

Adaptive Threshold Selection for Collaborative Target Tracking

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Abstract: A uniform threshold is not reasonable as a faraway sensor can hardly get the same signal strength as that of a near one from the target. To cope with this problem, we give an adaptive threshold selection (ATS) algorithm, in which we construct the minimum error probability cost function based on the probability of false positive and false negative of sensor nodes, and calculate the optimal detection threshold to select the nodes that attend in target tracking. The simulation results show that the proposed algorithm improves the tracking accuracy while reducing the network energy consumption.

1. Introduction

Wireless Sensor Networks (WSNs) are gaining diverse attentions due to their appropriateness to observe environments where the deployment of wired networks is either complicated or impractical [1]. WSNs can handle difficult tasks in a collaborative fashion and are becoming increasingly popular for demanding and safety critical applications, including large area monitoring, target localization, and target tracking [2]. In target tracking, sensor nodes that discover the target are awakened. Because of disturbance and noises in harsh environment, sensor nodes are unable to confirm whether a target is discovered, and this affects the performance of target tracking. A predefined threshold can minimize the probability of false alarms of sensors when detecting the presence of a target [3]. But a uniform threshold is not reasonable as a faraway sensor can hardly get the same signal strength as that of a near one from the target. In view of each sensor has different characteristic in detecting target, a dynamic threshold algorithm is proposed for improving the detection probability in [4]. In [5], a hierarchical decision fusion scheme is proposed to improve network-wide detection probability. Based on the signal energy and Gaussian noise, sensor node chooses its threshold, and improves the detection accuracy [6]. However, if the chosen threshold is too small, it is easy to appear false alarms. Therefore choosing the appropriate threshold is an optimization problem involving the probability of false alarm and the probability of false negative. Based on the minimum error probability cost function, we in this paper propose an adaptive threshold selection (ATS) algorithm to improve the tracking accuracy.

2. Problem Formulation

2.1 Detection Model

Assume that H_0 represents the hypothesis that the target is absent and that H_1 represents the other hypothesis that the target is present. Thus the signal intensity measurement m_i of sensor i is given by

$$H_0 : m_i \sim N(0, \sigma_i^2) \quad H_1 : m_i \sim N(g_i, \sigma_i^2) \quad (1)$$

where $w_i \sim (0, \sigma_i^2)$ is additive white Gaussian noise to which sensor i is exposed. In this paper, we assume that the target generates a constant signal c which is attenuated inversely proportional to the distance from the target raised to some power $\alpha \in \mathbb{R}$ which depends on the environment.

$r_i = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}$ is the distance from sensor i to the target. As a result, the signal intensity at any sensor i is given by [3]

$$g_i = \frac{c}{1 + r_i^\alpha} \quad (2)$$

2.2 Target Dynamic Model

We assume that the target is traversing the sensor field according to a linear discrete-time process disturbed by noise [7-9].

$$X(k+1) = F(\Delta t_k)X(k) + W(k, \Delta t_k) \quad (3)$$

where $X(k)$ represents the process state at time step k , which happens at time t_k ; $F(\Delta t_k)$ is the state-transition matrix at step k ; $W(k, \Delta t_k)$ is the process Gaussian noise with covariance matrix $Q(k, \Delta t_k)$; and $\Delta t_k = t_{k+1} - t_k$ is the sampling interval between t_k and t_{k+1} .

In this paper, we consider a 2-D model with $X(k) = [x_s(k) \ v_x(k) \ y_s(k) \ v_y(k)]^T$ at time step k . The state transition matrix $F(\Delta t_k)$ and the covariance matrix $Q(k, \Delta t_k)$ are given by

$$F(\Delta t_k) = \begin{bmatrix} 1 & \Delta t_k & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t_k \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad Q(k, \Delta t_k) = q \begin{bmatrix} \Delta t_k^3/3 & \Delta t_k^2/2 & 0 & 0 \\ \Delta t_k^2/2 & \Delta t_k & 0 & 0 \\ 0 & 0 & \Delta t_k^3/3 & \Delta t_k^2/2 \\ 0 & 0 & \Delta t_k^2/2 & \Delta t_k \end{bmatrix} \quad (4)$$

where q is a known scalar that represents the intensity of the process noise.

