On Distributed Fault-Tolerant Detection in Wireless Sensor Networks

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Abstract—In this paper, we consider two important problems for distributed fault-tolerant detection in wireless sensor networks: 1) how to address both the noise-related measurement error and sensor fault simultaneously in fault-tolerant detection and 2) how to choose a proper neighborhood size n for a sensor node in fault correction such that the energy could be conserved. We propose a fault-tolerant detection scheme that explicitly introduces the sensor fault probability into the optimal event detection process. We mathematically show that the optimal detection error decreases exponentially with the increase of the neighborhood size. Experiments with both Bayesian and Neyman-Pearson approaches in simulated sensor networks demonstrate that the proposed algorithm is able to achieve better detection and better balance between detection accuracy and energy usage. Our work makes it possible to perform energy-efficient fault-tolerant detection in a wireless sensor network.

Index Terms—Distributed event detection, fault tolerance, sensor fusion, energy-efficiency, wireless sensor networks.

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1 INTRODUCTION

Recent advances in wireless communications and electronics have enabled the development of low-cost wireless sensor networks. A wireless sensor network usually consists of a large number of small sensor nodes, which are equipped with one or more sensors, some processing circuits, and a wireless transceiver. The unique features of a sensor network, for example, random deployment in inaccessible terrains and cooperative effort, offer unprecedented opportunities for a broad spectrum of civilian and military applications, such as industrial automation, military tactical surveillance, national security, and emergency health care [1], [2], [3].

In particular, one of the important sensor network applications is monitoring inaccessible environments. Sensor networks are asked to determine event regions or boundaries in the environment with a distinguishable characteristic [4], [5], [6]. For example, sensor networks can be used to detect foreign chemical agents in the air and the water. The event could also be an unusually high chemical concentration that generates many safety and health concerns for the public [3].

There are two fundamental challenges in the event detection problem for a sensor network:

- The detection accuracy is limited by the amount of noise associated with the measurement and the reliability of sensor nodes. The sensor nodes are usually low-end inexpensive devices and sometimes exhibit unreliable behavior. For example, a faulty sensor node may issue an alarm even though it is NOT in an event region and vice versa, which adds an additional layer of complexity for the event detection problem. To achieve optimal overall detection accuracy, it is essential to consider both factors during detection and to limit the effects of inaccurate measurement or faulty behavior of individual components to a minimum.
- The source of energy for a sensor node is most often an attached battery cell. Centralized event detection algorithms, which require all sensor nodes to transmit their individual sensor measurements and their geographical locations directly to a central monitoring node, are not suitable for a wireless sensor network due to energy constraints. A localized and distributed detection algorithm is highly preferred for wireless sensor networks.

The basic idea of distributed detection [7] is to have each of the independent sensors make a local decision (typically, a binary one) and then combine these decisions at a fusion sensor to generate a global decision. Optimal distributed designs have been sought under both the Bayesian and the Neyman-Pearson performance criteria [8]. Statistically, the distributed event detection could be modeled as a hypothesis test problem. n sensors observe an unknown hypothesis. The sensor observations are independent and identically distributed, given the unknown hypothesis. Each sensor transmits its decision over a multiple access channel to a fusion sensor. Based on the received sensor decision, the fusion sensor makes the final decision regarding the unknown hypothesis.

In this paper, we propose a novel fault-tolerant energy-efficient event detection paradigm for wireless sensor networks. In many data centric applications of sensor networks, the nearby sensors are likely to have similar measurements. To disambiguate events from both noise-related measurement error and sensor fault, we exploit the

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fact that measurement noise and sensor faults are likely to be stochastically unrelated, while event measurements are likely to be spatially correlated. Our major theoretical contribution is summarized as follows:

- In our theoretical analysis, the sensor fault probability is formally introduced into the optimal event detection process. The optimal detection and sensor fault correction are nicely coupled in the proposed distributed event detection algorithm.
- We mathematically show that the optimal detection error due to both sensor fault and measurement error (for both the Bayesian and the Neyman-Pearson performance criteria) decreases exponentially with the increase of the sensor neighborhood size. A minimum neighborhood size exists for a given upper bound of the detection error.

Based on these theoretical results, we propose a fault-tolerant Bayesian detection scheme that considers both measurement error and sensor fault. The proposed algorithm also selects minimum neighbors for a given detection error bound such that the communication volume is minimized during the fault correction. When the required neighborhood size cannot be obtained for some sensors due to low connectivity in the sensor network, an alternative method is provided. In case the Bayesian detection is not applicable, a Neyman-Pearson detection method is presented and discussed.

The remainder of the paper is organized as follows: In Section 2, we present the Bayesian framework for distributed detection in wireless sensor networks and briefly review some related work in this area. Theoretical analysis of the proposed fault-tolerant detection scheme is presented in Section 3. In Section 4, we mathematically show that the optimal Bayesian detection error decreases exponentially with neighborhood size n and there exists an minimum n (thus, minimum energy consumption) for a given detection error bound. The detail of the proposed energy-efficient fault-tolerant detection algorithm is described in Section 5. An alternative Neyman-Person method is discussed in Section 6. In Section 7, we present our experiments and results. Our conclusions are given in Section 8.

2 STATEMENT OF THE PROBLEM AND RELATED WORK

In this section, we first describe the problem that we want to solve. Then, we briefly review some related works in the problem domain.

