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Research Article

Fault-Tolerant Target Localization in Sensor Networks

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Fault-tolerant target detection and localization is a challenging task in collaborative sensor networks. This paper introduces our exploratory work toward identifying the targets in sensor networks with faulty sensors. We explore both spatial and temporal dimensions for data aggregation to decrease the false alarm rate and improve the target position accuracy. To filter out extreme measurements, the median of all readings in a close neighborhood of a sensor is used to approximate its local observation to the targets. The sensor whose observation is a local maxima computes a position estimate at each epoch. Results from multiple epoches are combined together to further decrease the false alarm rate and improve the target localization accuracy. Our algorithms have low computation and communication overheads. Simulation study demonstrates the validity and efficiency of our design.

1. INTRODUCTION

The development of wireless sensor networks provides many exciting applications, including roadway safety warning [1], habitat monitoring [2], smart classroom [3], and so forth. Such networks rely on the collaboration of thousands of resource-constrained error-prone sensors for monitoring and control. One important task of a typical sensor network is to detect and report the locations of targets (e.g., tanks, land mines, etc.) with the presence of *faulty* sensor measurements. In our study, we seek fault-tolerant algorithms to identify the region containing targets and the position of each target.

Filtering faulty sensor measurements and locating targets are not trivial. Due to the stingy energy budget within each sensor, we have to seek localized and computationally efficient algorithms such that a sensor can determine whether a target presents and whether it needs to report the target information to the base station (to determine whether and where a target presents). The existence of faulty sensors exacerbates the “hardness” of the problem. False alarms waste network resource. They may mislead users to make wrong decisions. Therefore, target identification and localization algorithms must be fault-tolerant, must have a low false alarm rate, and must be robust.

In this paper, we propose fault-tolerant algorithms to detect the region containing targets and to identify possible targets within the target region. Here only the same kind of targets are considered. To avoid the disturbance of extreme measurements at faulty sensors, each sensor collects neighboring readings and computes the *median*, representing its local observation on the targets. Median is proved to be an effective robust nonparametric operator that requires no strong mathematical assumptions [4]. A median exceeding some threshold indicates the occurrence of a possible target. Whether a real target exists or not must be jointly determined by neighboring sensors at the same time. To localize a target within the target region, a sensor whose observation is a local maxima computes the geometric center of neighboring sensors with similar observations. We also explore time dimension to reduce the false alarm rate. Results from multiple epoches are combined to refine the target position estimates. Our algorithms have low computation overhead because only simple numerical operations (maximum, median, and mean) are involved at each sensor. The protocol has a low communication overhead too, since only sensors in charge of the location estimation report to the base station. Simulation study indicates that in most cases our algorithms can identify all the targets and only one report for one target is sent to the base station per epoch when up to 20% of the sensors are faulty, and when the network is moderately dense.

This paper is organized as follows. Related work and network model are sketched in Sections 2 and 3, respectively. Fault-tolerant target identification and localization algorithms are proposed in Section 4. Simulation results are reported in Section 5. We conclude our paper in Section 6.

2. RELATED WORK

Target detection and localization [5–8], target classification [9–11] and target tracking [12–15] have attracted many research activities in sensor networks. In this section, we focus on the related works in target localization and target identification.

Clouqueur et al. [5] seek algorithms to collaboratively detect a target region. Each sensor obtains the target energy (or local decision) from other sensors, drops extreme values if faulty sensors exist, computes the average, and then compares it with a predetermined threshold for final decisions. For these algorithms, the challenge is the determination of the number of extreme values. This is unavoidable when using "mean" for data aggregation. As a comparison, we explore the utilization of "median" to effectively filter out extreme values for target region detection.

Zou and Chakrabarty [6–8] propose an energy-aware target detection and localization strategy for cluster-based wireless networks. The cluster head collects event notification from sensors within the cluster and then executes a probabilistic localization algorithm to determine candidate nodes to be queried for target information. This algorithm is designed only for cluster-based sensor networks. The cluster head must keep a pregenerated detection probability table constructed from sensor locations. Each sensor reports the detection of an object to the cluster head based on its own measurements. This work does not consider fault-tolerance at all, thus the decision by cluster head may be based on incorrect information.

Fang et al. [9, 10] provide the algorithms for target counting and enumeration in sensor networks. A spanning tree is constructed to locate a possible target. The root of each tree has the maximal sensed signal power among all the nodes in the tree cluster. The tree structures which define the target region are formed step by step. Each node in the tree must relay its root information. Fault-tolerance is not considered in their protocols, therefore a faulty sensor may be elected as a leader and reports wrong target information.

