TARGET LOCALIZATION AND TRACKING IN NOISY BINARY SENSOR NETWORKS WITH KNOWN SPATIAL TOPOLOGY

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ABSTRACT

Target localization and tracking are two of the critical tasks of sensor networks in many applications. Conventional localization and tracking techniques developed for wireless systems that rely on direction-of-arrival or time-of-arrival information, are not suitable for low-power sensors with limited computation and communication capabilities. In this paper, we propose a low complexity and energy efficient localization and tracking method for binary sensor networks in noisy environments, where the sensors can only perform binary detection, and the physical links are characterized by additive white Gaussian noise channels. The proposed method is based on known spatial topology. An efficient wake-up strategy is used to activate a particular group of sensors for cooperative localization and tracking. We analyze the localization error probability and tracking miss probability in the presence of prediction errors. Simulation results validate the theoretic analysis and demonstrate the effectiveness of the localization and tracking mechanism.

***Index Terms*—** Localization, tracking, target detection, binary sensor networks, spatial topology

1. INTRODUCTION

Wireless sensor networks are composed of nodes with sensing, wireless communication and simple computation capabilities [1]. Most sensor networks consist of a large number of inexpensive and low-power wireless sensors, and usually achieve their objectives such as localization and tracking in a distributed and cooperative way. Existing localization approaches for wireless systems based on direction-of-arrival (DOA) or time-of-arrival (TOA) are not directly applicable in sensor networks, due to the power/size constraints of sensors.

As a low-power and bandwidth efficient solution, recently binary sensor networks have been proposed for localization and tracking [2–4]. In a binary sensor network, the spatial topology (location of all sensors) is usually assumed to be known. This could be realized at the time of network deployment or through a location service [5]. A typical sensor can only make a binary decision regarding a target or object of interest, and consequently, only one bit information needs to be sent from a sensor to a cluster head for further processing. For example, in [2], a binary sensor model is proposed in which a sensor can only detect whether a object is moving toward or away from it. With two convex hulls (one is formed by sensors returning one and the other is formed by sensors returning zero), the moving direction of a target can be tracked. However, to distinguish two targets with the same direction, an additional proximity bit is needed. A quadruplet of binary sensors are used in [3] to determine the range of velocity slope, where the computation is done in a distributed manner. In [4], a sensor can only detect a target within a certain range and returns a bit indicating whether a target is present in this range. It uses a weighted average of the locations of detecting sensors as the target's estimated location. This method is effective in tracking. However, each node needs to record the duration for which the target is in its range.

All of the above methods assume error-free transmission from sensors to a cluster head or a fusion center. More realistic binary sensor networks with noisy links are considered in [6,7]. Target tracking is formulated in [6] as a hidden state estimation problem over the finite state space of sensors, where the Viterbi algorithm is adopted to track an object. Particle filtering is used in [7] to fuse information collected from sensors. Although these two methods take noise into consideration, the computation involved is highly complex.

In this paper, we develop a low-complexity target localization and tracking method for noisy binary sensor networks. For simplicity, we assume that a sensor sends a "1' to a cluster head if a target exists within its detection range, and a "0" if a target does not exist within that range. The proposed method is based on a known network topology where the cluster head relies on the intersection of the detection areas of sensors to localize and track targets. Compared to the existing approaches, our proposed method takes into account noise in wireless links and yet remains low-complexity and bandwidth efficient with minimum power consumption.

The rest of the paper is organized as follows. In Section 2, we propose a low complexity target localization and tracking method by exploiting known spatial topology of sensor networks. In Section 3, we analyze the error probability of the localization method under the constraint of prediction errors. Monte Carlo simulation results are presented in Section 4 to validate the theoretic analysis. Section 5 concludes the paper.

2. TARGET LOCALIZATION AND TRACKING

2.1. Target Localization Using Spatial Topology

Consider a sensor field with sensors distributed according to a certain topology. The sensor field can be classified into many sensor clusters. Within each cluster, there are two types of sensors: a monitor sensor (also called cluster head herein) and detecting sensors. The monitor sensor is usually more powerful, and its job is to keep in listening status and to wake up a group of detecting sensors (using beacons) in a certain area to localize and track the targets in case a target enters the sensor field. The detecting sensors have a certain detection range. For simplicity, we assume that the range is a circle

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centered at the sensor with radius a. Because the minute size and low-power consumption requirement, the detecting sensors are assumed to have limited detection and communication capability. For example, the detecting sensors can only detect whether or not a target exists within its range and then send binary messages to the monitor sensor. Monitor sensors can execute relative complicated calculation and have a longer lifetime than detecting sensors.

