The Target Tracking of Wireless Sensor Network Using an Improved Unscented Particle Filter

Taoyun Zhou
Department of Information Science and Engineering, Hunan University of Humanities, Science and Technology, Loudi, China
e-mail: taoyun_2000@163.com

Yun Cheng
Department of Information Science and Engineering, Hunan University of Humanities, Science and Technology, Loudi, China
e-mail: chy6677@163.com

Pingyuan Liang
Department of Information Science and Engineering, Hunan University of Humanities, Science and Technology, Loudi, China
e-mail: liangpingyuan123@163.com

Abstract—Based on the analysis of Particle Filter (PF), this paper proposed an improved unscented particle filter (UPF) algorithm by utilizing unscented Kalman filter (UKF) to obtain an importance density function. This algorithm clustered the sensor network nodes through dynamic organization. Moreover, the single target moving uniformly and linearly in the network was tracked by applying the UPF into the target tracking of Wireless Sensor Network (WSN). Finally, a simulation comparison between UPF and PF was conducted using MATLAB. Simulation results showed that the improved UPF was capable of improving the utilization efficiency of particles and presented a stable tracking performance.

Keywords: wireless sensor network（WSN）; Dynamic cluster; target tracking; Particle filter(PF); unscented particle filter (UPF)

I. INTRODUCTION

The application of WSN has been a research focus in China in recent years[1,2]. Target tracking, as one of the main applications of WSN, is regarded as a nonlinear problem. Traditional Extended Kalman Filter (EKF) fails to satisfy the requirements of practical engineering application due to its low filtering accuracy when dealing with nonlinear problems[3,4]. Therefore, researchers pay attention on PF which can favorably solve nonlinear and non-Gaussian problems, and introduce PF into target tracking field[5]. PF is a kind of optimum regression Bayesian filter algorithm based on Monte Carlo Simulation and has been widely applied due to its simple calculation and theoretical capability of solving any nonlinear and non-Gaussian problem[6,7,8]. However, few number of particles has been main defect in PF; on this basis, an improved UPF is put forward. A computer simulation is performed to verify the validity and feasibility of the improved UPF. Results show that UPF can greatly reduce the particle number required by PF algorithm and therefore improves tracking accuracy.

II. TARGET TRACKING ALGORITHM OF WSN

A. *Dynamic Clustering Management*

The clusters are dynamically constructed and revoked according to the distances between sensor nodes and targets. The nodes nearest to the target act as the cluster heads and they are idle in most of the time. However, the sensor nodes focus on tracking when targets are found. The nodes detecting targets form a tracking cluster and operate particle filters on each child node of the cluster in a distributive form[9]. All the child nodes of the cluster send their own position data and the distance values from targets estimated by themselves to the cluster head. They transmit relevant parameters of filters to the cluster head of the next tracking cluster by tracking the former cluster head, update the posterior probability by using the newly measured data and finally fulfill the state estimation of the whole target on the base station. With the movement of the targets, each child node of the cluster constantly sends the latest target distance estimation to the cluster head which re-estimates the target positions[10].

B. *PF Algorithm*

PF is a kind of algorithm approximating to Bayesian filters based on Monte Carlo. Its core idea is to approximate the Probability Density Function (PDF) of the random variables of the system using some discretely random sampling points (particles), and to obtain the minimum variance estimation of the state through replacing the integral operation by sample mean values. It is applicable for any state and measurement mode under any environment because it is independent to the model of the system and cannot be limited by any linearization error and Gaussian noises assumption[8].