Li et al. [16] estimate target position by solving a nonlinear least squares problem. Target localization based on the time-of-arrival (TOA) [17] or the direction-of-arrival (DOA) [18] of acoustical/seismic signals has also been explored. Locating victims through emergency sensor networks in a centralized fashion has been studied in [19]. In [14, 15], a spanning tree rooted at the sensor node close to a target is used for target tracking, with target position estimated by the location of the root sensor. We propose much simpler algorithms for target identification and localization in this paper.

3. NETWORK MODEL

In this paper, we assume that N sensors are deployed uniformly in a $b \times b$ square field located in the two dimensional Euclidean plane $\mathcal{R}^2$, with a base station residing in the boundary. Sensors are powered by batteries and have a fixed radio range. The base station has a strong computational capability with an unlimited power supply. Power conservation and fault-tolerance are the major goals when designing algorithms for target localization.

Let $R(s_i)$ or R_i denote the reading of sensor s_i. Instead of a 0-1 binary variable, $R(s_i)$ is assumed to represent signal strength measurements on factors such as vibration, light, sound, and so on. A *target region*, denoted by $\mathcal{TR}$, is a subset of $\mathcal{R}^2$ such that it contains all the sensors that can detect the presence of the targets. A sensor's reading is *faulty* if it reports inconsistent and arbitrary values to the neighboring sensors [5]. Sensors with faulty readings are called *faulty sensors*. In this paper, we will use s_i to refer to either the ith sensor or the location of the ith sensor.

We assume that each sensor can compute its physical position through either GPS or some GPS-less techniques [20–22]. In this paper, we focus on the fault-tolerant target identification and localization, and thus the delivery of the target location will not be considered. We assume there exists a robust routing protocol in charge of the transmission of the target information to the base station.

All targets emit some kinds of signals (vibration, acoustic, light, etc.) when present. These signals will be propagated to the surrounding area with a decayed intensity. The following model is used to quantify the signal strength at location s_i for a target at location L [5]:

$$S(s_i) = \begin{cases} P_0, & \text{if } d < d_0, \\ \dfrac{P_0}{(d/d_0)^k}, & \text{otherwise,} \end{cases} \tag{1}$$

where P_0 is the signal intensity at L, $d = \|L - s_i\|$ is the Euclidean distance between the target and the sensor at s_i, d_0 is a constant that accounts for the physical size of the target, and $k \in [2.0, 5.0]$ [23] is a decay factor determined by the environment. The signal strength measured by a sensor at s_i is then

$$R(s_i) = S(s_i) + N(s_i), \tag{2}$$

where $N(s_i)$ represents the noise level at s_i. We assume $N(s_i)$ follows $\mathcal{N}(\mu, \sigma^2)$, a Gaussian distribution with mean μ and variance σ^2. For Gaussian white noise, $\mu = 0$. When more than one target present in the network, signals of multiple targets are summed at each sensor.

In this paper, we assume sensors can properly execute our algorithms even though their readings are faulty. In other words, we assume there is no fault in processing and transmitting/receiving neighboring measurements.

4. FAULT-TOLERANT TARGET DETECTION AND LOCALIZATION

In this section, we first describe an algorithm for target region detection. Then we present a procedure to estimate the locations of the targets from the sensors within the target region. We also propose an algorithm for data aggregation along temporal dimension to decrease the false alarm rate and improve the target position accuracy.

For any given sensor s_i,
(1) Obtain signal measurements $R_1^{(i)}, R_2^{(i)}, \dots, R_n^{(i)}$ from all sensors in $\mathcal{N}(s_i)$.
(2) Compute med_i of the set $\{R_1^{(i)}, R_2^{(i)}, \dots, R_n^{(i)}\}$ as the estimated reading $\widetilde{R}_i$ at location s_i.
(3) Determine *event sensors*. A sensor s_i is an event sensor if the estimated value $\widetilde{R}_i$ is larger than a predefined threshold θ_1.

Algorithm 1: For target region detection.

4.1. Target region detection

Our target region detection algorithm aims at finding all sensors that can detect the presence of the targets. Nodes closer to the targets usually have higher measurements. Faulty sensors may report arbitrary values.

Let $\mathcal{N}(s_i)$ denote a bounded closed set of $\mathcal{R}^2$ that contains a sensor s_i and additional $n-1$ sensors. The set $\mathcal{N}(s_i)$ represents a closed neighborhood of the sensor s_i. An example of $\mathcal{N}(s_i)$ is the closed disk centered at s_i with its radius equal to the radio range. Let $R_1^{(i)}, R_2^{(i)}, \dots, R_n^{(i)}$ denote the signal strength measured by the nodes in $\mathcal{N}(s_i)$. A possible estimate of signal strength at location s_i is

$$\widetilde{R}_i = \text{med}_i, \tag{3}$$

where med_i denotes the median of the set $\{R_1^{(i)}, R_2^{(i)}, \dots, R_n^{(i)}\}$. In other words, one could estimate R_i by the "center" of $\{R_1^{(i)}, R_2^{(i)}, \dots, R_n^{(i)}\}$.