Every active detecting sensor (sensor that has been waken-up) transmits one bit of information to the cluster head per duty cycle. The information could be coded to increase robustness against channel noise. For the simplicity of analysis, we assume that the uncoded bit sent by the ith sensor is D_i, and if a target is in the sensor's detection range, $D_i = 1$, and otherwise $D_i = 0$. Suppose that the transmission power is ρ, then the received signal at the cluster head from the ith sensor can be written as

$$x_i = \sqrt{\rho} D_i + n_i, \tag{1}$$

where n_i is additive white Gaussian noise with zero mean and variance σ^2. Similar to [2], we assume that a proper media-access control (MAC) protocol is employed so that signals from different sensors can be separated at the cluster head, and the sensor locations (spatial topology) are known at the cluster head as well. The problem considered here is how to locate the target in the sensor field from $x_i, i = 1, \ldots, M$, where M is the number of active sensors.

We use an example to illustrate our proposed localization method in the following. In Fig. 1, suppose that S_1, S_2, S_3, S_4 are four active detecting sensors. This area is partitioned into subareas by the detection ranges of the four sensors. In this example, the number indicates how many sensors among S_1, S_2, S_3, S_4 can detect a target in each subarea. Each subarea is uniquely determined by the detection sequence. For example, if four active sensors S_1, S_2, S_3, S_4 return a detection sequence $[D_1, D_2, D_3, D_4] = [1, 1, 1, 0]$, then the cluster head can determine that the target is located at the subarea indicated with a "3" that is closest to sensor S_1.

Apparently, the resolution of this low complexity localization method is to the level of subareas, which may not be as high as that offered by more sophisticated DOA or TOA based approaches. However, when the density of the sensor field increases, this method can also provide accurate localization that may be sufficient for many applications, at extremely low complexity and power cost. An important component of the proposed scheme is how to wake-up a group of detecting sensors. In the following, we present an energy efficient wake-up strategy for localization and tracking of targets.

2.2. Tracking with Prediction Errors

When the network is set up, all monitor sensors communicate with each other to divide the whole network region into some subregions. They partition the region based on their neighboring monitor sensors. Here we use region and subregion to differ from area and subarea mentioned before. Suppose that a monitor sensor A_1 has four monitor neighbors: A_i, $i = 2, \ldots, 5$. We use $\perp A_1 A_i$ to denote the bisector of $A_1 A_i$. Then the subregion enclosed by $\perp A_1 A_i$, $i = 2, \ldots, 5$, is a subregion that is monitored by A_1. Sensor A_1 activates binary sensors in its subregion if it is necessary and collects information returned by binary sensors in the subregion.

All binary detecting sensors are waken up periodically to detect possible targets. Once a target is detected for the first time, the monitor sensor assigns a unique ID to the target. Suppose that a target has been localized at least in two subareas in a sequence and the centers of two subareas are respectively (x_{i-1}, y_{i-1}), (x_i, y_i) in a two-dimensional coordinate. Then, the monitor sensor predicts the

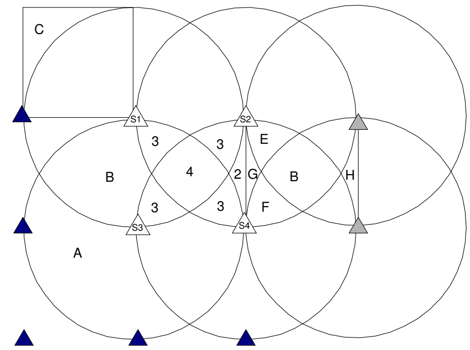

Fig. 1. An illustration of localization in a binary sensor network.

next position of the target as $(2x_i - x_{i-1},\ 2y_i - y_{i-1})$, assuming that the target moves in the same direction with a constant speed. Therefore, the monitor sensor wakes up four sensors that are closest to the target's predicted location. The detection results of the four sensors are sent back to the monitor sensor for further localization and tracking decisions. If the predicted location is out of the subregion covered by the current monitor sensor, it informs another corresponding monitor sensor to continue to track the target.