2.3 Energy Model

Energy is consumed during sensing, communication and processing. $E_t(l, d) = E_{elec}l + \varepsilon_a ld^2$ is the energy consumption required to transmit an l -bit message over a wireless distance d where E_{elec} is the electronic energy and ε_a is the amplifier energy [10]. The energy consumption to receive l -bit message is $E_r(l, d) = E_{elec}l$. The energy consumption used to sense and execute is much smaller than that of the communication, so it can be ignored.

3. Adaptive Threshold Selection

3.1 Probabilistic Model

This section introduces the method for detecting the target. According to (3) the probability of getting the measurement m_i for sensor i is expressed as

$$p(m_i | H_0) = \left(\frac{1}{\sqrt{2\pi}\sigma_i} \right) \exp\left[-\left(\frac{m_i^2}{2\sigma_i^2} \right) \right] \quad p(m_i | H_1) = \left(\frac{1}{\sqrt{2\pi}\sigma_i} \right) \exp\left[-\left(\frac{(m_i - g_i)^2}{2\sigma_i^2} \right) \right] \quad (5)$$

The threshold value of the sensor i is assumed as Th_i . According to the measured value in detection model, sensor i compares its signal intensity measurement with its threshold Th_i . If it is greater than Th_i , the sensor decides 1 which means it detects the target, otherwise it decides 0 which means it doesn't. According to (5), the false positive probability and the false negative probability can be expressed as

$$P_{fp}(Th_i) = P(m_i \geq Th_i) = 1 - \Phi\left(\frac{Th_i}{\sigma_i} \right) \quad P_{fn}(Th_i) = P(m_i < Th_i) = \Phi\left(\frac{Th_i - g_i}{\sigma_i} \right) \quad (6)$$

3.2 Minimum Error Probability Cost Function

According to the probability of false alarm and false negative we construct the following cost function J representing the overall error

$$J(Th_i) = \omega \times P_{fp}(Th_i) + (1 - \omega) \times P_{fn}(Th_i) \quad (7)$$

where $0 \leq \omega \leq 1$ is a user specified weight that should be chosen with care according to the application. Therefore, we hold that the target is present when $\frac{p(m_i | H_1)}{p(m_i | H_0)} > \frac{\omega}{1 - \omega}$.

After simplification, we have the threshold of sensor i is

$$Th_i = \frac{(1 + r_i^\alpha) \sigma_i^2}{c} \ln \frac{\omega}{1 - \omega} + \frac{c}{2(1 + r_i^\alpha)} \quad (8)$$

3.3 Cluster Forming Based on Adaptive Threshold

We regard the sensing radius R_s as a boundary that only if a target is within the radius distance can it be detected. Hence the maximum *Region of Influence* (RoI) of a target is a circular region with the target's position as the center and radius of R_s . Some sensor nodes in this area may not transmit the target information. Sensor nodes selected again according to the threshold that selected based on the probability of false positive and false negative can improve the tracking accuracy of the network.

In Figure 1, the dashed line indicates the node selection boundary theoretically. The solid line shows the more realistic one. In the dashed line, the white circles denote as false negative nodes and grey circles denote as false alarm nodes. We select sensor i as cluster member s_i when its signal strength value m_i is larger than its Th_i .