Note that med_i in (3) should not be replaced by the mean $(R_1^{(i)} + R_2^{(i)} + \cdots + R_n^{(i)})/n$ of the set $\{R_1^{(i)}, R_2^{(i)}, \dots, R_n^{(i)}\}$. This is because the sample mean cannot represent well the "center" of a sample when some values of the sample are extreme. Nevertheless, median is widely used to estimate the "center" of samples with outliers. Its conditional correctness is proved in [4]. Faulty sensors may have extreme values, representing outliers in the sample set. Faulty readings have little influence on med_i as long as most sensors behave properly.

The procedure of target region detection is described as follows.

Intuitively, an event sensor is a sensor that can detect the presence of the targets. Compared to the value fusion method for target region detection in [5], which computes the mean after dropping η highest and η lowest values, Algorithm 1 employs the robust operator median so that it effectively eliminates the effects of faulty sensors without exploiting any complicated algorithm for the estimation of η.

4.2. Target Localization

Algorithm 1 is used to detect the presence of targets. It does not tell how many targets exist and where they are. Shifting the task of target localization to the base station by sending the measurements of all sensors in the target region is too expensive in terms of energy consumption. Therefore, we consider to delegate one sensor to communicate with the base station for each target and compute the position of the target locally. The following algorithm is employed to locate the targets in the target region.

(1) Obtain estimated signal strength $\widetilde{R}_1^{(i)}, \widetilde{R}_2^{(i)}, \dots, \widetilde{R}_m^{(i)}$, from all m event sensors in $\mathcal{N}(s_i)$ if s_i is an event sensor.
(2) Determine *root sensors*. An event sensor s_i is a *root sensor* if

$$\begin{gathered} m \geq n/2, \\ \widetilde{R}_i \geq \max\{\widetilde{R}_1^{(i)}, \widetilde{R}_2^{(i)}, \cdots, \widetilde{R}_m^{(i)}\}. \end{gathered} \tag{4}$$

(3) For each root sensor s_i, estimate the location of a possible target by the geometric center of a subset of event sensors in $\mathcal{N}(s_i)$. Let $\{s'_{i1}, s'_{i2}, \dots, s'_{iq}\}$ be the subset of event sensors in $\mathcal{N}(s_i)$ such that $\widetilde{R}_j^{(i)'} \geq \widetilde{R}_i - \theta_2$ for $1 \leq j \leq q$, where $\widetilde{R}_j^{(i)'}$ is the estimated signal strength from s'_{ij} and θ_2 is a threshold that mainly characterizes the target size. Denote the x and y coordinates of s'_{ij} by $x(s'_{ij})$ and $y(s'_{ij})$, respectively, and set

$$\begin{aligned} \widetilde{L}_i(x) &= [x(s'_{i1}) + x(s'_{i2}) + \cdots + x(s'_{iq})]/q, \\ \widetilde{L}_i(y) &= [y(s'_{i1}) + y(s'_{i2}) + \cdots + y(s'_{iq})]/q \end{aligned} \tag{5}$$

$\widetilde{L}_i(x)$ and $\widetilde{L}_i(y)$ are the estimated coordinates for a possible target close to s_i.

Algorithm 2: For target localization.

Note that in step (1) of Algorithm 2, m can be smaller than n. A sensor is selected as a root sensor if its estimated signal strength is a *maxima* among event sensors in $\mathcal{N}(s_i)$. Nodes closer to the targets usually have larger measurements and thus have a higher probability to become root sensors. Furthermore, the number of root sensors is constrained by (4). A root sensor uses (5) to compute the location of a target based on the locations of some neighboring nodes. As a comparison, most related works in literature [9, 10, 14, 15] utilize the position of the root sensor as an approximation of the target position.

4.3. Temporal dimension consideration

We observe that the two algorithms proposed in Sections 4.1 and 4.2 explore only spatial information for data aggregation. In reality, sensors sample their observations periodically. By investigating along the temporal dimension, performance for target detection and localization can be improved, as verified by simulation study in Section 5. In this section, we discuss how the base station can identify false alarms and improve the target position accuracy by using location estimates obtained at T epoches from root sensors. For better elaboration, we call the location estimates by root sensors the *raw data*.