The PF algorithm is composed of the following basic steps:

Step1. Collecting samples $x_0^i, i=1,\ldots,N$ from the prior distribution $p(x_0)$;

Step2. Collecting sample set $\left\{x_k^i\right\}_{i=1}^N$ from the reference distribution $q(x_k \left| x_{k-1}, z_k\right.)$ and calculating the normalized weight value w_k^i at the time of *k*:

$$\tilde{w}_k^i = \tilde{w}_{k-1}^i \frac{p(z_k \left| x_k^i\right.) p(x_k^i \left| x_{k-1}^i\right.)}{q(x_k^i \left| x_{k-1}^i, z_k\right.)} \quad (1)$$

$$w_k^i = \frac{\tilde{w}_k^i}{\sum_{j=1}^N \tilde{w}_k^j} \quad (2)$$

Step3. Re-sampling: replacing $\left\{x_k^i\right\}_{i=1}^N$ by using the new sampling value $\left\{x_k^{i*}\right\}_{i=1}^N$ to satisfy probability $p\left\{x_k^{i*} = x_k^i\right\} = w_k^j$, and updating the weight value $w_k^i = N^{-1}$;

Step4. Outputting the approximately posterior probability density of x_k:

$$p(x_k \left| z_{1:k}\right.) = \frac{1}{N}\sum_{j=1}^N \delta(x_k - x_k^j) \quad (3)$$

Step5. Outputting the estimation:

$$\hat{x}_k = \sum_{i=1}^N w_k^i \tilde{x}_k^i \quad (4)$$

$$p_k = \sum_{i=1}^N w_k^i (\tilde{x}_k^i - \hat{x}_k)(\tilde{x}_k^i - \hat{x}_k)^T \quad (5)$$

And back to **Step2.**

In order to reduce the influence of the phenomenon of particle degeneration which is the biggest defect of PF, it is required to using the most effective methods including selecting the Importance Density Function and adopting the re-sampling method. Re-sampling method can decrease the diversity of particles and reduce the calculation amount and robustness. Therefore, this study proposes an improved UPF algorithm by utilizing UKF to select the Importance Density Function.

C. Improved UPF Algorithm

The number of the particles meeting certain conditions is required by UKF rather than a large amount of particle points. The posterior distribution represented by these particle numbers can describe the second moment of the real posterior distribution. The concrete steps for UPF to generate the Importance Density Function using UKF can be expressed as follows:

Step1. Calculating the initial value x_0^i : $p(x_0)$, and letting the weight value $w_k^i = N^{-1}$ and $i = 1,\text{L}\ , N$;

Step2. Calculating the mean value $\hat{x}_k^i$ and the variance p_k^i of the particle set $\{x_k^i\}_{i=1}^N$ utilizing UKF;

Step3. Extracting x_k^i from the Importance Density Function $q(x_k^i \left| x_{0:k-1}, x_{1:k}\right.)$: $N(\hat{x}_k^i, p_k^i)$;

Step4. Computerizing the weight values of particles:

$$w_k^i = w_{k-1}^i p(y_k \left| x_k^i\right.) \quad (6)$$

Step5. Normalizing the weight values:

$$w_k^i = \frac{w_k^i}{\sum_{i=1}^N w_k^i} \quad (7)$$

Step6. Calculating effective particle numbers:

$$N_{eff} = \frac{1}{\sum_{i=1}^N (w_k^i)^2} \quad (8)$$

Step7. If $N_{eff} < N$, then resample the sampling set $\{x_k^i\}_{i=1}^N$ of sampling particles, otherwise, turn to **Step8**;

Step8. State updating:

$$x_k = \sum_{i=1}^N x_k^i w_k^i \quad (9)$$

Finally, the nodes of the cluster head of the tracking cluster in the sensor network send the estimations of the state and variance to the base station which combines the estimated data to obtain a global estimate according to the time order.

III. MODAL FOUNDATION AND SIMULATION ANALYSIS

A Modal Foundation

It is supposed that the targets move uniformly and linearly in a two-dimensional plane, there are 3 nodes of the tracking cluster during the movement of the targets and the sensor network can cover the whole region in which the targets move.

The equation of the motion state of targets is defined as follows[7]:

$$X(k) = \Phi X(k-1) + Gw(k-1) \quad (10)$$

The observation equation is given below:

$$Z(k) = \sqrt{x_k^2 + y_k^2} + v_k \quad (11)$$

In which, state transition matrix $\phi = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$, the driven array of process noise

$G=\begin{bmatrix} 0.5 & 0 \\ 1 & 0 \\ 0 & 0.5 \\ 0 & 1 \end{bmatrix}$, $X(k)=(x_k, \dot{x}_k, y_k, \dot{y}_k)^{\mathrm{T}}$ is the vector of target state, $w(k)$ is the process noise and $v(k)$ refers to observation noise. Both $w(k)$ and $v(k)$ can be regarded to be the Gaussian processes with the mean value of zero under ideal conditions.

