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DISTRIBUTED PARTICLE FILTER FOR TARGET TRACKING IN WIRELESS SENSOR NETWORK

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ABSTRACT

In this paper, distributed particle filter for target tracking in wireless sensor network was proposed. The key issue of distributed particle filter is sensor selection. Because of the limited resources, the fusion of the observation by the selected sensor must reduce uncertainty of the target state distribution without receiving any actual sensor observations. Our sensor selection is computationally much simpler than other sensor selection approaches. Simulation results show that our approach can reach very well performance for target tracking.

1. INTRODUCTION[1]

Target tracking is one of the most important applications of wireless sensor network. The limited on-board resources of sensor node and the limited wireless bandwidth are the major constraints of performing target tracking in wireless sensor network. In order to save resources, target tracking should be implemented in a distributed way. That is to say, traditional centralized processing method is not suitable to the need of sensor network. But how to implement the target tracking in distributed way? Due to the perfect performance in target tracking area by particle filter, we discussed below how to implement distributed particle filter in wireless sensor network.

Contrary to the traditional processing methods, which have a processing centre, there is not any processing centre in a distributed particle filter. In distributed particle filter, the task of target tracking is performed by the collaboration of sensor nodes. In order to perform tracking task, the sensor node that takes the responsibility of implement the particle filter at current time must report his results to one of its neighbours. There are many neighbour nodes, which one will become the processing unit at the next time? So we face the sensor selection problem: how to select the most effective sensor so as to reach a good performance of target tracking. One criterion for sensor selection is based on information-theoretic. From the information-theoretic point of view, different sensor contributes different information gains to the uncertainty of target state distribution. Selecting the most informative sensor can reduce the most uncertainty of target state and do not use more resources than necessary. Trough the sensor selection, we can track the target in a distributed way and therefore prolong the life of sensor network.

There have been several investigations into information-theoretic methods to implement sensor selection. Zhao et. al. [1][2] have used the mutual information between the predicted sensor observation and the current target state distribution to select the most informative sensor. Wang and Yao[3] proposed a novel entropy-based heuristic approach for sensor selection based on their experiments. But both the methods above employed the grid-based methods to perform sensor selection. To our best knowledge, the complexity of grid-based methods increases when the dimension of target state space increases. So if the dimension of state space is much larger than there, the computation complexity will be beyond the capacity of sensor nodes. In this paper, we proposed a particle filter based method to perform sensor selection. It is computationally more efficient than grid-based methods proposed in[1][2][3].

The rest of this paper is organized as followed. Section 2 discusses the distributed particle filter for target tracking in wireless sensor network. Section 3 describes our sensor selection methods and compares its computation complexity to the grid-based methods in[1][2][3]. Section 4 analyzes the performance of our distributed particle filter for target tracking by computer simulations. Section 5 makes a conclusion of this paper.

2. DISTRIBUTED PARTICLE FILTER FOR TARGET TRACKING

In this section, we discuss the distributed particle filter for target tracking in wireless sensor network.

Let $\{x_t, t=0, 1, 2...\}$ denote the state of target at time t, and $\{z_t, t=1, 2, 3...\}$ denote the corresponding measurement of sensor nodes. Then, the dynamic equation of the target state and the measurement equation of sensor nodes can be described by:

$$x_{t+1} = f(x_t) + u_t \tag{1}$$

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$[\{x_t^i, w_t^i\}_{i=1}^N] = DPF[\{x_{t-1}^i, w_{t-1}^i\}_{i=1}^N, z_t]$

Step 1：sample $x_t^i \sim q(x_t \mid x_{t-1}^i, z_t)$ $i = 1, 2...N$

Step 2：decide the important weighted $\hat{w}_t^i = \hat{w}_{t-1}^i \dfrac{p(z_t \mid x_t^i) p(x_t^i \mid x_{t-1}^i)}{q(x_t^i \mid x_{t-1}^i, z_t)}$ $i = 1, 2...N$

normalize $\hat{w}_t^i$ to be w_t^i $i = 1, 2...N$,

decide $\hat{N}_{eff} = \dfrac{1}{\sum_{i=1}^{N} (w_t^i)^2}$

step 3：if $\hat{N}_{eff} < N_{th}$， then resample $\{x_t^i, w_t^i\}_{i=1}^N$， or turn to next step

step 4：select the next leader by sensor selection algorithm，then transmit $\{x_t^i, w_t^i\}_{i=1}^N$ to the next leader

Table 1: Distributed Particle Filter

$$z_t = g(\mathrm{x_t}) + v_t \quad (2)$$

where function $f(x)$ and $g(x)$ may be linear or nonlinear. In this paper, we consider that $g(x)$ is nonlinear. State noise $u_t \sim N(0, Q)$ is white and stationary. Measurement noise $v_t \sim N(0, R)$ is white and stationary, and independent of the state noise u_t.