2.1 Statement of the Problem

N sensor nodes are deployed over an interested region to perform event detection, i.e., to detect whether an interested event has happened or not. In general, we assume that sensor network covers the entire event region and the sensors are fully connected to each other within their communication radius. We also assume that each node could determine its location through beacon positioning mechanisms [9] or by exploiting the Global Positioning System (GPS). Through a broadcast/acknowledge protocol, each sensor node is also able to locate the neighbors within its communication range.

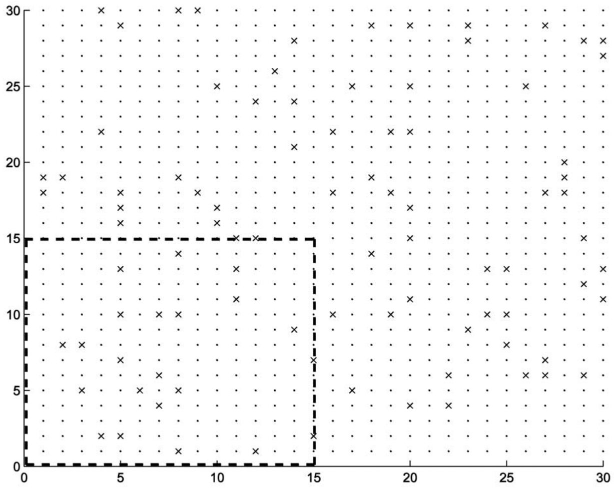

Fig. 1. A sample scenario: 900 sensors are distributed over an interested region with the single event region (enclosed inside the square with the bold dashed line). "·" denotes a healthy sensor, while "×" denotes a faulty sensor.

A sensor node could make its binary decision (for example, "event" or "no-event" for high chemical concentration or normal situation, respectively) independently based on its own measurement from the noisy environment. The network considered is also likely to contain faulty sensor nodes due to harsh environment and manufacturing reasons. Normally, an event, if it happens, should be detected as "event" by sensors at the location. The faulty behavior we consider occurs when the detection decision is converted to "no-event" due to the sensor fault or vice versa. It is obvious that both noise-related measurement error and sensor fault make the sensor decision unreliable, i.e., a sensor may report "event" although it is not in an event region or report "no-event" when it is actually in an event region. Fig. 1 shows a sample scenario of the sensor network we consider. It is clear that each sensor has its own neighbors, which are in the event region or no-event region or both (near to the boundary).

For simplicity of analysis in this paper, we assume the ground truth is the same for all n neighbors of nodes i: If node i is in an event region, so are its neighbors and vice versa. Our assumption is valid for all sensors except the sensors at the event boundary. In sensor networks deployed with high densities, this assumption is reasonable as the number of the boundary nodes are relatively small. How to identify the boundary and process information accordingly are challenging tasks for event detection in wireless sensor networks, which is not included in this paper.

2.2 Related Works

Let us consider a two-layer detection system that consists of n sensors and a fusion sensor (see Fig. 2 for details). When the sensor observations are independent and identically distributed (i.i.d.) given the unknown hypothesis, identical binary quantizers are employed at the sensors to obtain n binary decisions. These preliminary decisions are then combined at the fusion sensor to make a final decision

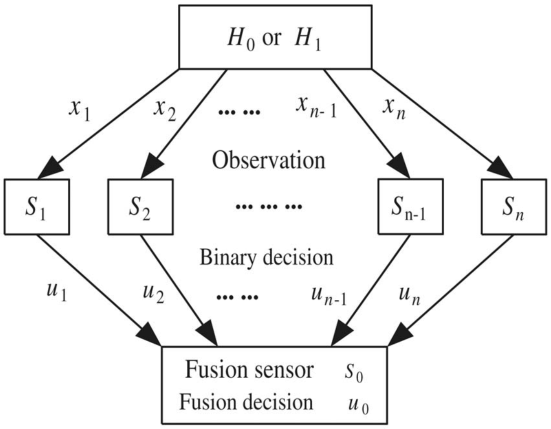

Fig. 2. Distributed event detection.

regarding the unknown hypothesis (H_0 or H_1). Studies show that such a detection process asymptotically achieves the performance of centralized detection [10], [11], [12]. Let x_i denote the observation of the ith sensor, $i = 1, \dots, n$. When H_j is true, x_i follows the probability distribution function $p(x_i|H_j)$, $j = 0, 1$. Let u_i denote the binary decision (0 or 1) of the ith sensor, which is the output of the likelihood ratio threshold test [8],

$$\frac{p(x_i|H_1)}{p(x_i|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda, \tag{1}$$

where λ is the common threshold used for all sensor nodes.

The sensor nodes transmit their decisions to the fusion center. Based on the received sensor decisions, the fusion sensor makes the final decision u_0 and the optimum fusion rule in this case is a k-out-of-n rule [13], [14]. Letting $u_0 = 0$ if the fusion sensor decides H_0 and letting $u_0 = 1$ if the fusion sensor decides H_1, we have

$$u_0 = \begin{cases} 1, & u_1 + \cdots + u_n \geq k \\ 0, & u_1 + \cdots + u_n < k, \end{cases} \tag{2}$$

where k is an integer between 1 and n. In our assumption, all u_i's are spatially correlated and belong to the same neighbors. They have approximately the same measurements from their local environment. It is reasonable to use u_0 for fault-tolerant correction in the following discussion.

