A Lightweight Filter-Based Target Tracking Model in Wireless Sensor Network

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Abstract. Target tracking is an important research in Wireless Sensor Network (WSN), which detects and estimates the event source based on the data of multiple sensors. In this domain, the accuracy of tracking, the choosing of communication nodes and the real-time performance are the main direction of research. In this paper, the local density and distributed filter are investigated. Based on those above, a lightweight filter-based target tracking model is proposed, which use the local density to determine the communication nodes, and use the distributed filter to reduce the interval of sampling. The simulation shows the local density-based communication algorithm is stable and flexible.

Keywords: Local density · Distributed filer · Target tracking
WSN

1 Introduction

Wireless sensor network (WSN) is a typical Ad Hoc network which is highly distributed and self-organized [1, 2], which has many popular applications, such as target tracking, industrial process monitoring and control, air pollution monitoring, and machine health monitoring, and so on.

Target tracking is an important research which detects and estimates the event source based on the data of multiple sensors [3, 4]. Sometimes, kinds of interferences decrease the accuracy of measurements. Therefore, a filter is adopted to weaken the impact of these interferences.

The filter is used to extract a wanted signal from unwanted interferences. When the system dynamics and observation models are linear, the Kalman filter (KF) [5] can be used to calculate the minimum mean squared error (MMSE) estimate. And in most cases, the sensor nodes are always deployed in the harsh environment, without being recharged or replaced [6, 7]. Therefore, energy efficiency in in-network data processing is very important for WSN.

J. Zheng et al. (Eds.): ADHOCNETS 2018, LNICST 258, pp. 139–143, 2019.
https://doi.org/10.1007/978-3-030-05888-3_13

In this paper, a lightweight filter-based target tracking model in WSN is presented, which reduce the computing overhead of sensor nodes. The rest of the paper is organized as follows. In Sect. 2, the related works are introduce. In Sect. 3, the lightweight filter-based target tracking algorithm is introduced. A multi-stable system is structured to verify the proposed algorithm in Sect. 4. And the conclusion of this work in Sect. 5.

2 Related Works

Tracking moving target using WSN technology is a thought-provoking and well-established research area. Most of related researches can be divided into two parts: face-based and filter-based. The face-based target tracking algorithms usually divide the network into regions, cells, grids, clusters, trees, etc., and track the target in a distributed manner. Bhuiyan et al. [8] proposed target tracking algorithm with monitor and backup sensors in WSN. And then they consider target tracking using "face prediction," instead of "target location prediction in faces" presented in their previous work to get the full advantages from this face-based tracking [9].

And in filter-base target tracking algorithms, Both Beard et al. [10] use the Bayesian estimation method to track the target. Moreover, Yang et al. [11] present a sequential fusion estimation method for maneuvering target tracking in asynchronous wireless sensor networks.

Face-based target tracking algorithms utilize several sensor nodes around the target, which make these algorithms more energy-efficient. And filter-based target tracking algorithms have general requirements on node management and node distribution.

In this paper, a lightweight filter-based target tracking model in WSN is presented to reduce the demands on sensor nodes and increase the fault tolerance. In this algorithm, a definition of local density is proposed, which is used to confirm the communication probability of neighbor nods. And a communication probability is structured to confirm the communication nodes.

3 The Lightweight Filter-Based Target Tracking Model

3.1 The Local Density

In WSN, the sensor nodes are deployed in the monitor field randomly, and the distribution is not uniform strictly. Then, the definition of local density is presented naturally, which express the density for each node. In WSN, the local density of node i can be calculated according to the formula as follows:

$$\rho_i = \frac{N_i}{S_i}, \tag{1}$$

where S_i is the monitor area of node i, and N_i is the number of sensor nodes in S_i.

In WSN, a target can be monitored by many nodes around it. And in general, not all the nodes which monitor the target transmit the message to the base station. Therefore, the local density can be used to calculate the communication probability for each node.

3.2 Communication Probability of Nodes

In this part, the communication probability for each node should be confirmed. In this probability, two relevant factors are considered. The first one is the local density and another one is the distance between the nodes to target. Then the communication probability is given according to these two factors.

$$P_c(p,d) = \min\left\{k_1 \frac{n_0}{\pi R^2 \rho} \frac{(R-d)}{R}, k_2 \frac{(R-d)}{R}, 1\right\}, \tag{2}$$

where R is the detection radius, n_0 is the expectation number of communication nodes, k_2 is given constant and k_1 is an auxiliary constant. For a known WSN, k_2 can be confirmed according to the formula $\sum P_c(\rho, d) = n_0$ when k_1 is given.

3.3 Distributed Filter Algorithm

In most filter-based target tracking algorithms, it is assumed that the target moves in the uniform rectilinear motion between two interfacing time instant with an uncertain noise. Obviously, the estimate is more precise if the time instant is shorter. However, in one time instant, the WSN should calculates the estimate and communicates. And in most cases, sensor node computes the estimate value according to the relevant filter method, which may prolong the minimum time instant.