The essence of particle filter is to approximate the posterior target state distribution by a series of weighted samples of state. Assuming that we can obtain the approximation of posterior target state distribution at time $t-1$, denoting as $\{x_{t-1}^{\mathrm{i}}, w_{t-1}^i\}_{i=1}^N$, where N is the number of particles. We name the processing sensor node at time $t-1$ as leader node. According to $\{x_{t-1}^{\mathrm{i}}, w_{t-1}^i\}_{i=1}^N$, leader node can obtain the estimated value $\hat{x}_{t-1} = \sum_{i=1}^{N} w_{t-1}^i x_{t-1}^i$ of target position at time $t-1$ under MMSE criterion. According to this estimated value and some information of sensor node, we can select one sensor node among leader's neighbours to be the leader at next time, then leader can transmit the information of target state to the next leader. After receiving the information from the former leader, the leader at time t can update the target state using its measurement. We will discuss sensor selection algorithm in detail in Section 3. Table I describes the algorithm of distributed particle filter for target tracking. Where $q(.)$ is important function, $N_{th} = N/3$.

3. SENSOR SELECTION

In this section, we discuss our sensor selection algorithm in detail. Subsection 3.1 formulates the sensor selection problem for target tracking. Subsection 3.2 discusses our sensor selection method. Subsection 3.3 validates our methods by computer simulation. Subsection 3.4 compares the complexity of our method to that of other sensor selection methods.

3.1 Sensor Selection Problem

In the distributed target tracking, the uncertainty of target state is reduced by repeatedly selecting sensor with maximal expected information gain, the observation of selected sensor is incorporated into the posterior distribution of target state by particle filter to increase tracking performance. Due to the limited resources of sensor node, the key issue is how to evaluate the information gain of different sensor nodes without actually retrieving sensor measurements.

We can formulate this sensor selection problem for target tracking as follows. Given

(1) prior distribution of target
(2) positions of sensor nodes
(3) measurement model of sensor: $p(z_t \mid x_t)$
(4) dynamic model of target: $p(x_{t+1} \mid x_t)$

The objective of sensor selection is to find the sensor k whose measurement z_{t+1}^k maximizes the mutual information $I(x_{t+1}; z_{t+1}^k \mid z_t)$:

$$\hat{k} = \arg\max_{k \in s} I(x_{t+1}; z_{t+1}^k \mid z_t) \quad (3)$$

Where

$$I(x_{t+1}; z_{t+1}^k \mid z_t) = \int p(x_{t+1}, z_{t+1}^k \mid z_t) \log \frac{p(x_{t+1}, z_{t+1}^k \mid z_t)}{p(x_{t+1} \mid z_t) p(z_{t+1}^k \mid z_t)} dx_{t+1} dz_{t+1}^k$$

and s is the set of sensor nodes.

3.2 Particle Filter based Sensor Selection

There have been several articles[1][2][3] to solve the sensor selection problem. But to our best knowledge, they all used the grid-based method to perform sensor selection. When the dimension of target state is increasing, the complexity of grid-based method is increasing quickly. In order to solve this problem, we proposed a particle filter based new method to perform sensor selection.

In practical, if we can decide the $p(x_{t+1}, z_{t+1}^k \mid z_t)$, $p(x_{t+1} \mid z_t)$ and $p(z_{t+1}^k \mid z_t)$, we can determine the equation (3). According to particle filter, we can obtain

$$p(x_t \mid z_t) \approx \sum_{i=1}^{N} w_t^i \delta(x_t - x_t^i) \tag{4}$$

and we know that

$$p(x_{t+1} \mid z_t) = \int p(x_{t+1} \mid x_t) p(x_t \mid z_t) dx_t \tag{5}$$

substituting equation (4) into equation (5), we have

$$p(x_{t+1} \mid z_t) = \sum_{i=1}^{N} w_t^i p(x_{t+1} \mid x_t^i) \tag{6}$$

According to MMSE criterion, we can obtain that the estimated state at time t is $\hat{x}_t = \sum_{i=1}^{N} w_t^i x_t^i$ .Using the dynamic equation (1), we can obtain N samples of target state at time $t+1$, which are denoted by $\{x_{t+1}^i\}_{i=1}^N$. Then we have

$$p(x_{t+1}^i, z_{t+1}^k \mid z_t) = p(z_{t+1}^k \mid x_{t+1}^i) p(x_{t+1}^i \mid z_t) \tag{7}$$