For all the sensors, letting P_F denote the identical false alarm probability and P_D the identical detection probability, we have

$$P_F = P(u_i = 1|H_0) \tag{3}$$

and

$$P_D = P(u_i = 1|H_1). \tag{4}$$

The quality of the fusion sensor decision u_0 is measured by the system false alarm probability Q_F and the system detection probability Q_D,

$$Q_F = \sum_{i=k}^{n} \binom{n}{i} P_F^i (1 - P_F)^{n-i}, \tag{5}$$

$$Q_D = \sum_{i=k}^{n} \binom{n}{i} P_D^i (1 - P_D)^{n-i}. \tag{6}$$

Under the Bayesian detection framework, the probability of detection error with n sensor nodes is given by

$$P_e^n = q_0 Q_F + q_1 (1 - Q_D), \tag{7}$$

where q_0 and q_1 denote the prior probabilities of H_0 and H_1, respectively.

Zhang et al. show that, given k, the probability of detection error is a quasiconvex function of λ and has a single minimum that is achieved by the unique optimal λ_{opt} [15]. The overall optimal solution is obtained by optimizing (λ, k) pair via the SECANT algorithm [13].

More recently, Krishnamachari and Iyengar introduced a fault-tolerant event detection method for wireless sensor networks [6]. Based on the observation that the sensor faults are likely to be stochastically uncorrelated, while event measurements are likely to be spatially correlated, they propose letting an individual sensor node communicate with its n neighbors and using their binary decisions to correct its own decision. A majority voting scheme is shown to be the optimal decision scheme for fault correction in their work. The scheme has the advantage of being completely distributed and localized—each node only needs to obtain information from its neighbor sensors in making its decisions. In this paper, we propose improving the effectiveness (in terms of fault tolerance) and the efficiency (in terms of energy consumption) of their approach by considering two additional important questions:

- How do we include the decision error caused by the noisy measurement during fault-tolerant event detection? In Krishnamachari and Iyengar's work [6], they only consider the sensor fault problem. The measurement error is not discussed by assuming that a preset threshold enables each sensor node to make its own binary decision. However, the measurement inaccuracy has direct impact on the effect of fault correction. To achieve better detection accuracy and better fault correction, a decision scheme should take both measurement error and sensor fault into consideration by optimizing the threshold pair (k, λ). Actually our study indicates that both k and λ need to be adjusted with sensor fault rates to achieve the optimal detection. A majority voting scheme does not hold its optimality if H_0 and H_1 are not equally likely. Theorem 2 in [6] is only a special case for $q_0 = q_1$.
- How do we decide a proper neighborhood size n for a sensor node? To our knowledge, this problem has not been studied in the literature. Currently, the neighborhood size n is usually determined by the maximum communication radius of a sensor node. In general, the detection performance should improve with more neighbor sensors since more observations are obtained for the same event. However, increasing the number of active sensors may cause energy consumption and traffic congestion in wireless sensor networks, which ultimately degrades the performance of the detection [16].

The first problem is theoretically analyzed in Section 3. In Section 4, we mathematically show that there exists a minimum n for a given bound of detection error, which in turn allows us to keep the communication volume at its minimum during the fault correction.

3 THEORETICAL ANALYSIS OF FAULT-TOLERANT DETECTION

In this section, we first discuss optimal distributed detection without considering sensor fault. The sensor fault probability is then formally introduced and theoretical analysis is provided.

3.1 Distributed Detection without Sensor Fault

Define two situations in event detection:

$$\begin{array}{ll} H_0: & \text{normal} \\ H_1: & \text{event.} \end{array}$$

The objective of the distributed detection is to choose the optimal thresholds (λ, k) at each sensor, given q_0, q_1, and the neighborhood size n (usually determined by the maximum communication radius of a sensor node). Zhang et al. studied this problem and their work can be summarized as the following theorem without proof (refer to [13] for the detail of the proof).

Theorem 1. *For fixed n and k, the probability of detection error P_e^n is a quasiconvex function of λ and has a single minimum that is achieved by the unique optimal λ_{opt}. λ minimizes P_e^n if it satisfies*

$$ln\frac{q_1}{q_0} + ln\lambda + (k-1)ln\frac{P_D}{P_F} + (n-k)ln\frac{1-P_D}{1-P_F} = 0. \tag{8}$$

The optimal $(\tau(= ln\lambda), k)$ pair could be obtained based on (8) via an optimization algorithm. Each neighborhood sensor then makes its own decision with τ and the fusion sensor makes its final decision based on the k-out-of-n rule.

3.2 Detection with Sensor Fault

Let $P_f(= \beta + \gamma)$ be the probability of the sensor fault. β denotes the probability of type I sensor fault: Originally, an event is not detected and the decision is converted to an event detected due to the sensor fault. γ denotes the probability of type II sensor fault: An event is detected originally and the decision is converted to an event undetected by the sensor fault. Let $\widetilde{P}_F$ and $\widetilde{P}_D$ be false alarm and detection probability, respectively, after the consideration of sensor fault. We have

$$\begin{aligned} \widetilde{P}_F &= P_F + \beta(1-P_F) - \gamma P_F \\ &= P_F(1-P_f) + \beta, \end{aligned} \tag{9}$$

$$\begin{aligned} \widetilde{P}_D &= P_D + \beta(1-P_D) - \gamma P_D \\ &= P_D(1-P_f) + \beta. \end{aligned} \tag{10}$$