Assume both Algorithms 1 and 2 are executed once per epoch. The base station receives a sequence of raw data, denoted by $\{\widetilde{L}^{(1)}, \widetilde{L}^{(2)}, \dots \widetilde{L}^{(t)}, \dots\}$, from root sensors, where

(1) For each epoch, apply Algorithms 1 and 2. All root sensors report their target position estimates to the base station.
(2) After collecting raw data for T epoches, the base station apply K-means clustering algorithm to identify groups for targets. For each group $\mathcal{G}_i$ with cardinality $|\mathcal{G}_i|$,
- If $|\mathcal{G}_i| < T/2$, then report a false alarm.
- Otherwise, report a target and obtain the estimate of the position of the target, denoted by $\widetilde{L}$, using the geometric center of all raw data within $\mathcal{G}_i$.

Algorithm 3: For target identification.

each $\widetilde{L}$ is two dimensional. The base station then applies an appropriate clustering algorithm to group the received location estimates for final target position computation. Each group corresponds to one target.

Note that the base station may observe a group computed by a group of neighboring faulty sensors. Such a group represents a false alarm and may be signaled in the following way. If the size of a group is less than half of T, with a high probability this group is a false alarm based on majority vote.

Based on the previous analysis, we propose the following target identification algorithm (Algorithm 3) exploring both temporal and spatial information.

Note that the communication overhead of our algorithms is low, even though location estimates are sent to the base station. As indicated by the simulation study in Section 5, in most cases only one message per target will be sent to the base station per epoch in moderately dense sensor networks.

5. SIMULATION

5.1. Performance metrics

Evaluation of the target detection and localization algorithms includes two tasks: evaluating the degree of fault-tolerance and evaluating the accuracy of the estimated positions of targets. The degree of fault-tolerance has been considered in our prior work [24].

To evaluate the accuracy of the estimated positions of the targets, we first define *position error* $e(\widetilde{L}_{\alpha^i})$ for the target at location L_{α^i} to be the Euclidean distance between $\widetilde{L}_{\alpha^i}$ and the real target location L_{α^i}, that is,

$$e(\widetilde{L}_{\alpha^i}) = ||\widetilde{L}_{\alpha^i} - L_{\alpha^i}||. \tag{6}$$

We use the average of the position errors for all targets to evaluate the accuracy of our algorithms,

$$e(\mathcal{L}) = \frac{[e(\widetilde{L}_{\alpha^1}) + e(\widetilde{L}_{\alpha^2}) + \cdots + e(\widetilde{L}_{\alpha^p})]}{p}, \tag{7}$$

where p is the total number of the targets in the network. Obviously, smaller $e(\mathcal{L})$ indicates higher position accuracy.

5.2. Simulation setup

MATLAB is used to perform all simulations. The sensor nodes are deployed in a 32×32 square region, which resides in the first quadrant such that the lower-left corner and the origin are colocated. Sensor coordinates are defined accordingly. We fix the transmission range of each sensor to be 3.1, and vary the number of sensor nodes to get different network densities. Network density is defined as the average number of one-hop neighbors for each sensor. Sensors are randomly deployed according to the uniform distribution. We choose $\mathcal{N}(s_i)$ to be the set containing all one-hop neighbors of s_i.

In the simulation for multiple targets detection and localization, three targets are located in the network region, where the coordinates of each target position are randomly sampled from $[8, 10]$. The distance between each target pair is not less than $4d_0 = 8$. We also evaluate the performance of the algorithms when one target is deployed. In this scenario, the target coordinates are chosen in the similar way.