Let

$$p(z_{t+1}^k \mid z_t) = \sum_{i=1}^{N} p(x_{t+1}^i, z_{t+1}^k \mid z_t) \tag{8}$$

Based on $\{x_{t+1}^i\}_{i=1}^N$, position information of sensor nodes and equation (2), we can predict the measurement z_{t+1}^k of sensor k at time $t+1$ without retrieving sensor measurement. Then via equation (6), (7) and (8), we can approximate equation (3) by

$$\tilde{I}_k = \sum_{i=1}^{N} p(x_{t+1}^i, z_{t+1}^k \mid z_t) \log \frac{p(x_{t+1}^i, z_{t+1}^k \mid z_t)}{p(x_{t+1}^i \mid z_t) p(z_{t+1}^k \mid z_t)}$$

Let $M = \{1, 2.....K\}$ be the set of the leader node's neighbours. Let

$$L = \arg\max_{k \in M} \{\tilde{I}_k\}$$

Then sensor L is the leader node at the next time. If the element of L isn't exclusive, randomly select one of the elements of L to be the next leader.

3.3 Simulation

This subsection evaluates the performance of our sensor selection. The interested area is $200m*200m$, and 200 sensor nodes are considered, which distribute randomly at that area. Let $x_t = (x_t^1, x_t^2)$ be the target state at time t, corresponding velocity is (v_t^1, v_t^2), then the dynamic equation[4] is denoted by $x_{t+1}^1 = x_t^1 + v_t^1$, $x_{t+1}^2 = x_t^2 + v_t^2$ and

$$\begin{cases} v_{t+1}^1 = v_t^1 + e_t^1 \\ v_{t+1}^2 = v_t^2 + e_t^2 \end{cases} \tag{9}$$

Sensing model is denoted by

$$z_t = \arctan\left(\frac{x_t^2 - \bar{x}_t^2}{x_t^1 - \bar{x}_t^1}\right) + e_t \tag{10}$$

Where $(\bar{x}_t^1, \bar{x}_t^2)$ is the position of sensor node, $e_t^i \sim N(0, 0.2^2)$, $i = 1, 2$ and $e_t \sim N(0, 0.05^2)$ are white and stationary, and independent of each other. Assuming that the initialization position of target is $x_0 = (5, 5)$, the initialization velocity of target is $v_0 = (2, 1.5)$. The important function is $p(x_{t+1}^i \mid x_t^i)$, then we have

$$w_{t+1}^i \propto w_t^i p(z_t \mid x_t)$$

In order to compare different sensor selection criterions, we define below there sensor selection criterions.

(1) Nearest Neighbor (NN): we select the sensor node that has min distance between the sensor nodes and the leader node as the next leader. That is

$$leader = \arg\min_{s \in M} sqrt((x_s - x_l)^2 + (y_s - y_l)^2)$$

where M is the set of leader node's neighbours, (x_s, y_s) and (x_l, y_l) are the coordinates of sensor s and sensor l, respectively.

(2) Max Information (MI): the reader can see the subsection 3.2 to reach the details of this criterion.

(3) Nearest Real Target (NRT): Assuming that we can obtain the true position of target, then we select the sensor node that has min distance between true position of target and the sensor node as the next leader. That is, the current leader can obtain the true measurement of its neighbours.

$$leader = \arg\min_{s \in M} sqrt((x_s - x)^2 + (y_s - y)^2)$$

where (x_s, y_s) and (x, y) are the coordinates of sensor s and target, respectively. The reader must remember that this is the ideal situation, because we can't obtain the true posi-