Without loss of generality, let's assume $\beta = \gamma = \frac{1}{2}P_f$. We can write

$$\widetilde{P}_F = P_F(1-P_f) + \frac{1}{2}P_f, \tag{11}$$

$$\widetilde{P}_D = P_D(1-P_f) + \frac{1}{2}P_f. \tag{12}$$

The system false alarm probability $\widetilde{Q}_F$ and the detection probability $\widetilde{Q}_D$ are given by

$$\widetilde{Q}_F = \sum_{i=k}^{n} \binom{n}{i} \widetilde{P}_F^{\,i} (1-\widetilde{P}_F)^{n-i}, \tag{13}$$

$$\widetilde{Q}_D = \sum_{i=k}^{n} \binom{n}{i} \widetilde{P}_D^{\,i} (1-\widetilde{P}_D)^{n-i}. \tag{14}$$

The probability of detection error $\widetilde{P}_e^n$ to be minimized is then

$$\widetilde{P}_e^n = q_0\widetilde{Q}_F + q_1(1-\widetilde{Q}_D). \tag{15}$$

Since P_f is a constant, according to Theorem 1, when n is fixed, for a given k, λ minimizes $\widetilde{P}_e^n$ if it satisfies

$$ln\frac{q_1}{q_0} + ln\lambda + (k-1)ln\frac{\widetilde{P}_D}{\widetilde{P}_F} + (n-k)ln\frac{1-\widetilde{P}_D}{1-\widetilde{P}_F} = 0 \tag{16}$$

or

$$\begin{aligned} &ln\frac{q_1}{q_0} + ln\lambda + (k-1)ln\frac{P_D(1-P_f)+\frac{1}{2}P_f}{P_F(1-P_f)+\frac{1}{2}P_f} \\ &+ (n-k)ln\frac{1-P_D(1-P_f)-\frac{1}{2}P_f}{1-P_F(1-P_f)-\frac{1}{2}P_f} = 0. \end{aligned} \tag{17}$$

Similarly to the case without sensor fault, the optimal threshold pair (λ, k) for fault-tolerant distributed detection could be obtained based on (17) via an optimization algorithm.

4 ENERGY EFFICIENCY: HOW DO WE CHOOSE THE NEIGHBORHOOD SIZE?

As discussed in the previous section, sensor nodes need to communicate locally to make fault-tolerant detections. The energy consumption during sensor node communication may include transmitter circuit energy, transmitter amplifier energy, and receive circuit energy [17]. To model the energy consumed by a sensor node, factors such as communication volume, transmission time, communication distance, and communication protocol efficiency have to be considered. If we could choose a minimum neighborhood size n for a given detection error bound, the communication volume during detection will be minimized and, consequently, the energy consumption is reduced.

Under the Bayesian framework, the detection scheme that optimizes the (λ, k) pair gives us the minimum detection error $P_{e,min}^n$ (or $minP_e^n$). We claim that $P_{e,min}^n$ decreases exponentially with the increase of neighborhood size n. To prove this claim, we first introduce the Chernoff Theorem [18], [19], [20] without proof.

Theorem 2 (Chernoff). *For a sequence of n i.i.d. observations $x = (x_1, x_2, \ldots, x_n)$, the minimum probability of detection error is bounded by*

$$P^n_{e,min} \leq \left(\sum p(u_i = 1|H_0)^{\alpha} p(u_i = 0|H_1)^{1-\alpha}\right)^n \tag{18}$$

for all $0 \leq \alpha \leq 1$, where $p(u_i = 1|H_0)$ and $p(u_i = 0|H_1)$ are the probability density functions for false alarm and missing detection, respectively.

We then claim:

Lemma 1. *The minimum probability of detection error $P^n_{e,min}$ approaches 0 exponentially with infinite neighborhood size n except for the extreme case that $p(x_i|H_0) = p(x_i|H_1)$ for all is.*

Proof. Since $P^n_{e,min} \leq (\sum p(u_i = 1|H_0)^{\alpha} p(u_i = 0|H_1)^{1-\alpha})^n$ for all $0 \leq \alpha \leq 1$, without loss of generality, let us choose $\alpha^* = 1$. The upper bound of $P^n_{e,min}$ is then simplified to $(\sum p(u_i = 1|H_0))^n$. $\sum p(u_i = 1|H_0)$ is the probability of false alarm and it satisfies $0 < \sum p(u_i = 1|H_0) < 1$ except for the extreme case of $p(x_i|H_0) = p(x_i|H_1)$ for all is. It directly follows that the upper bound of $P^n_{e,min}$ in (18) approaches 0 exponentially as n approaches ∞. We also have $P^n_{e,min} \geq 0$.

Now, we have

$$\begin{aligned} 0 &\leq \lim_{n\to\infty} P^n_{e,min} \\ &\leq \lim_{n\to\infty} (\sum p(u_i = 1|H_0)^{\alpha^*} p(u_i = 0|H_1)^{1-\alpha^*})^n = 0. \end{aligned} \tag{19}$$

By the squeeze theorem, $P^n_{e,min} \to 0$ exponentially as $n \to \infty$. The proof is completed. □

Proposition 1. *Given sensor fault probability P_f, the minimum probability of detection error $\widetilde{P}^n_{e,min}$ approaches 0 exponentially with infinite neighborhood size n except for the extreme case that $p(x_i|H_0) = p(x_i|H_1)$ for all is.*

Proof. According to Theorem 2, it is straightforward that the following inequality still holds:

$$\widetilde{P}^n_{e,min} \leq \left(\sum \widetilde{p}(u_i = 1|H_0)^{\alpha} \widetilde{p}(u_i = 0|H_1)^{1-\alpha}\right)^n \tag{20}$$

for all $0 \leq \alpha \leq 1$, where $\widetilde{p}(u_i = 1|H_0)$ and $\widetilde{p}(u_i = 0|H_1)$ are the probability density functions for false alarm and missing detection, respectively, when considering the sensor fault probability P_f. With Lemma 1, $\widetilde{P}^n_{e,min} \to 0$ exponentially as $n \to \infty$. The proof is completed. □

Remark 1. With Lemma 1 and Proposition 1, it is straightforward that, for a given upper bound of the detection error, the minimal neighborhood size n_{min} exists.

