Sensors & Transducers, Vol. 160, Issue 12, December 2013, pp. 431-436

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Sensors & Transducers

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Study on Target Tracking and Distributed Particle Filter in Binary Sensor Networks

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Received: 23 October 2013 /Accepted: 22 November 2013 /Published: 30 December 2013

Abstract: To further reduce the wireless sensor target tracking traffic and improving target tracking in real time. This paper describes a distributed particle filter algorithm for target tracking in binary sensor network, this algorithm can be applied to the cluster head replacement process, at this time, only needs error variance and transmission filter value between cluster heads, and no longer need to pass particles. On the other hand, this algorithm can achieve an appropriate adjustment of the filter variance online particle count, thus contributing to gradually reduce the amount of algorithm's calculation. *Copyright © 2013 IFSA.*

Keywords: Binary sensor network, Target tracking, Distributed particle, Filter algorithm.

1. Introduction

In binary wireless sensor network application process, target tracking is one of its more important content, and such content gradually attracted people's attention. Binary sensor network has the following basic features: Firstly, calculate the energy finite set of nodes; secondly, limited bandwidth. Cooperative operation between nodes in a large number of data transmission is based; thirdly, limited energy. Typically, battery is the energy source for binary sensor network node, and can not be charged up, transmission information which will have greater energy consumption. Affected by these basic characteristics, the conventional target tracking algorithm in wireless sensor networks can be effectively applied. Compared with the conventional sensor networks, sensor networks only able to transmit a binary "1" or "0", so as to maximize energy savings and bandwidth [1]. At present, the binary sensor network tracking algorithm through knowledge of geometry, sensors detect the radius and the network structure to locate, but its accuracy is usually poor; while filtering through the particle filter algorithm for target tracking algorithm is usually choose a centralized algorithm, this will produce a greater energy consumption, and thus poor real-time [2]. Therefore, distributed particle filter algorithm is more able to meet the actual needs, which usually target clustering algorithm based on the location of the current implementation of dynamic group clusters, although some scholars have proposed a set of clusters of the optimization method, however, require the alternating process of cluster head send large amounts of data, and thus will have a greater energy consumption, and occupy a certain amount of bandwidth [3]. In this paper, the binary sensor networks for target tracking and distributed adaptive particle filter algorithm discussed analysis of this algorithm in the replacement cluster head, it

will not produce more in the cluster head weights between the data and the large number of particles. Taken over by the simulation experiment shows that this algorithm in the algorithm time consuming, traffic and tracking accuracy, etc. is more advantageous and effective [4].

2. Dynamic Clustering of Binary Sensor Network

2.1. Binary Sensor Network

Different binary sensor network model is suitable for different algorithms, the author analyzed the binary sensor network model as follow: According to the different algorithms, you can choose the appropriate binary sensor network model. The author discusses the model are as follows:

Node n process the received signal strength in the local, the latter based on the following criteria in order to pass information of binary sensor network to fusion center [5].

First, the comparative analysis of the threshold value γ of the received signal $y_{n,t}$, if the threshold is greater than the signal value $y_{n,t}$, no transmission of any message.

Second, if the threshold γ is less than the signal value $y_{n,t}$, then the information will be transmitted to the fusion center. Therefore, only the threshold value γ is less than the signal value $y_{n,t}$, the fusion center can receive the information sent by the node [6]. Sent to the fusion center node n measurements are:

$$z_{n,t} = \varepsilon_{n,t} + s_{n,t}\beta_n, \tag{1}$$

Among them, $S_{n,t}$ is defined in formula (2), β_n have a direct link between binary sensors, $N(\bullet)$ is a Gaussian distribution, $\varepsilon_{n,t}$ is the measurement noise, the value is N [7].

$$s_{n,t} = \begin{cases} 0, if y_{n,t} > \gamma \\ 1, if y_{n,t} \le \gamma \end{cases}, \tag{2}$$

The strength of the received signal model is expressed as:

$$y_{n,t} = v_{n,t} + g_n(x_t) = v_{n,t} + \frac{d_0^a \psi}{|r_n - l_t|}, n = 1,2,\ldots\ldots N, \tag{3}$$

2.2. Dynamic Clustering

In the centralized structure of the binary sensor network tracking, all nodes will be sent to the central node's own observations, the central node will receive the fixed target estimates, however, the use of this approach will have a greater node energy consumption and traffic distributed dynamic clustering particle tracking method can effectively avoid the centralized tracking the existence of various defects [8]. This strategy can be described as follows:

First, wireless sensor networks track the target appears, the sensor nodes within the detection area will be awakened node measurement, the cluster head node is the maximum node.