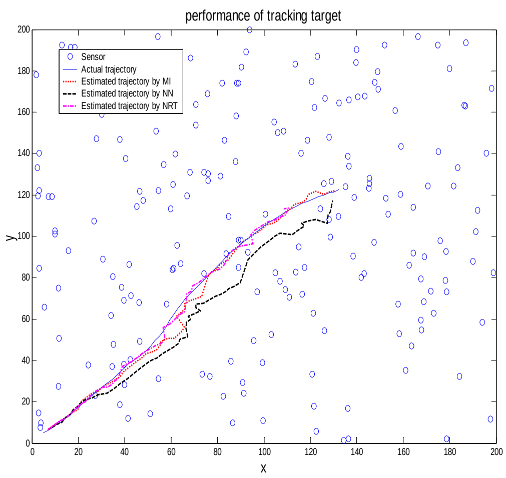

Figure 1: Performance of target tracking under different criterions

tion of target. We define this criterion because we can use it to compare the situation that we can obtain the true measurement of sensor node with our method, which we can't obtain the true measurement of sensor nodes.

Figure 1 describes the performance curves of target tracking under different sensor selection criterions. In figure 1, the solid line denotes the actual trajectory of target. The dotted line denotes the estimated trajectory under MI criterion. The dashed line denotes the estimated trajectory under NN criterion. The dash-dot line denotes the estimated trajectory under NRT criterion. From figure 1, we can see that the trajectory under NRT criterion is very close to the true trajectory of target. The target tracking under MI performs well and the performance under NN is the worst. It is important to mention that the curve under MI is very similar to the curve under NRT, which imply that our sensor selection method can predict the measurement very well.

Figure 2 and figure 3 show the sensor leader selection scenario for target tracking. From figure 2, we can find that the positions of sensor leader distribute uniformly near the actual trajectory, and form the figure 3, we can see that the sensor leader centralize at the one side of interested area. So we say that our sensor selection method is more robust than that of NN criterion.

In the former simulations, we assume that the sensor range is large enough and the sensor node can't be the leader repeatedly. Now we study how the range of sensor impact on the sensor selection criterion, in this situation, the sensor nodes can be the leader repeatedly. Figure 4 5 6 show the sensor selection under different sensor ranges. Form those figures, we can find that when the range of sensor become smaller and smaller, the performance of tracking become worse and worse. When the sensor range reach 15, we can see there only one sensor leader during the tracking process and the performance is the worst, the tracker even lost the target in the end.

3.4 Computational Complexity

In this subsection, we analyze the computational complexity

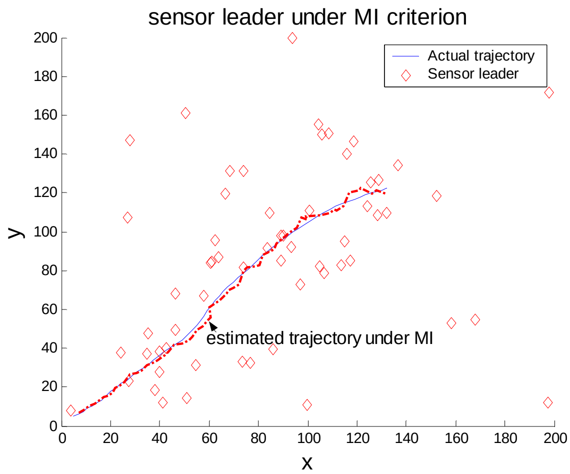

Figure 2: sensor leader selection under MI criterion

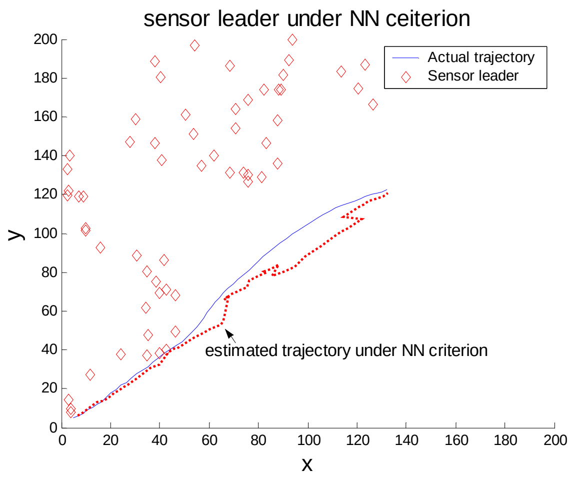

Figure 3: sensor leader selection under NN criterion

of our sensor selection and compare it to that of the grid-based sensor selection criterions. For M -dimensional target tracking, assuming that the M -dimensional target state subspace with non-trivial probability density is discretized into a grid of $\overbrace{n \times n \times \ldots n}^{M}$, then the total cost for method proposed by Wang and Yao is $O(n^M)$ [3]. Because the dimensional of sensor measurement is $M-1$-dimension when the target state is M -dimension, the total cost for method proposed by Zhao is $O(n^{2M-1})$ [3]. With the dimension of target increasing, the computational complexity will be beyond the capability of sensor node. The total cost of our particle filter based sensor selection is $O(N)$, where N is the particle number, which is independent of the dimension of target state and the sensor observation. So our method is immune to the dimension of target state space.