With Remark 1, it is finally possible to perform an energy-efficient fault-tolerant detection for a given bound of detection error and better balance between detection accuracy and energy consumption is achieved.

5 AN ENERGY-EFFICIENT FAULT-TOLERANT DETECTION ALGORITHM

We propose a two-loop search algorithm to find the optimal solutions for a given bound of detection error $P_{e,bound}$ and a sensor fault probability P_f. In the inner loop, the optimal (τ, k) pair is obtained through numerical optimization for a fixed n. In the outer loop, a binary search is employed to find the minimum n that satisfies the given error bound.

Specifically, for a given P_f, we first find $\widetilde{P}_F$ and $\widetilde{P}_D$ based on the known observation signal. $\widetilde{Q}_F$ and $\widetilde{Q}_D$ are then obtained by (13) and (14). We set n at n_{max} initially and compute the minimum detection error $\widetilde{P}^n_{e,min}$ based on the numerical solution of (17). Recall that $\widetilde{P}^n_{e,min}$ is a decreasing function of neighborhood size n, as stated in Proposition 1. If $\widetilde{P}^n_{e,min} \geq P_{e,bound}$, the algorithm stops and outputs τ, k, and n; otherwise, we set n at $\frac{1}{2}n_{max}$ and repeat the above computation. If $\widetilde{P}^n_{e,min}$ goes beyond $P_{e,bound}$ because neighborhood size n is reduced too much, we set $n = \frac{3}{2}n$ in the next iteration.

The following sequence of steps illustrates our algorithm in detail.

Input: q_0, q_1, detection error bound $P^n_{e,bound}$, sensor fault probability P_f, and the maximum neighborhood size n_{max}
Output: optimal τ, k, and n

```
$n$ = $n_{max}$
$T_{max}$ = $n_{max}$
$N_{max}$ = $n_{max}$
$N_{min}$ = 0
WHILE TRUE
        FOR $k = 1$ TO $n$
                FOR $i = k$ TO $n$
                        FOR EVERY $\tau$
                                Find $\widetilde{Q}_F(n, i, k, \widetilde{P}_F)$
                                     $\widetilde{Q}_D(n, i, k, \widetilde{P}_D)$
                        END FOR
                END FOR
                Find $\widetilde{P}^n_{e,min}(q_0, q_1, \widetilde{Q}_F, \widetilde{Q}_D)$
                and corresponding $\tau$
        END FOR
        IF $\widetilde{P}^n_{e,min}(q_0, q_1, \widetilde{Q}_F, \widetilde{Q}_D) < P^n_{e,bound}$
        THEN $T_{max}$ = $N_{max}$
                $N_{max}$ = $\frac{1}{2}(N_{max} + N_{min})$
                $n$ = $N_{max}$
        ELSE
                IF $n < T_{max}$
                THEN $N_{min}$ = $N_{max}$
                        $N_{max}$ = $N_{max}$ + $\frac{1}{2}(T_{max} - N_{max})$
                        $n$ = $N_{max}$
                ELSE RETURN $\tau$, $k$, $n$
                END IF
        END IF
END WHILE
```

Once we obtain the optimal τ, k, and n, an energy-efficient fault-tolerant distributed detection scheme is proposed as follows:

1. Based on the given error bound and sensor fault probability, compute and set (preset before the deployment or through broadcasting after the deployment) τ, k, and n in each sensor node.
2. Each sensor obtains its binary decision u_i based on its measurement and $\tau (= ln\lambda)$ with threshold test.
3. Each sensor obtains the binary decisions of its n neighbors $u_1, u_2, \dots, u_n$ (randomly selected within the communication radius) and computes $u_1 + \dots + u_n$.
4. Each sensor makes its final fault-tolerant decision based on the k-out-of-n rule.

In practical applications of wireless sensor networks, some sensors may not have enough neighbors n_{min} (optimal n) as required by the proposed algorithm. This could happen when sensors are nonuniformly randomly deployed and/or when sensors have low connectivity due to the harsh environment or limited power. One straightforward solution is to deploy more sensors to achieve the optimal solution. In the case that the additional deployment is impossible, an alternative solution is to store m triples $(n_1, k_1, \tau_1), (n_2, k_2, \tau_2), \dots, (n_m, k_m, \tau_m)$ in each sensor node, where $n_i < n_j$ for $i < j$. For a sensor without enough neighbors, a triple (n_i, k_i, τ_i) is used for the detection, where n_i is the largest value less than the optimal n. Even though not optimal, the detection performance is still satisfactory in our experiment (see Section 7 for details). In this situation, when the number of sensors within a sensor communication radius is greater than the optimal number n_{min}, we randomly choose n_{min} sensors among them as optimal neighbors of this sensor. Otherwise, the optimal neighbors of this sensor is n_i.