The prediction of the target's next location may have some error due to randomness of the movement of the target. In this case, it may be necessary to wake up more than four sensors to locate a target. An illustration of the wake-up strategy is shown in Fig. 1. Suppose that the monitor sensor determines that the target is within the square formed by four sensors (indicated by S1 through S4). Then, the monitor sensor wakes up these four sensors to further locate the target. We refer this as the first round of detection. However, this prediction may be wrong, e.g., if all four sensors return zero to the monitoring sensor. In this case, a second round is necessary, in which the monitoring sensor wakes up more sensors surrounding the initial square, based on the assumption that even if a prediction is wrong, it is most likely not very far away from the true location of the target. The process can continue until the target is located or a pre-set threshold on the number of sensors that can be waken up is met.

Specifically, for the square topology shown in Fig. 1, our wake-up strategy works in the following way. In the first round, sensors S1–S4 are waken up, and then

1. If three or more sensors return 1's to the cluster head, the target is considered located. No more sensors need to be waken up for this duty cycle.
2. If only one sensor (e.g., S3 in Fig. 1) returns a "1", the cluster head wakes up five more sensors (i.e., the five ones indicated by dark-shaded triangles in Fig. 1) for a second round detection. Since the area covered by S3 but not S1, S2, and S4, i.e., area A, can only be covered by one or more sensors of the five dark-shaded ones.
3. If only two sensors on the same edge of the square (e.g., S2 and S4) return 1's, the cluster head wakes up two more sensors (i.e., the two lightly shaded triangles to the right of S2 and S4) for a second round detection, because the target can be in areas 2, G, E, B, or F as shown in Fig. 1.
4. If only two sensors on the diagonal of the square (e.g., S1 and S4) return 1's, a localization error occurs and the four sensors are asked to retransmit signals to the cluster head.
5. If no sensor returns a "1", the cluster head wakes up all 12 sensors surrounding the square formed by S1–S4 for a second round of detection.

Depending on the result of the second round of detection if activated, the monitor sensor may have to wake up additional sensors for a third round detection, similar (but not exactly the same) to the procedure describe above, which is omitted here due to space limitation. This process continues until the target is located or a pre-set number of rounds is reached due to energy limitation.

Because the communication channel is noisy, localization error is unavoidable. In the following section, we analyze the probability of localization error using the proposed localization mechanism, in the presence of possible prediction errors of the monitor sensor.

3. ANALYSIS OF LOCALIZATION ERROR PROBABILITY

Taking into account the noise effect of the physical channel, the communication between sensors and the cluster head is no longer perfect (as shown in (1)). We first consider the localization error probability when the prediction of the monitoring sensor is error-free, i.e., the proper four sensors are waken up. Then, prediction error is taken into account in our analysis.

3.1. Zero Prediction Error

At the cluster head, hard-decision is performed on the signal received from each sensor. In other words, the cluster head decides whether D_i is 1 or 0 from x_i in a maximum likelihood sense. Based on the decisions, the cluster head can locate the target to a single subarea in the field. However, if because of noise, the cluster head makes a wrong decision on D_i, then the target may be detected erroneously in a wrong subarea. The localization error probability depends on noise power σ^2, signal power ρ, and the number of sensors involved.

From (1), it is ready to verify that the average probability of error for the decision on each sensor's signal (i.e., decide 1 as 0, or vice versa) is $P_e = Q(\sqrt{\rho}/(2\sigma))$, where the Q-function is defined as $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt$.

For the aforementioned square topology, correct localization of target in a subarea requires correct decisions on signals sent by four sensors if there is no prediction error. Therefore, the localization error probability is $P_{\text{square}} = 1 - (1 - P_e)^4$.

Suppose that the number of subareas in a sensor field is N, and the localization error probability for the nth subarea is R_n. If the location of the target is uniformly distributed in a sensor field, then the average localization error probability of the sensor network is

$$P = \sum_{n=1}^{N} a_n R_n, \tag{2}$$

where a_n is the normalized area for the nth subarea. According to (2), one has to consider network topologies case by case to obtain the exact probability of localization error. However, a good approximation can be obtained for a type of networks where the sensors are uniformly placed in the field, which is stated as follows.