In order to show the superiority of our method in computational complexity, we use two-dimensional target tracking as an example to compare the computational complexity of different sensor selection criterions. We assume that the two-

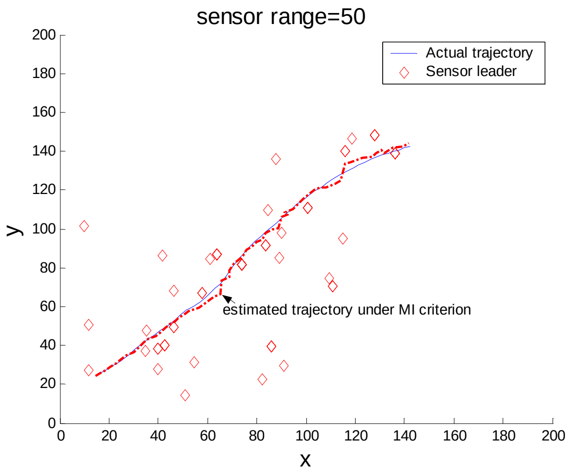

Figure 4: sensor selection under sensor range=50

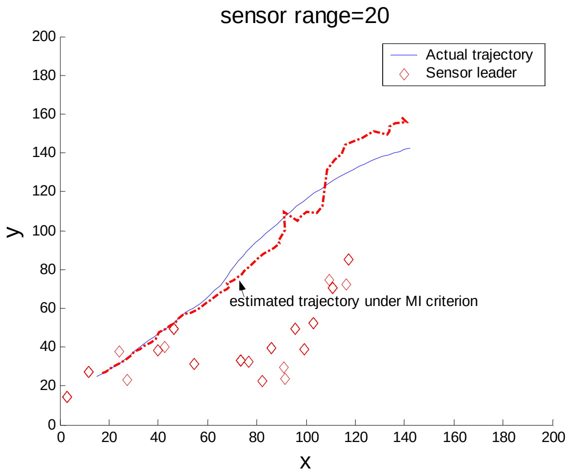

Figure 5: sensor selection under sensor range=20

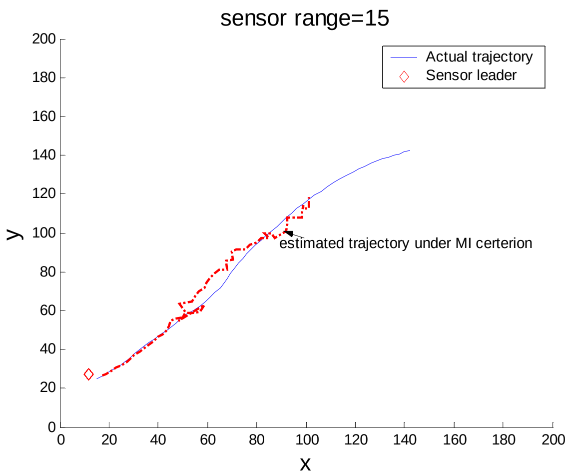

Figure 6: sensor selection under sensor range=15

dimensional target state subspace with non-trivial probability density is $100m*100m$, which is discretized into a grid of $100*100$. Then the total cost for method mentioned in[3] is $O(100^2)$ and the total cost for method mentioned in[1][2] is $O(100^3)$. The total cost of our method is $O(1000)$, because according to our experiments, performance of particle filter is quite well when the particle number reaches about several thousands. In general, our particle filter based sensor selection is computationally much simpler than the grid-based mentioned in[1][2][3], especially when the dimension of target stat is high.

4. CONCLUSION

In this paper, we have discussed the distributed particle filter for target tracking in wireless sensor network. The key issue of distributed particle filter is sensor selection. Based on particle filter, we have proposed a new sensor selection criterion, which is computationally much simpler than other sensor selection criterions. Because of its computational effectivity, our sensor selection is more suitable to wireless sensor network. The effectiveness of our method has been evaluated by computer simulations. The simulation results showed that our method performed well for target tracking in wireless sensor network.

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