In our theoretical analysis for fault correction, we assume that all sensors transmit data correctly over a multiple access channel (MAC). However, depending on the MAC protocol used, communication errors may also affect the performance of event detections. In its simplest form, the communication error affects the decision making in a similar way as the sensor fault, which reverses a sensor's original local decision. Noisy communication links could thus be modeled as additional sensor faults in the detection process. The optimal parameter triple (n, k, τ) in the proposed algorithm has to be computed accordingly, based on the adjusted sensor fault probability.

6 THE NEYMAN-PEARSON APPROACH

In many practical situations, the prior probabilities q_0 and q_1 may be unknown. The Bayesian method discussed in the previous sections is not appropriate in solving this kind of problem. In these cases, we could employ the Neyman-Pearson criterion and work with the probability of system false alarm, Q_F, and the probability of system detection, Q_D, in designing the detection rule. Usually, it is desirable to make Q_F as small as possible and Q_D as large as possible. Obviously, these are conflicting objectives. Thus, in the Neyman-Pearson approach, the goal is to maximize Q_D while keeping Q_F below or equal to an accepted level θ. In the following, we limit our discussion to binary decisions of sensor nodes and k-out-of-n fusion rules.

We apply the Neyman-Pearson criterion to the detection problem with different neighborhood size n. For a given n, our goal is to choose the threshold pair (λ, k) that yields the maximal Q_D while keeping Q_F below an accepted value θ. The Lagrange multiplier method is used to solve this constrained optimization problem. For the fixed k and n, the system probability of detection error is a quasiconvex function of λ and the Lagrange multiplier method is suitable [13]. We define the objective function as follows:

$$L_e^n(\lambda, s) = 1 - Q_D + s(Q_F - \theta), \tag{21}$$

where s is the Lagrange multiplier and $s \geq 0$. $L_e^n(\lambda, s)$ is minimized with respect to s and λ for the fixed k and n.

Lemma 2. *The minimum system probability of detection error $L_{e,min}^n(\lambda, s)$ is a decreasing function of n.*

Proof. Let $s = q_0/q_1$, with (7) and some mathematical manipulations, we have

$$L_e^n(\lambda, s) = \frac{1}{q_1} P_e^n - \frac{q_0}{q_1}\theta. \tag{22}$$

and

$$L_{e,min}^n(\lambda, s) = \frac{1}{q_1} P_{e,min}^n - \frac{q_0}{q_1}\theta, \tag{23}$$

where $q_0 = \frac{s}{1+s}$ and $q_1 = \frac{1}{1+s}$. Since $P_{e,min}^n$ is a decreasing function of n, as proven in Lemma 1, so does $L_{e,min}^n(\lambda, s)$. The lemma is proven. □

Similarly to the Bayesian method, with Lemma 2 we can choose the minimum number of neighbor sensors with an accepted false alarm rate θ in the Neyman-Pearson method if energy conversation is our top concern. To find the optimal threshold pair (λ, k), we solve the following set of equations:

$$Q_F - \theta = 0, \tag{24}$$

$$ln\frac{1}{s} + ln\lambda + (k-1)ln\frac{P_D}{P_F} + (n-k)ln\frac{1-P_D}{1-P_F} = 0, \tag{25}$$

or

$$\widetilde{Q}_F - \theta = 0, \tag{26}$$

$$\begin{aligned} ln\frac{1}{s} + ln\lambda + (k-1)ln\frac{P_D(1-P_f)+\frac{1}{2}P_f}{P_F(1-P_f)+\frac{1}{2}P_f} \\ + (n-k)ln\frac{1-P_D(1-P_f)-\frac{1}{2}P_f}{1-P_F(1-P_f)-\frac{1}{2}P_f} = 0, \end{aligned} \tag{27}$$

when sensor fault is considered.

7 EXPERIMENTS AND DISCUSSION

In this section, we present our experimental results for the proposed detection algorithm. We consider the detection of known signals in Gaussian noise. The event to be observed by the sensor is $x_i = s_i + z_i$, where $s_i = \pm d$ is the interested signal and z_i is a Gaussian random variable with zero mean and unit variance. Define

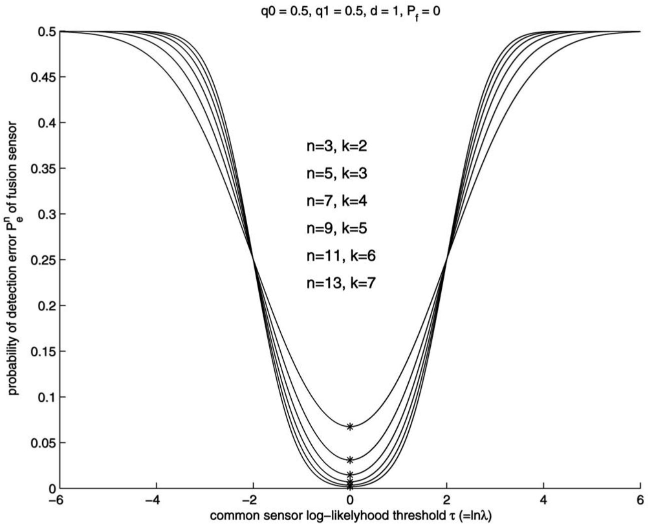

Fig. 3. Probability of detection error P_e^n versus log-likelihood ratio threshold τ for the case of $q_0 = 0.5$, $q_1 = 0.5$, $d = 1$, and $P_f = 0$.

$$\begin{array}{lll} H_0 & : & s_i = -d \\ H_1 & : & s_i = d. \end{array} \tag{28}$$

The log-likelihood ratio τ_i for this problem is $\tau_i = 2dx_i$. The sensor false alarm and detection probabilities are given by

$$P_F = Q\Big(\frac{\tau}{2d} + d\Big) \tag{29}$$

and

$$P_D = Q\Big(\frac{\tau}{2d} - d\Big), \tag{30}$$

where τ is the log-likelihood ratio threshold and

$$Q(z) = \int_z^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx. \tag{31}$$

Our objective is to find the optimal τ, k, and n, given the prior probabilities q_0, q_1, a detection error bound $P_{e,bound}$, sensor fault probability P_f, and the maximum neighborhood size n_{max} (determined by the maximum communication radius of a sensor node).