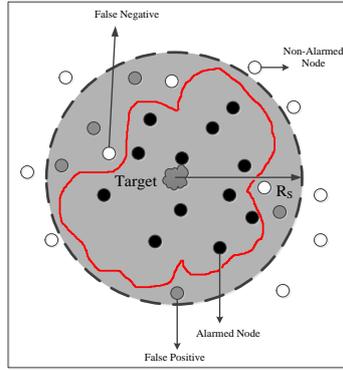


Fig. 1 Node selection boundary

4. Simulation Experiment

4.1 Simulation Conditions

For the simulations we use a rectangular $300m \times 300m$ sensor field with $N = 1000$ sensors. We assume that sensors in the network have different additive noise variances. The signal intensity is $c = 10^3$ and α in Eq. (2) is set to 2. The measurement model for sensor i is expressed [3]

$$z_i(k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} x_i(k) + u_i(k) \quad (9)$$

The initial states of the tracking process is $[20 \ 1 \ 20 \ 1]^T$. All the sensor nodes are assumed to have the same measurement noise variances σ_i^2 . The other simulation parameters are expressed by table 1.

Table 1 Simulation Parameters

$[T_{\min}, T_{\max}]$	q	σ_i^2	R_s	ω	ϵ_a	E_{elec}	l
$[0.1s, 0.5s]$	1	0.1	30m	0.5	10pJ/b/m ²	50nJ/b	264

4.2 Simulation results

In this simulation, the target travels in the WSN with a trajectory for 150s. In Figure 2 the real target trajectory is plotted. Note that the Adaptive sampling (AS) algorithm and the adaptive threshold selection (ATS) algorithm have the same calculation method about sampling interval [11].

The tracking error for the ATS algorithm and the AS algorithm is shown in Figure 3. The ATS algorithm can get rid of the sensor nodes that do not sense the target, and so has smaller tracking error.

The total energy consumption of different algorithms for 20 simulation runs is plotted in Figure 4. The total energy consumption of the ATS algorithm is less than that of the AS algorithm for the ATS algorithm reduces the number of cluster members by second-selection. Thus the total energy is further saved.

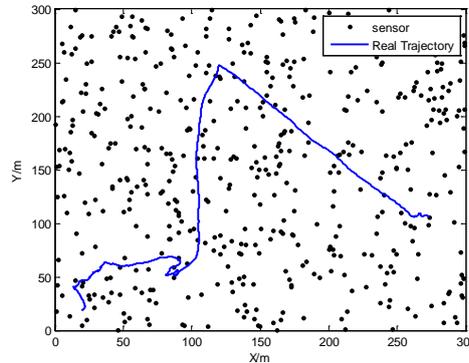


Fig. 2 Real trajectory for the target

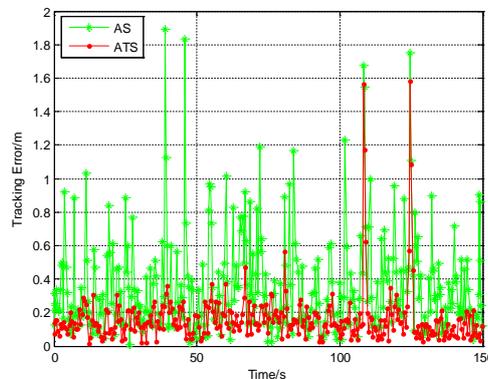


Fig. 3 The tracking error

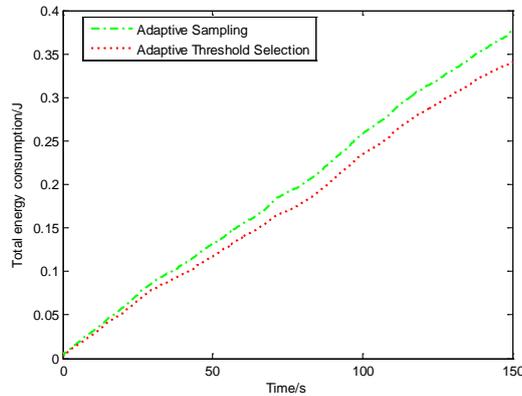


Fig. 4 The total energy consumption

5. Conclusions

In this paper, according to the probability of false positive and false negative of the sensor node, we construct the minimum error probability cost function to calculate the optimal detection threshold, and propose an ATS algorithm that improves the tracking accuracy and reduces energy consumption.

Simulation results show that the ATS algorithm has higher tracking accuracy and less energy consumption when we choose sensor nodes with adaptive threshold.

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