Second, the cluster head in a single hop communication area and all the nodes in the cluster head together constitute a dynamic clustering of target tracking, and thus the state of the target estimated in real time, other single- hop node is outside the region back to sleep [9].

Third, during the movement of the target track, it reaches a certain critical state, some nodes to achieve the maximum detection range, and to accurately predict the subsequent position, in accordance with the basic principles of the cluster group be re-group clusters, and to identify new cluster head.

Fourth, the new cluster head to send the original cluster head of state information and measurement data, and re-estimate the target state.

Fifth, the clustering process will evolve over time and repeated until the target from the binary wireless sensor network area [10].

3. Distributed Particle Filter for Binary Sensor Network

In the cluster head exchange process, the binary sensor networks for distributed object tracking particle filter algorithm requires a large bandwidth, the author presents a distributed particle filter algorithm, this algorithm can realize no particles between cluster heads transmission, thereby greatly reducing the computation [11].

Distributed particle filter algorithm is based on the extracted particle in density function, and the particle weight is set as:

$$Wi \infty p(z \mid x) Wi - 1, \tag{4}$$

Since the observation noise has strong independence, so,

$$p(z_1 \mid \mathrm{X}) = \prod_{\mathrm{n}=1}^{N} p(z_{n,1} \mid X), \tag{5}$$

Then, $\mathrm{p}(z_{n,1}X)$ can be expressed as:

$$\begin{aligned} &\mathrm{p}(z_{n,1} \mid X) = p(z_{n,1} \mid s_{n,1} = 0, x) p(s_{n,1} = 0 \mid x) \\ &+ p(z_{n,1} \mid s_{n,1} = 1, z) p(s_{n,1} = 1 \mid x) = \\ &p(z_{n,1} \mid s_{n,1} = 0) p(s_{n,1} = 0 \mid x) + \\ &p(z_{n,1} \mid s_{n,1} 1) p(s_{n,1} = 1 \mid x) \end{aligned} \tag{6}$$

$$\mathrm{p}(z_{n,1} \mid s_{n,1}) = N(\beta_n s_{n,1}, \delta^2), \quad (7)$$

where $z_{n,1}$ represents the measurement of node n at time t. At the same time,

$$\mathrm{p}(s_{n,1} = 1 \mid x) = Q(\frac{\gamma - g_n(x) - \mu_v}{\delta_v}), \quad (8)$$

$$\mathrm{p}(s_{n,1} = 0 \mid x) = 1 - Q(\frac{\gamma - g_n(x) - \mu_v}{\delta_v}), \quad (9)$$

In short, the application steps of the distributed particle filtering algorithm in the binary sensor network target tracking are:

First, initialization t = 0. Samples from the prior distribution, and $x \sim p(x_0)$, i = 1,2, ..., N_0, where, N_0 is the initial number of particles.

Second, tracking the target at time t into a binary sensor network, and the formation of the cluster group. Cluster nodes can group detected at time t to a binary target tracking sensor network, after its γ compared with a threshold value, exceeds the threshold value is divided into a group of nodes, and a maximum of the cluster head in a single hop range within the cluster head node group as the core cluster [12].

Third, the upload traffic. Cluster head node within the cluster node to accept sending "1", and the other nodes in the sleep state control, to complete the transmission node also into a sleep state, and the implementation of a cluster head node status assessment.

Fourth, the cluster head node.