We first illustrate some interesting properties on the relationship among P_e^n, $P_{e,min}^n$, n, and τ without considering sensor fault. Then, we present and discuss the performance of the proposed detection scheme on several simulated sensor networks.

7.1 Interesting Properties on P_e^n, $P_{e,min}^n$, n, and τ

Fig. 3 shows the probability of detection error against the log-likelihood ratio threshold τ, with equal prior probabilities ($q_0 = 0.5$, $q_1 = 0.5$), fixed $d = 1$, and different neighborhood size n. The (n, k) pairs in the figure indicate the optimal fusion rule for the given n. "*" indicates the minimum probability of detection error for the corresponding (n, k) pair. The top pair ($n = 3, k = 2$) corresponds to the curve with the highest "*" position; the second pair ($n = 5, k = 3$) corresponds to the curve with a "*" in the second highest position, and so on. From Fig. 3, we can see clearly that:

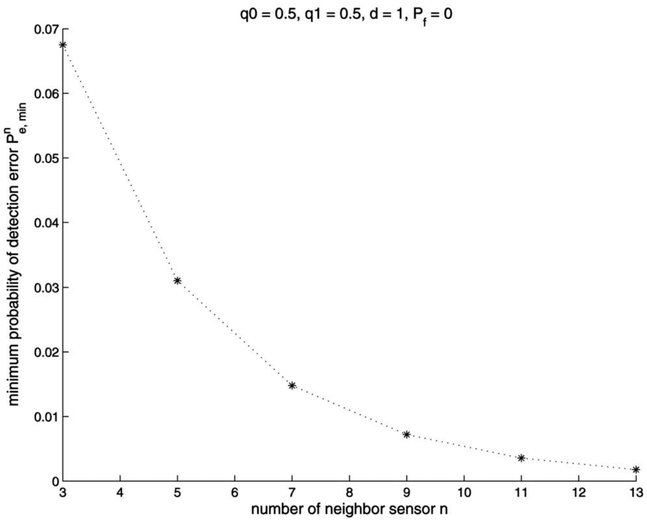

Fig. 4. Minimum probability of detection error $P_{e,min}^n$ versus the neighborhood size n for the case of $q_0 = 0.5$, $q_1 = 0.5$, $d = 1$, and $P_f = 0$.

- The optimal log-likelihood ratio threshold is always at $\tau = 0$ (or $\lambda = 1$) for equal prior probabilities.
- The minimum detection error decreases when n increases, which confirms Lemma 1.

Fig. 4 gives another way to look at the minimum probability of detection error, $P_{e,min}^n$, against different neighborhood size n, which is included in Fig. 3. The exponential decrease of $P_{e,min}^n$ is obvious. The unequal prior probability case with $q_0 = 0.75$ and $q_1 = 0.25$ is shown in Fig. 5 and Fig. 6. The (n, k) pairs and their corresponding curves are matched in the same way as before. It is clear that the relationship between $P_{e,min}^n$ and n still holds for unequal prior probabilities. We also notice that $P_{e,min}^n$ is further reduced for the same neighborhood size n when compared with the equal prior probability case. Actually, our experiment shows that the absolute difference between the two prior probabilities $|q_0 - q_1|$ is proportional to the reduction rate of

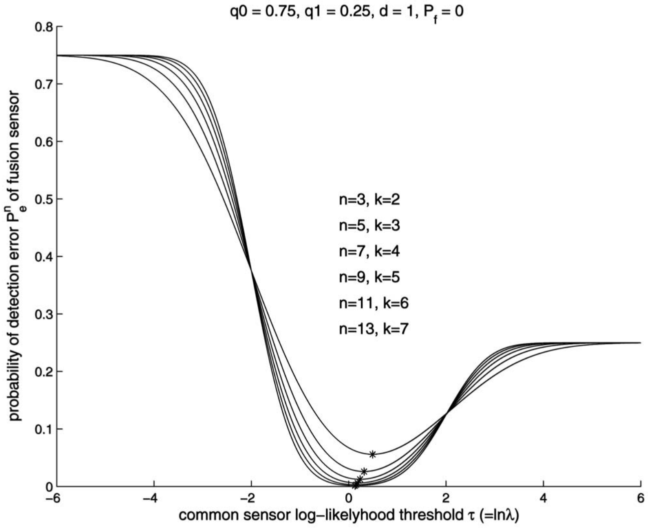

Fig. 5. Probability of detection error P_e^n versus log-likelihood ratio threshold τ for the case of $q_0 = 0.75$, $q_1 = 0.25$, $d = 1$, and $P_f = 0$.