On the other hand, the filter-based target tracking algorithms usually obtain the estimate according to the state equation and measurement equation. And these two equations can be computed in sensor nodes and base station, respectively. The distributed filter algorithm is shown as follows (Table 1):

Table 1. The distributed filter algorithm (for the k^{th} iteration)

Time (T)	Sensor nodes (SNs)	Base station (BS)
Max{$2T_{trans} + T_{cal}$, $T_{cal'}$}	Receive the state parameters (T_{trans}) Calculate the $(k + 1)^{\text{th}}$ estimated value for each node (T_{cal}) Transmit the value to BS (T_{trans})	Calculate the $(k + 1)^{\text{th}}$ state parameters ($T_{cal'}$)
Max{$T_{collect}$, $2T_{trans} + T_{fusion}$}	Collect the measurement data ($T_{collect}$)	Receive the estimated value (T_{trans}) Fusion all the values (T_{fusion}) Transmit the $(k + 1)^{\text{th}}$ final estimated value and the $(k + 1)^{\text{th}}$ state parameters (T_{trans})

Compared with the common filter algorithms, the distributed filter algorithm can save half of filter time at most.

4 Simulation

In this part, 1000 sensor nodes are deployed in the 200 × 200 area randomly, and MATLAB is used to simulate. Firstly, a target is generated for 100 times randomly, and the distribution of number of communication nodes is simulated and shown in Fig. 1.

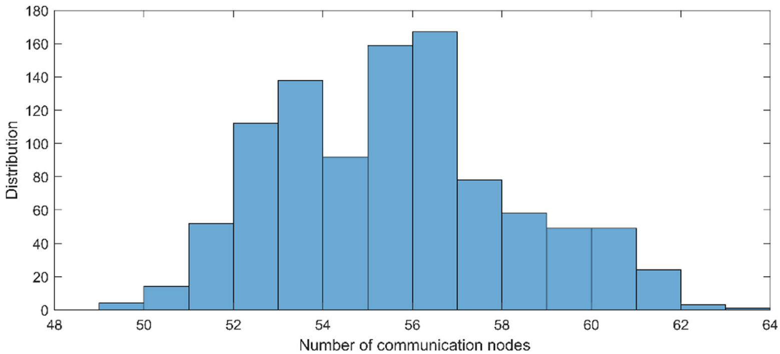

Fig. 1. The distribution of number of communication nodes

In this simulation, the target locates inside the monitor area, which means the minimum distance between the target and the edge of monitor area is longer than the radius of investigation. And

$$n_0 = 0.5\bar{n}, k_1 = k_2 = 3.$$

In this case, Fig. 1 shows that the numbers of communication nodes are focus between 51 and 62. The mean and variance of this distribution are 55.6028 and 6.9465. On the other hand, the expectation of communication nodes n_0 = 55.5230. Therefore, the proposed communication probability can satisfy the requirement of WSN.

Then, the parameters k_1 and k_2 are discussed respectively and shown in Fig. 2. In this simulation, $n_0 = 0.6\bar{n} = 63.8748$. As shown in Fig. 2, when $k_2 < 1.3$, the expectation of communication nodes (Ecom) can't arrive at n_0 with $k_1 \in [1, 10]$. Besides, when $k_1 \in [6, 6.3]$, k_2 is stable around n_0.

According two simulations above, the proposed local density-based communication algorithm ensure a stable communication nodes with suitable parameters.

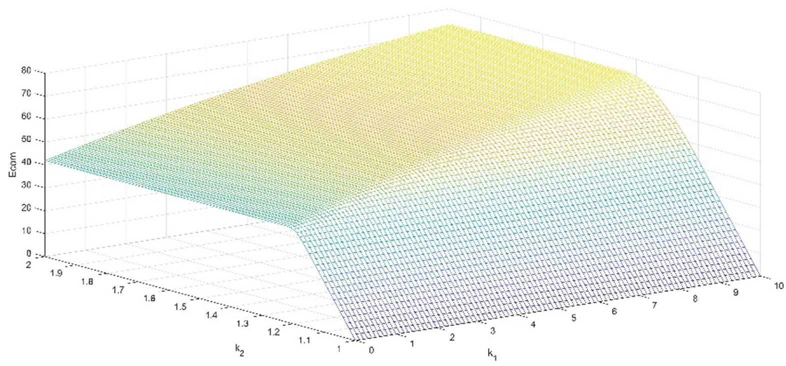

Fig. 2. The expectation of communication nodes with different k_1 and k_2

5 Conclusion

In this paper, a lightweight filter-based target tracking model is presented, which chose stable communication nodes, reduce the interval of sampling and increase the accuracy of estimate. And the simulations discuss how to confirm the parameters and show a well performance in stable on communication.

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