \ldots, N} \), is estimated as follows:

\[ \hat{I}^*_{N(g_k)} = \frac{1}{N} \sum_{i=1}^{N} g_k(X_{k}^{(i)}) \omega_{k}^{(i)} = \frac{1}{N} \sum_{i=1}^{N} g_k(X_{k}^{(i)}) \sigma_{k}^{(i)} \]

Wireless sensor networks have a localized target tracking features, namely multi-target intersection outside the area, you can multi-target tracking problem, seen as separate multiple single target tracking. So, to solve the wireless sensor networks multi-target tracking problem the core is how to measure the value of the acoustic sensor node to make the appropriate separation.

Consider the following case, the target at the \( t_1 \) time T1 and T2 into the target intersection area, when the node i is located in the intersection area, while the acoustic signal obtained from the T1 and T2, and outputs the measured value \( z_i(t) \).

Localized by the target tracking shows that when \( t < t_1 \), T1 and T2 of the track, a single target
tracking, target tracking at this time can be achieved, that the amount of \( t_1 \) time before the sensor node to obtain the measured value has been obtained at the \( t_2 = t_1 + \Delta t \) time the measured value maneuvering targets, and thus get the location of the target time, speed and other information.

The above ideas with particle filter tracking algorithms, particle filter tracking algorithm is based on the prediction of multi-objective, as follows:

For each target K, perform the following algorithm

1) \( t = 0 \), set reference probability density function of the sample \( q(x_i \mid x_{i-1}) = \rho(x_i \mid x_{i-1}) \) and initialize particle distribution

\[
x_0^i - \rho(x_0) \text{, } w_0^i = 1/N, i = 1, \ldots, N
\]

2) When \( t > 0 \),

\[\text{for } i = 1: N, x_k^{(i)} = q(x_k^{(i)} \mid z_{k,i})\]

Calculating weights

\[
w_k^{(i)} = w_{k-1}^{(i)} \frac{p(z_{k,i} \mid x_k^{(i)}, z_{k-1,i})}{q(x_k^{(i)} \mid x_k^{(i-1)}, z_{k,i})}
\]

3) According to the type of normalized weights.

\[
\tilde{w}_k^{(i)} = \frac{1}{\sum_{i=1}^{N} w_k^{(i)}}
\]

4) Predict the measured value.

According to the target maneuvering model, predict the target position

\[
\tilde{x}_{k+1} = f(\tilde{x}_k) + w_{k,t}
\]

According to the measurement model, measurement of nodes in \( S_j \) this forecast the amount of value \( k \)

\[
\tilde{z}_{k+1} = h(\tilde{x}_{k+1}, S_j)
\]

5) Repeat Steps 2-4, until the end of track.

3. Simulation and Performance Analysis

The most important parameters to measure the performance of target tracking problem tracking accuracy is the goal, target tracking algorithm based on wireless sensor networks sensor nodes should save energy security in the context of a high tracking accuracy as possible to meet the short track consumption and response time. The main goal of this section, consider tracking accuracy and energy consumption are two performance indicators, improved particle filter algorithm (MEPF) experiments presented in this chapter and the traditional distributed particle filter (DPF) were compared, the main difference is that the importance of density select the method and particle filter node selection function in terms of both simulated target tracking accuracy and energy consumption in two ways.

The simulation model is using acoustic signal attenuation as the observation model. Wiener model using model systems as a target maneuver. Respectively as shown in Equation (8) and Equation (9).

\[
x_{k+1} = \begin{bmatrix} 1 & 0 & 0 & T \\ 0 & 0 & 1 & 1 \\ T & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} X_k + \begin{bmatrix} T \\ T^2 / 2 \\ T^2 / 2 \\ T \end{bmatrix} v_k \tag{8}
\]

\[
Z(t) = \gamma_i \sum_{k=1}^{k} \frac{a_k(t)}{\| \rho(t) - r \|^\beta} + w_i(t) \tag{9}
\]
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References


5. Conclusions

In this paper, first introduces the basic theory of Bayesian filtering and particle filtering, elaborated the importance sampling, importance sampling and resembling process, analysis of the particle filter degradation. Combining the RPSA algorithm and the dynamic clustering algorithm, is presents a multi-objective extended Calman particle filtering (MEPF) algorithm. The MEPF algorithm uses the importance density function extended Calman filter to generate a particle filter, improve the efficiency of particle filter, particle degeneracy phenomenon is weakened. MEPF algorithm based on node cooperation mechanism, the cluster head node the particle set assigned to each sensor node in parallel operation, there is no information exchange between each sensor node, the existence of information exchange between only the sensor nodes and cluster head, so as to improve the computational efficiency, balance the energy consumption of network nodes. The simulation results show that, MEPF algorithm is proposed in this paper can realize the tracking and prediction of target tracking is good, still has a better tracking accuracy in less number of particles under.