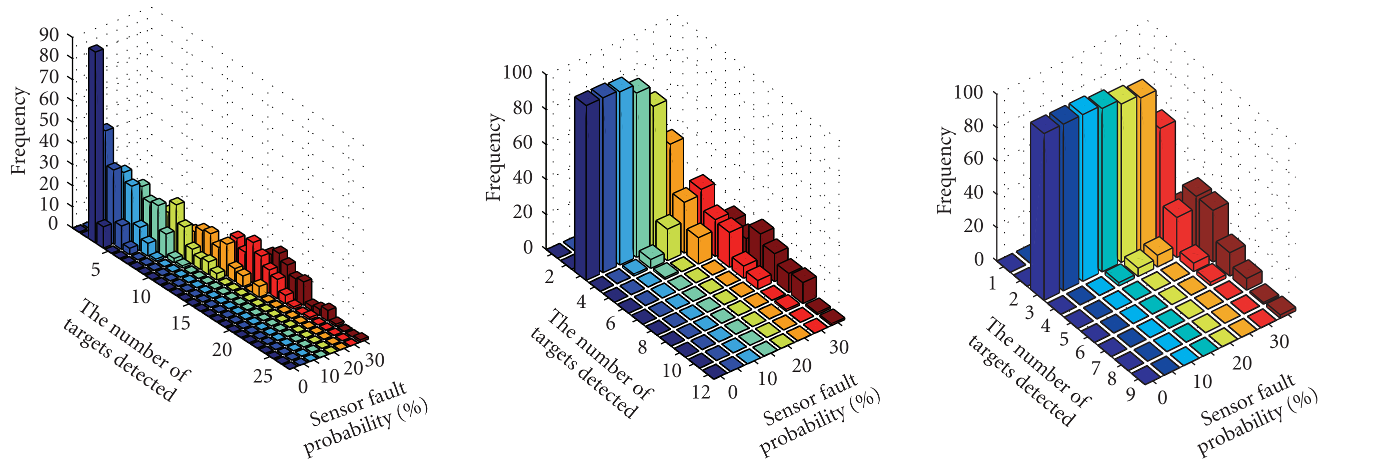
In this paper, we consider identification and localization problem for targets of the same kind, thus we assume all the targets to have the same signal intensity. The signal intensity P_0 from each target is set to 30. Signal model follows (1) with $d_0 = 2$ and $k = 2$. (We have simulated the cases of $k = 3, 4, 5$, and obtained similar results. We only report the result for $k = 2$ in this paper.) For sensor s_i, its noise level $N(s_i)$ is drawn from $N(\mu, \sigma^2)$ with $\mu = 0$ and $\sigma = 1$, characterizing both environment disturbance and sensor measurement error. The readings of a faulty sensor are randomly chosen from $[0, 60]$.

The base station classifies the position estimates from different epoches into different groups based on the distances of pairwise estimates and d_0. A group indicates the existence of a target only if its cardinality is not less than half of the number of epoches under consideration.

Note that two thresholds (θ_1 in Algorithm 1 and θ_2 in Algorithm 2) are needed to make decisions. Throughout the simulation, we choose $\theta_1 = 3\sigma = 3$, showing that a normal sensor has a low probability $(1 - 99.7\%)$ to report a noise value that is larger than 3σ. To estimate the locations of the detected targets, we set $\theta_2 = 4$. This means that sensors in close proximity of a root sensor will contribute to the target position estimation if the deviation of their (estimated) signal strengths from that of the root sensor is at most 4.

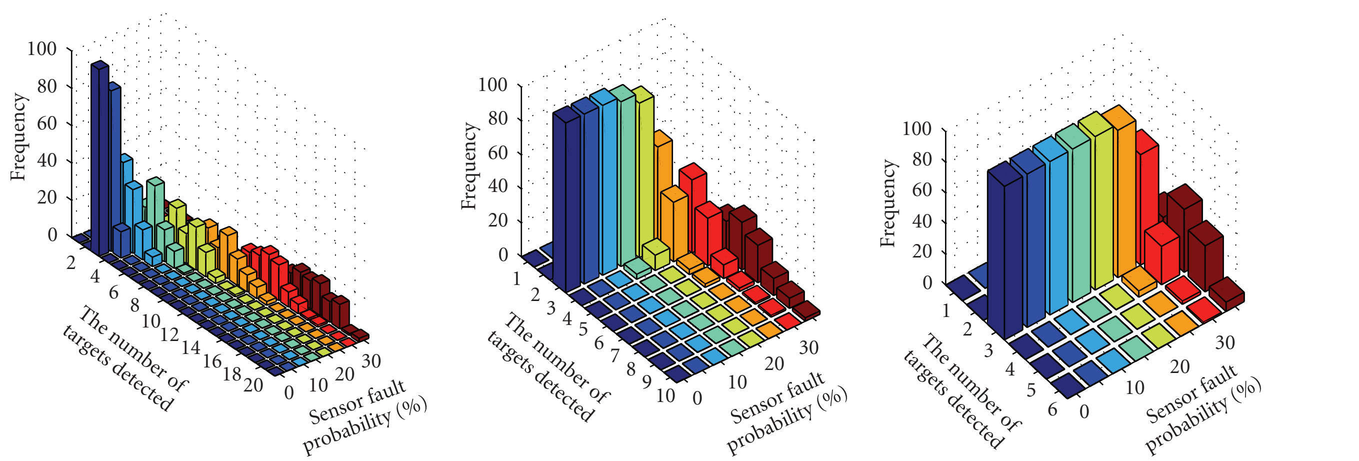
5.3. Simulation results

In this section, we report our simulation results, with each representing an averaged summary over 100 runs. In our prior work [24], we have evaluated the degree of fault-tolerance of our algorithms through two parameters: the correction accuracy and the false correction rate. We also have studied the accuracy for target localization when only one target presents in the network. We note that for a low network density and a high sensor fault probability, the base



(a) Density = 10 (b) Density = 30 (c) Density = 50

Figure 1: The number of targets detected when three targets are deployed. Here, $T = 1$ and density = 10, 30, 50, respectively.