Proposition 1 *Suppose that a sensor field has a total area A, the detection area of each sensor is c, and the number of sensors in the field S. If the sensors are uniformly placed in the field, then the average error probability in* (2) *can be approximated as:*

$$\bar{P} = 1 - (1 - P_e)^k, \text{ with } k := \lceil cS/A \rceil. \tag{3}$$

Using (3), we can calculate that for the square topology, the parameter k is $k = \lceil \pi a^2 N/(a^2 N) \rceil = 4$. Thus, according to Proposition 1, the approximate localization error probability with the square topology is $\bar{P}_{\text{square}} = 1 - (1 - P_e)^4$, which matches P_{square}.

3.2. Non-zero Prediction Error

We use the square topology as an example again to analyze the localization error probability in the presence prediction error. We assume that the actual location of the target follows a distribution $f(x, y)$ with respect to the predicted target location (x_o, y_o).

Let $P_s(i)$ be the probability that the target is located in the square region surrounded by the sensors waken up till the ith round, which can be calculated as $P_s(i) = \int_{S(i)} f(x, y) dxdy$, where $S(i)$ denotes the area surrounded by the sensors waken up till the ith round. Let $P_i(j)$ denote the probability that a target is covered by j sensors waken up till the ith round. We can calculate $P_i(j)$ as $P_i(j) = \int_{C(i,j)} f(x, y) dxdy$, where $C(i, j)$ is the area covered by j sensors till the ith round. For example, as shown in Fig. 1, $C(1, 3)$ is the area of the four subareas indicated with a “3”.

If only one round of detection can be used, the localization error probability is given by $P_1 = 1 - (1 - P_e)^4 P_s(1)$. If up to two rounds of wake-up is possible, the localization error probability can be calculated as follows. We first activate four sensors to detect the target. If they return three or more 1's and the monitor sensor has detected them correctly, the target is properly localized. This situation can occur only when the target is located in subareas of the first square covered by three or more sensors. Therefore, the probability that the target can be localized in the first round is $(1 - P_e)^4 (P_1(3) + P_1(4))$. If only one sensor returns 1, according to our wake-up strategy, five additional sensors are activated. Now the decision of the monitor sensor is based on information of $4 + 5 = 9$ sensors, so the probability of correct localization in this case is given by $(1 - P_e)^9 P_1(1)$. If two sensors on the same edge of the square return 1, two more sensors are activated. The probability of correct localization is $(1 - P_e)^6 P_1(2)$. If no sensor returns 1 in the first round, twelve more sensors are activated. In this case, the target may be located in subareas such as C and H or outside of the area covered by the second round as shown in Fig. 1. The probability of correct localization in this case is $(1 - P_e)^{16} (P_s(2) - P_1(1) - P_1(2) - P_1(3) - P_1(4))$. Therefore, if up to two rounds of detection are allowed, the localization error probability is given by

$$\begin{aligned} P_2 =& 1 - (1 - P_e)^4 (P_1(3) + P_1(4)) - (1 - P_e)^6 P_1(2) \\ & - (1 - P_e)^{16} (P_s(2) - P_1(1) - P_1(2) - P_1(3) - P_1(4)) \\ & - (1 - P_e)^9 P_1(1). \end{aligned} \tag{4}$$

It can be shown that if up to n rounds of wake-up are allowed, the error probability is given by (for $n \geq 3$)

$$\begin{aligned} P_n =& 1 - (1 - P_e)^4 (P_1(3) + P_1(4)) - (1 - P_e)^6 P_1(2) \\ & - (1 - P_e)^9 P_1(1) - (1 - P_e)^{16} \Big[P_s(2) - P_1(1) \\ & - P_1(2) - P_1(3) - P_1(4) \Big] - \sum_{i=3}^{n} \Big\{ (1 - P_e)^{(4(i-1)^2+2)} \\ & \cdot P_{i-1}(2) + (1 - P_e)^{(4(i-1)^2+3)} P_{i-1}(1) + (1 - P_e)^{4i^2} \\ & \cdot (P_s(i) - \sum_{h=1}^{4} P_{i-1}(h)) \Big\}. \end{aligned} \tag{5}$$

4. SIMULATION RESULTS

We present the Monte Carlo simulation results to validate the performance analysis on localization error probability of the proposed