Using Equation (10) to calculate the required number of particles N;

$$\mathrm{N}(t) = \sqrt{\frac{mP_{t-1}}{C}}, \quad (10)$$

In a normal distribution formula $\mathrm{N}(\hat{\mu}_{t-1}, P_{t-1})$ to obtain N particles;

According to Equation (1) to (5), updated $\{x_{0,t-1}, w_{t-1}\}_{i=1}^{N_t}$;

Output the variance estimation results obtained by Equation (11), and the state estimation result obtained by the equation (12).

$$\mathrm{P}_t = \sum_{i=1}^{N_t} w(x_t - \hat{\mu}_t)(x_t - \hat{\mu}_t)^T, \quad (11)$$

$$\hat{u}_t = \sum_{i=1}^{N_t} w_t x_t, \quad (12)$$

Fifth, exchanging the information. Node selection algorithm in accordance with the proper selection of the one node to the next node sends a $(\hat{\mu}, P_t)$ to implement the next time state estimation [13].

Various stages of normal distribution $N(\hat{\mu}_{t-1}, P_{t-1})$ determined by the filtering error variance P_t and the filtered output values $\hat{\mu}_t$, and represent the distribution of the particle at time t, so when updating the cluster head, just need to error variance between cluster heads and transmission filtered value is determined, and no particles passed between cluster heads. On the other hand, this algorithm can be filtered based on the variance, the online number of particles be adjusted accordingly, thus reducing the amount of computation algorithm.

4. The Simulation Experiment and Result Analysis

4.1. Simulation Model

This paper makes the following description of target motion model:

$$x_t = G_t x_{t-1} + G_u u_t, \quad (13)$$

Among them, $x_t = [x \bar{x} y \bar{y}]$ is the state vector, $\bar{x}$ represents the velocity of tracking target, X represents the target location.

$$G_u = \begin{bmatrix} 1 & \sin mT & 0 & -\frac{1-\cos mT}{m} \\ 0 & \cos mT & 0 & -\frac{\sin mT}{m} \\ 0 & \frac{\cos mT}{m} & 1 & \frac{\sin mT}{m} \\ 0 & \sin mT & 0 & \cos mT \end{bmatrix}, G_u = \begin{bmatrix} \frac{T^2}{2} & 0 \\ 1 & 0 \\ 0 & \frac{T^2}{2} \\ 0 & 1 \end{bmatrix}, \quad (14)$$

$$m = \frac{a}{\sqrt{x^2 + y^2}}, \quad (15)$$

where $\bar{x}, \bar{y}$ is the component of the velocity of the target track at the current time; a=2; u_t is the process noise of the system, it will be directly affected the target acceleration; T is the sampling interval.

The specific amount of random binary sensor nodes in the range of 120×100 sow, and is set to the performance of all the nodes are identical, each node does not affect each other, each node of the other nodes in the specific location of the node single hop communication range of around 10 m, 25 m detection range at around. With sampling interval T=1 s, the observed signal reception threshold model γ=2.5, the variance value δ^2=0.01, the noise value $\hat{\mu}_t$=1. If d=1 m, the signal energy ψ = 5000 [14].

Using the traffic model to assess the energy consumption, if passed between each cluster head for the Gaussian mixture model, then the comprehensive energy consumption of all time is:

$$N_e + N_f + 3cN_c N_f N_s + N_i N_n, \quad (16)$$

Which represents the state variable median, the value is 4; indicating switching cluster head, the cluster head and the number of hops between cluster head, because as a single hop communication distributed particles, which is usually the value 1; expressed cluster head node with cluster node data transmission hops, as a; indicates all cluster nodes, according to the difference between crude and its hops some changes will occur; and represent integers and floating-point data type required bytes amount, usually a value of 8, ranging from 16 [15].

4.2. Interpretation of Result

Comparative analysis on the accuracy of the root mean square error, the calculation formula is as follows:

$$RMSE = \frac{\sqrt{\sum_{t=1}^{T}[(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2]}}{T}, \qquad (17)$$

Among them, $\hat{y}_t$ and $\hat{x}_t$ are respectively estimated T values; and respectively t moments of true value; T is the sampling frequency.

A binary sensor network in target tracking is turn maneuver motion state, this paper to track the target through a distributed adaptive particle filtering algorithm. The target binary sensor network tracking trajectory and the trajectory of moving object, as shown in Fig. 1. Among them, the target trajectory and target tracking are, thus, the accuracy of target tracking in line with the actual needs.