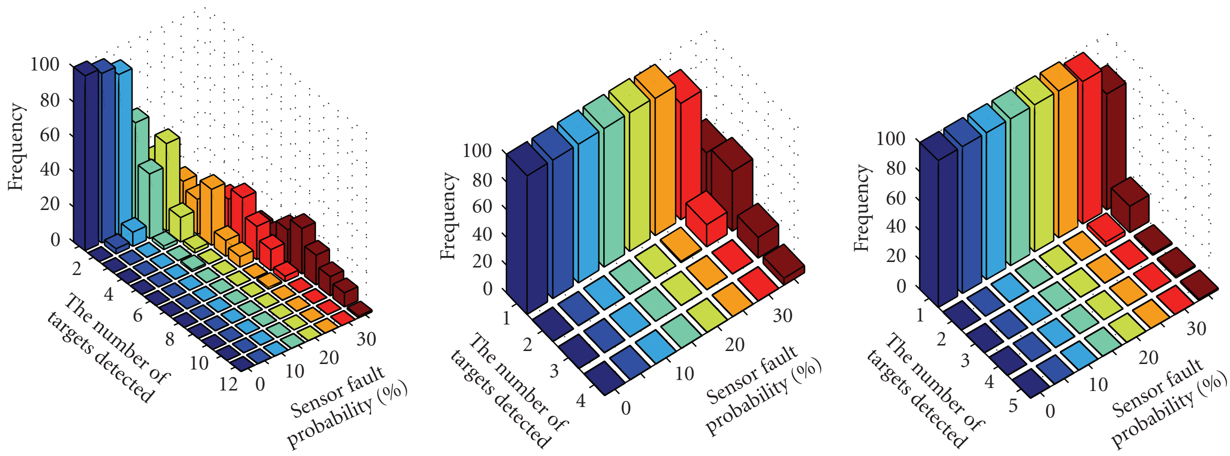
(a) Density = 10 (b) Density = 30 (c) Density = 50

Figure 2: The number of targets detected when three targets are deployed. Here, $T = 9$ and density = 10, 30, 50, respectively.

station fails to locate the real target with a reasonably high false alarm rate. Furthermore, the simulation results in [24] also indicate that it is sufficient to overcome the disturbance of the Byzantine behavior of faulty sensors using the readings from 9 epoches. Thus in this paper we choose to use $p \leq 0.35$ and $T = 1$ or 9 for multiple target detection and localization, where p is the sensor fault probability.

We first study the number of targets detected when three targets present in the network. The targets are apart enough so that different targets can be identified. Figures 1 and 2 illustrate the number of targets detected by the base station when position estimates from 1 epoch and from 9 epoches are exploited, respectively.

First, we observe that in moderately and high dense networks, the probability of reporting the existence of three targets is high. The false alarm rate is less than 0.1 for $p \leq 0.20$ and density = 30, 50 when aggregating over 9 epoches, as shown in Figure 2. By comparing Figure 1 with Figure 2, we observe that the number of reported targets contributing to the false alarm rate can be reduced by increasing T. We also notice that the average numbers of position estimates sent to the base station at each epoch are 3.18 and 3.05 for $p = 0.20$ and density = 30, 50, respectively (as shown in Figures 1(b) and 1(c)). This indicates that in many cases, only three root sensors need to send their target location estimation to the base station at each epoch. Therefore, the communication overhead of our algorithms is low. In Figure 1(a), we observe that false alarm exists under density = 10 and $T = 1$ when faulty sensors do not exist. It is possible for some sensors to be a local maxima due to the accumulation of the signal strength from all targets. Therefore, median is not robust enough under low density.



(a) Density = 10 (b) Density = 30 (c) Density = 50

Figure 3: The number of targets detected when one target is deployed. Here, $T = 9$ and density $= 10, 30, 50$, respectively.

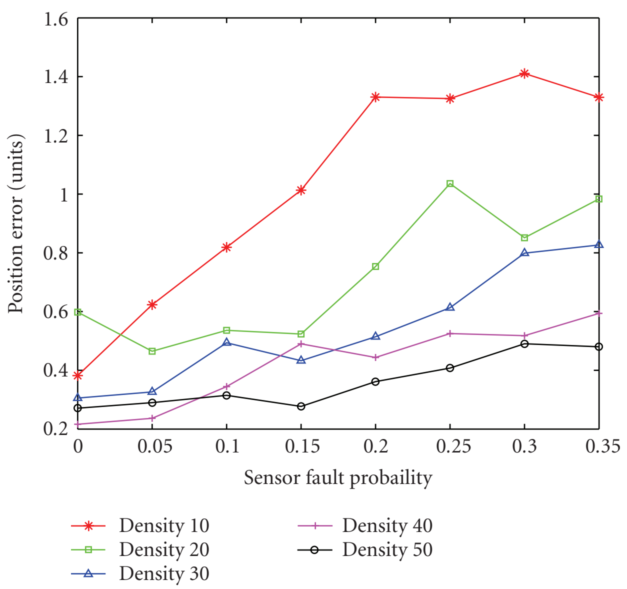


Figure 4: Position error versus p with different network densities when three targets are deployed. In this scenario, $T = 1$.