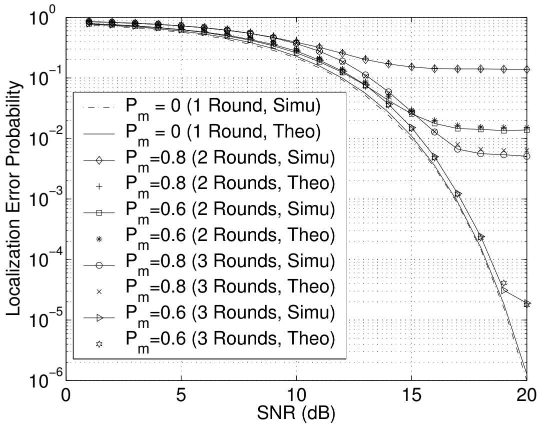

Fig. 2. Comparison of localization error probability when a maximum of two and three rounds of sensor wake-up is allowed. "Theo" stands for theoretic analysis results, and "Simu" stands for simulated results.

scheme. Suppose that each sensor's detection range is of unit length. A square sensor field of side length 200 units is covered by sensors deployed with a square topology. The received signal-to-noise ratio (SNR) at the cluster head is defined as ρ/σ^2. There is one target to be localized in each realization. For each SNR value, we generate 5×10^6 realizations of random target locations in the sensor filed. We assume that the actual location of the target follows the 2-dimensional standard normal distribution with respect to the predicted target location (x_o, y_o).

In Fig. 2, we plot the localization error probability of the proposed scheme under different wake-up rounds and prediction errors, where P_m denotes the monitor sensor's prediction error probability. When $P_m = 0$, four sensors are waken up and only one round of detection is necessary. When $P_m > 0$, up to two or three rounds of detection are allowed. It can be seen from Fig. 2 that the simulation results match well with the theoretic analysis results in all cases. An error floor is observed for the cases when the prediction error is large, which is due to the fact that a certain percentage of the targets are out of the area covered by all wake-up sensors in the maximum allowable rounds.

When the prediction error is large, we may increase the allowable wake-up rounds to reduce the probability of localization error. If we compare the localization error probabilities when a maximum of two and three rounds of detection are allowed, it is clear that an additional round of wake-up sensors can significantly reduce the localization error probability (e.g., by more than one order of magnitude with 80% prediction error, and more than two orders of magnitude with 60% prediction error).

For the purpose of comparison, our tracking simulation setup is similar to that of [8]. Sensors are deployed in a $600\text{m} \times 600\text{m}$ square region. Every sensor's normal communication range is 35m and the sensors are deployed according to the square topology. We simulate the miss probability under different sensor radius to target speed ratios, as we find that this ratio affects the performance most. For each sensor radius to target speed ratio, we perform our tracking algorithm and the Distributed Predictive Tracking (DPT) algorithm of [8] at 1000 tracking points. DPT uses triangulation for localization. Fig. 3 shows the simulation result. From Fig. 3, we can see the miss probability decreases with the increasing of sensor radius to target speed ratio. When the sensor radius to target speed ratio is smaller than 27, our method has lower miss probability. When the ratio is bigger than 27, DPT's miss probability is marginally smaller than ours. Moreover, a ratio greater than 27 corresponds to the deployment such that sensors are far away from each other or the target's speed is very low.

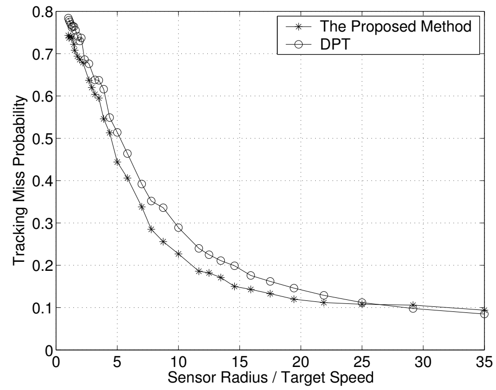

Fig. 3. Comparison of tracking miss probabilities of our proposed method and DPT under different sensor radius to target speed ratios.

5. CONCLUSIONS

We have proposed a low-complexity target localization and tracking method by exploiting spatial topology of a binary sensor network in noisy environments. An efficient wake-up strategy is used to activate a particular group of sensors for cooperative localization and tracking. We have studied the localization error probability and tracking miss probability with possible prediction errors. Monte Carlo simulation results validate our theoretic analysis. It is shown that in the presence of prediction errors, additional round of sensor wake-up can significantly reduce the localization error probability. The proposed tracking strategy also offers competitive performance in terms of miss probability when compared to the existing approaches that require much higher complexity and more complicated sensors.

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