B Simulation Analysis

It is assumed that the sampling interval of the initial state $T=1s$, $X_0=(0.5 \quad 0.8 \quad 0.5 \quad 0.9)^T$ and N=100. By conducting the Monte Carlo Simulation on PF and UPF for 500 times, respectively, the following results are obtained: the curves of position errors in the X and Y directions (as displayed in Fig .1 and Fig .2) and the curves of velocity errors in the X and Y directions (as shown in Fig .3 and Fig .4) based on the MATLAB platform.

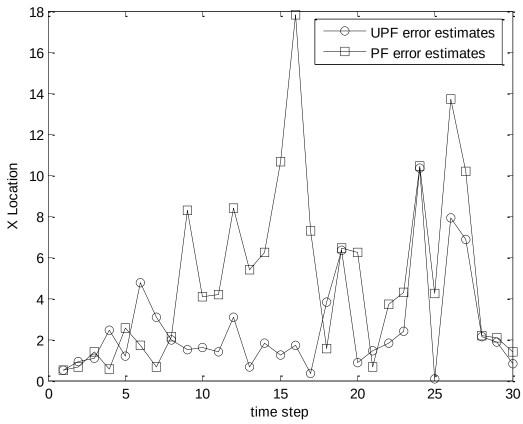

Figure1. Curve of the position errors in X direction

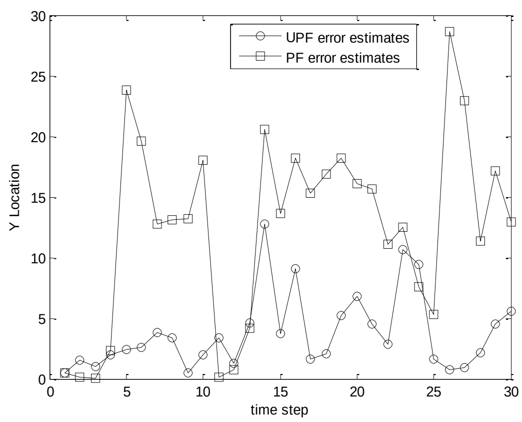

Figure2. Curve of the position errors in Y direction

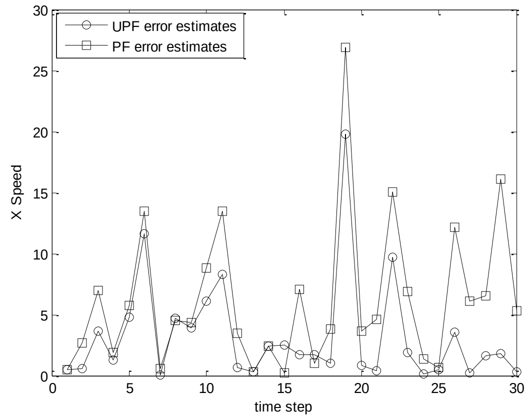

Figure 3. Curve of the velocity errors in X direction

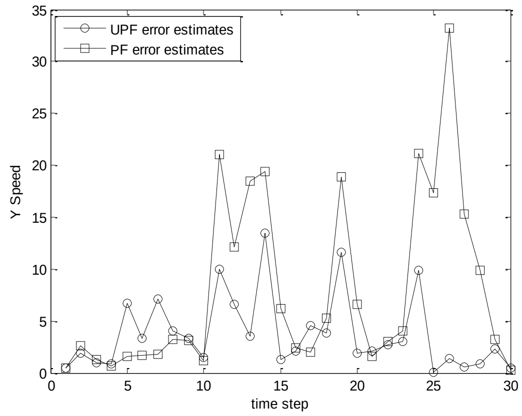

Figure 4. Curve of the velocity errors in Y direction

Fig .1to Fig .4 show that, for UPF, the mean values of position errors in the X and Y directions are 2 and 3, respectively; while the mean values of velocity errors in the X and Y directions are 4 and 5, respectively. For PF, the mean values of position errors in the X and Y directions are 7 and 18, respectively; while the mean values of velocity errors in the X and Y directions are 10 and 15, respectively. In other words, the estimation errors of UPF are far less than those of PF under the same condition. Therefore, it can be concluded that UPF can favorably overcome the problem of particle degeneration in the PF algorithm and shows comparatively stable filtering accuracy.