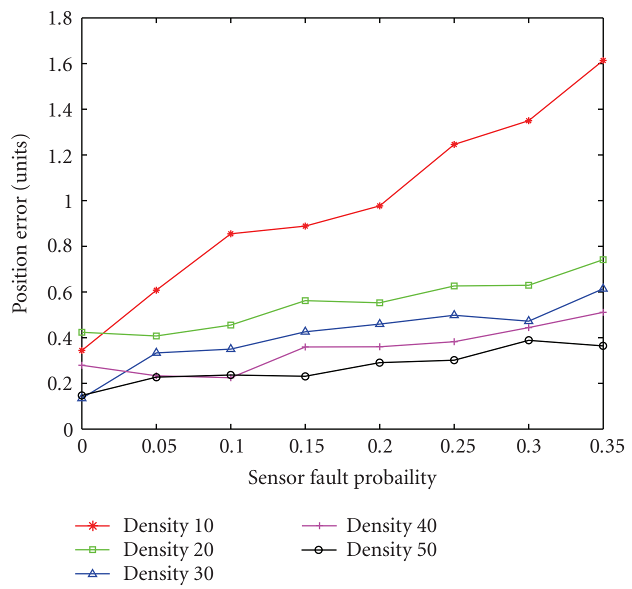
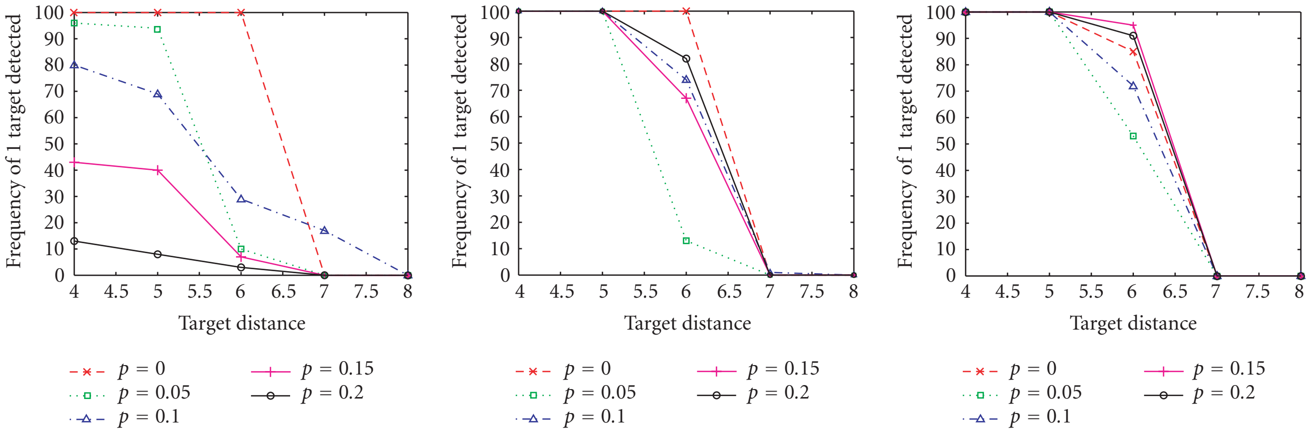


Figure 5: Position error versus p with different network densities when three targets are deployed. In this scenario, $T = 9$.