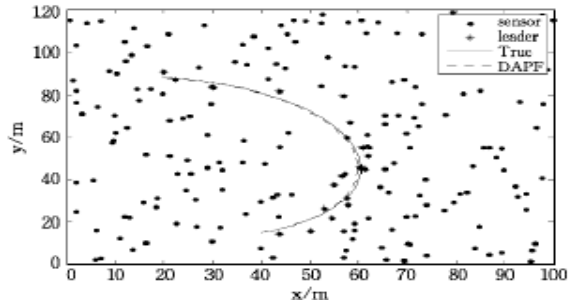

Fig. 1. Binary sensor network target tracking trajectory and target trajectory.

Time consuming of DAPF distributed adaptive particle filter, DPF distributed particle filter and CPF centralized particle filtering algorithm, as shown in Fig. 2.

Time-consuming comparison of different particle under three kinds of algorithm is shown in Table 1.

From Table 1 and Fig. 2 shows the results of the analysis, the number of particles in the same case, DPF distributed particle filter and particle filter CPF centralized consuming significantly more than DAPF distributed adaptive particle filter consuming, therefore, DAPF has better real-time. On the other hand, if the number of particles is smaller, the DPF and DAPF smaller difference between the time-consuming, however, DAPF amount will not be time-consuming changes in the number of particles corresponding changes in the number of particles on the algorithm does not real-time impact. In contrast, CPF is the fetus amount of calculation, and the impact when in fact, as the number of particles will increase the DPF has increased the amount of calculation, can be seen, DAPF The main advantage of a greater number of particles.

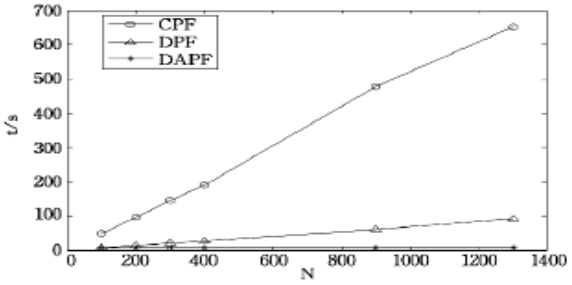

Fig. 2. Time consuming of three algorithms.

Table 1. Time-consuming comparison of different particle under three kinds of algorithm.

Number of particles	DAPF	DPF	CPF
100	7.7910	6.7651	47.7127
200	7.6182	13.1215	95.7621
400	7.4162	25.9854	188.7646
900	8.0179	61.0952	478.2987
1300	8.1246	90.0973	651.1205

In order to assess the accuracy tracking algorithm, shown in Table 2, it shows the mean square error of the three algorithms.

Table 2. The results of root mean square error of the three algorithms.

Number of particles	DAPF	DPF	CPF
100	0.1905	0.2591	0.3935
200	0.1222	0.1741	0.1661
400	0.1934	0.0712	0.2624
900	0.2045	0.0478	0.1037

Table 2 shows the results of the analysis, if the number of particles less, including the number of particles 100 and 200, DAPF can be achieved to minimize the mean square error. With the gradual increase in the number of particles, DPF and CPF tracking accuracy will also gradually increase and improve tracking accuracy DPF significantly higher than CPF, but the real-time algorithm will have some negative impact. However, DAPF RMSE is usually

not affected by the impact of the number of particles, can be seen, DAPF the accuracy of the algorithm does not produce significant effects on the number of particles, mainly because the number of particles in the algorithm to adjust the primary basis for each time variance, and thus to maximize the accuracy of the same conservative estimates. Therefore, compared with the low accuracy requirements applicable to the case, by the tracking accuracy and computation such as integrated indicators, DAPF has more ideal tracking performance.

Given a binary sensor network target tracking problem has a certain particularity, to measure the effectiveness of the algorithm was the main indicators of traffic, the use of traffic described herein formula for binary sensor networks to DAPF, DPF and GMM algorithms based total traffic analyzed, as shown in Table 3.

Table 3. Three algorithms comparative analysis of the traffic.

Number of particles	DAPF	GMM-DPF	DPF
100	141607	9255	141607
200	256778	8458	256778
400	512772	8452	512772
900	1095180	8076	1095180

Table 3 shows the results of the analysis, although significantly greater than the amount of traffic DPF GMM-DPF, however, DAPF traffic is minimal, significantly smaller than the other two algorithms, can be seen, DAPF the minimum bandwidth required, and the energy consumption Min.