IV. CONCLUSIONS

In summary, WSN is a kind of typically nonlinear and non-Gaussian system. Given traditional linear filtering algorithm presents slow convergence speed and poor tracking performance. Therefore, this study proposed an improved UPF algorithm by using UKF to produce an Importance Density Function based on the analysis of PF. Moreover, the UPF was used for the target tracking of WSN, in which, the nodes of the sensor network were clustered through dynamic organization. Finally, the single target moving uniformly and linearly in the network was tracked by separately utilizing UPF and PF based on the MATLAB platform. The simulation results indicated that the improved UPF algorithm could preferably overcome the problem of particle degeneration in the PF, thus increased the utilization efficiency of the particles and presented a stable tracking performance.

ACKNOWLEDGMENT

This work was financially supported by the Hunan Provincial Natural Science Foundation of China (12JJ2040), the Research Foundation of Education Committee of Hunan Province, China (09A046, 11C0701, 13C435), the Construct Program of the Key Discipline in Hunan Province, China, the Aid program for Science and Technology Innovative Research Team in Higher Educational Institute of Hunan Province, and the Planned Science and Technology Project of Loudi City, Hunan Province, China.

REFERENCES

[1] HUANG Yan, LIANG Wei hua , YU Hai bin.Tracking algorithms based on particle filter for wireless sensor .networks[J]. Control and Decision. 2008, 23(12): 1389-1394

[2] Akyildiz I F, Su W, Sankarasubramaniam Y, et al. Wireless sensor networks: A survey [J].Computer Networks, 2002, 38(4) :393-422.

[3] Ma Hui, Ng Brian. Collaborative signal processing framework and algorithms for targets tracking in wireless sensor networks[C] . Proc of SPIE. Brisbane,2006, 6035: 1-12.

[4] Arulam palam M S, Maskell S, Gordon N, et al. A tutorial on particle filters for online nonlinear/ non-Gaussian Bayesian tracing [J]. IEEE Trans on Signal Processing, 2002, 50(2) : 174-188.

[5] Coates M. Distributed particle filters for sensor networks [C] . Proc of 3rd Int Symposium on Information Processing in Sensor Networks. Berkeley: ACM Press, 2004: 99-107.

[6] ZOU Gang, SHI Zhang song, LIU Zhong. Comparison of Decentralized Particle Filter Algorithms in Sensor Networks for Passive Tracking[J]. CHINESE JOURNAL OF SENSORS AND ACTUATORS J].2007.20(6):1344-1348

[7] YANG Yue ping, DONG Hui ying, SONG Chao fan. A Study on the Target Tracking in Sensor Networks Based on Improved Particle Filtering[J]. TRANSACT IONS OF SHENYANG L IGONG UN IVERSITY. 2007.26(6):1-4

[8] Sheng X, Hu Y-H , Ramanathan P. Distributed Particle Filter with GMM Approximation for Multiple Targets Localization and Tracking in Wireless Sensor Network[C] / / Fourth International Symposium on Information Processing in Sensor Networks, 2005, 181-188.

[9] Chong C Y, Kumar S P. Sensor Networks: Evolution, Opportunities, and Challenges [C]// Proceedings of the IEEE,2003,91: 1247-1256.

[10] QU Jian-feng, CHAI Yi, and GUO Mao-yun. Target Tracking Algorithm Based on Parallel Particle Filtering in Wireless Sensor Networks[J].Journal of University of Electronic Science and Technology of China. 2011.40(2):231-236