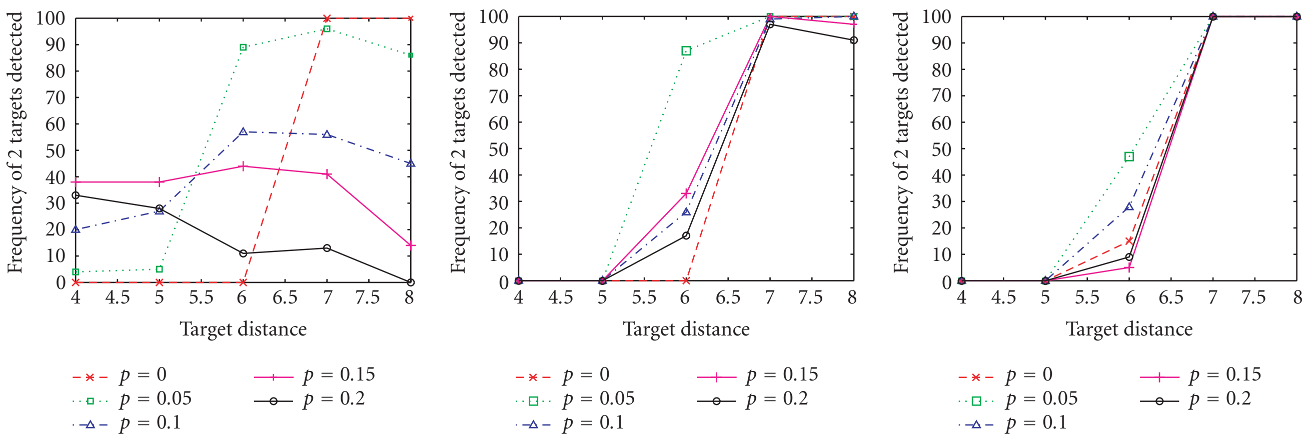
For comparison, we study the performance in the scenario when only one target exists. Similarly, the number of reported target leading to the false alarm rate can be reduced by temporal aggregation. Here, we only report the number of targets detected by the base station for $T = 9$. As shown in Figures 3(b) and 3(c), the false alarm rate equals to 0 for $p \leq 0.20$ and density $= 30, 50$ by aggregating over 9 epoches. Our algorithms have better performance for one target identification since there is no interference of signal strengths from multiple targets.

Figures 4 and 5 illustrate the position error in units versus p for multiple target localization under different network densities. Both figures demonstrate that our algorithms obtain a high accuracy for target localization. As shown in Figure 5, position errors are less than 0.5 unit when density $\geq$ 30 and $p \leq 0.25$. By comparing Figures 4 and 5, we observe that position errors are decreased when position estimates from multiple epoches are exploited. Note that position errors generally increase with higher p when the network density is fixed. We also note that a higher density could decrease position errors. This is reasonable since in higher density networks, more sensors are involved in the computation, which brings in more information, and thus results in more accurate results. For the case when only one target presents, the position errors show the similar trends when position estimates from 1 epoch and from 9 epoches



(a) Density = 10 (b) Density = 30 (c) Density = 50

FIGURE 6: Frequency of one target detected versus target distance when two targets are deployed, $T = 9$, and density $= 10, 30, 50$, respectively.



(a) Density = 10 (b) Density = 30 (c) Density = 50

FIGURE 7: Frequency of two targets detected versus target distance when two targets are deployed, $T = 9$, and density $= 10, 30, 50$, respectively.

are exploited. The results are not shown here for space constraint.

5.4. Discussion

The simulation results reported in the previous section reveal the high performance of our algorithms for target detection and localization in moderate and high density networks when $p \leq 0.20$. The false alarm rate is decreased and the target position accuracy is increased by exploring both temporal and spatial aggregation.

We notice that two targets may be identified as a single one when their locations are very close. It is necessary to study the sensitivity of our algorithms for targets that are close to each other. Thus, we evaluate our algorithms for the scenarios when two targets are deployed at different positions.

Figures 6 and 7 illustrate the frequency of one target being detected and two targets being detected, versus the variable distance between the two targets under different sensor fault probabilities for density $= 10, 30, 50$, respectively. We observe that the frequency of one target detected normally decreases and the frequency of two targets detected increases when their distance gets larger. Two targets are distinguishable when their distance is equal or larger than 8. Note that in our simulation we consider targets with size $d_0 = 2$ and the decay factor $k = 2$. These two parameters are key factors to the sensitivity of our algorithms. Under these settings, for moderately or highly dense networks, the probability that two targets are ambiguous is high when their distance is less than 6. It is also interesting to notice that the two targets are more easily to be distinguished with higher p when density $= 10$, due to the relatively high disturbance of fault sensors.

Our algorithms may fail when the locations of the two targets are very close. One and only one local maxima may be formed at a sensor that has roughly the same distance to both targets, due to the accumulation of the target signal strength.

In this case, the energy level at the root sensor may be explored. We target this as our future research.

6. CONCLUSION

In this paper, we present fault-tolerant algorithms for target identification and localization in sensor networks. In this study, data aggregation is conducted along both temporal and spatial dimensions for decreasing the false alarm rate and increasing the target position accuracy. Simulation results verify the efficiency and effectiveness of our design.

This paper is exploratory in that we use “median” instead of “mean” to locally aggregate neighboring readings to filter out faulty measurements. We report the simulation results when the target region contains multiple targets. We believe that this idea can be extended to target classification and target tracking, and decide to explore along this direction in the future.

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