5. Conclusion

Binary sensor network target tracking process for distributed particle filter algorithm, cluster head in the exchange of a greater bandwidth, in order to further improve the system's real-time target tracking, reduce energy consumption and traffic, reduce computation, the author presents a binary network adaptation and self- distributed model combining particle filter, also discusses a target tracking in binary sensor networks, distributed adaptive particle filter. This model is a dynamic clustering algorithm based on the replacement cluster head, just need to be passed between cluster heads and filter error variance values and other information, and will not produce large amounts of particles to pass, on the other hand, this algorithm can variance with filtering based dynamic adjustment of the number of particles, thereby achieving a reduction in the amount algorithm. To illustrate the effectiveness of this algorithm, the simulation process, the communication volume, mean square error and algorithms consuming aspects such as, for DAPF, DPF and CPF algorithms such a comparative study, the test results confirmed, DAPF algorithm traffic and consuming less than DPF and CPF algorithm, can be seen, DAPF algorithm has a small bandwidth and good real-time and other significant advantages. Another negative, the number of particles does not change DAPF algorithm RMSE direct impact magnitude, so the tracking accuracy and computation integrated indicators such as starting, known DAPF significantly better than the DPF and CPF algorithms.

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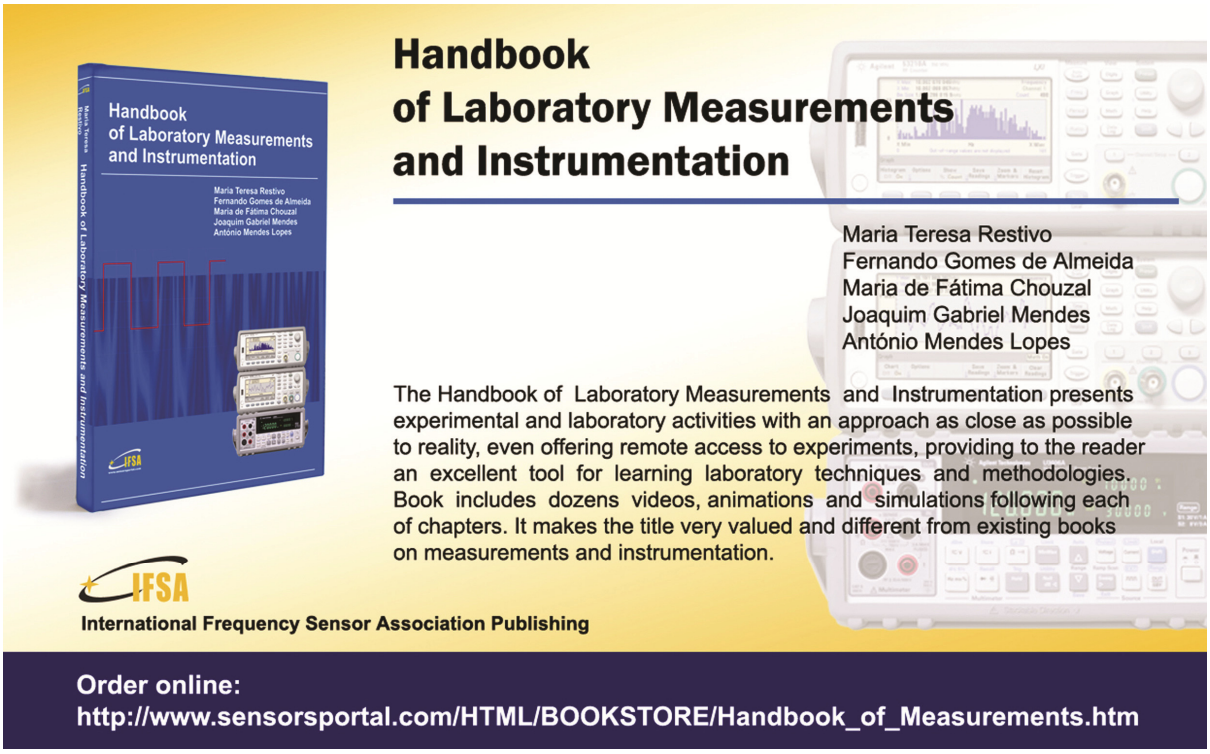
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