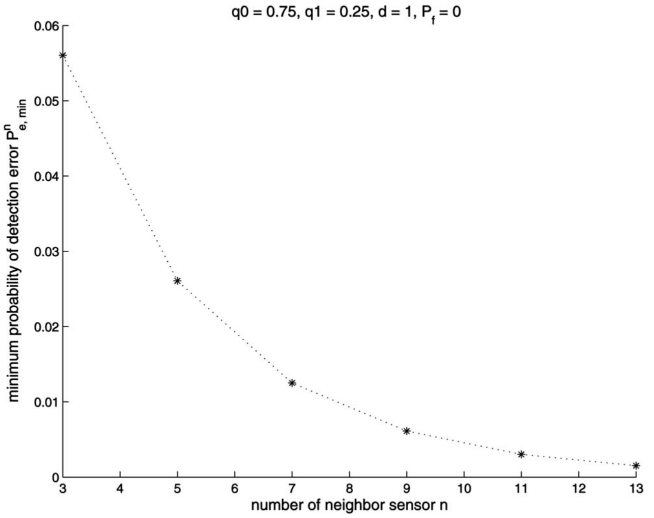

Fig. 6. Minimum probability of detection error $P^n_{e,min}$ versus the neighborhood size n for the case of $q_0 = 0.75,\ q_1 = 0.25,\ d = 1$, and $P_f = 0$.

$P^n_{e,min}$. In other words, $P^n_{e,min}$ decreases more quickly against n with a larger $|q_0 - q_1|$. Fig. 7 shows that $P^n_{e,min}$ decreases even quicker with the increase of n for the case of $q_0 = 0.9$ and $q_1 = 0.1$. This result indicates that, if we have prior knowledge about the events in advance, less energy (smaller n) is needed to maintain the same level of detection accuracy. We observe that Lemma 1 only holds for the optimal solution solved from (8) and some suboptimal solutions nearby, as shown in Fig. 3 and Fig. 5. In general, the probability of detection error P^n_e is NOT always a decreasing function of n. If a log-likelihood threshold τ is chosen outside the small interval around optimal τ, the detection error will actually increase as n increases. This result provides a counterexample to the conjecture that the more neighbor sensors, the better detection accuracy. Clearly, the conjecture is wrong if the threshold is selected inappropriately.

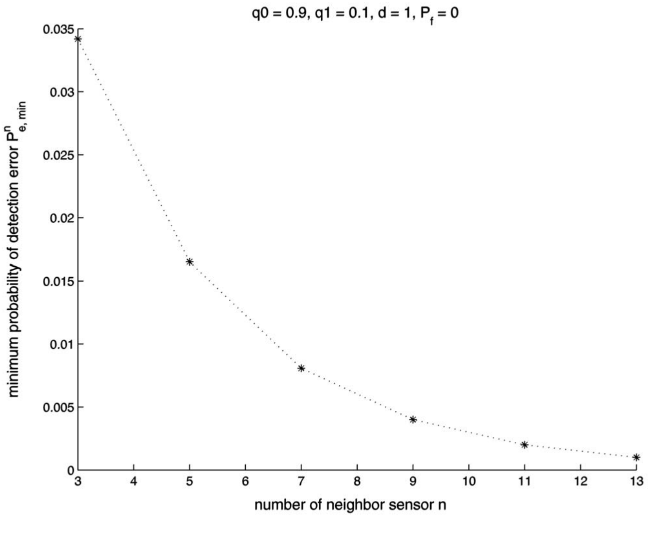

Fig. 7. Minimum probability of detection error $P^n_{e,min}$ versus the neighborhood size n for the case of $q_0 = 0.9$, $q_1 = 0.1$, $d = 1$, and $P_f = 0$.

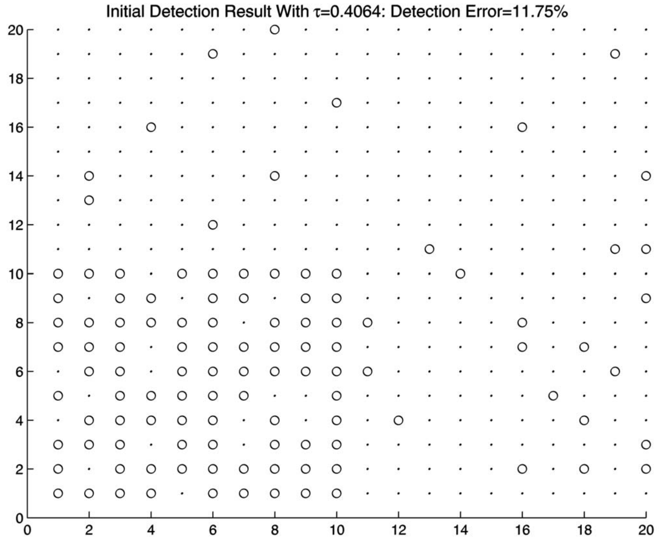

Fig. 8. Initial detection results with $\tau = 0.5964$.

7.2 Detection Performance

We test the proposed detection scheme in several simulated sensor networks. In all our experiment designs, the event signal is randomly sampled from a Gaussian distribution with the center at 1 and unit variance. The background signal is randomly sampled from a Gaussian distribution with the center at -1 and unit variance. The prior probabilities for the background and event are set at $q_0 = 0.75$ and $q_1 = 0.25$, respectively. We also assume that the event region is in the 10 by 10 area at the bottom-left corner of the operation zone. For the initial detection, each sensor gives its local decision according to Step 2 of the proposed detection scheme and obtains its final decision based on Steps 3 and 4.

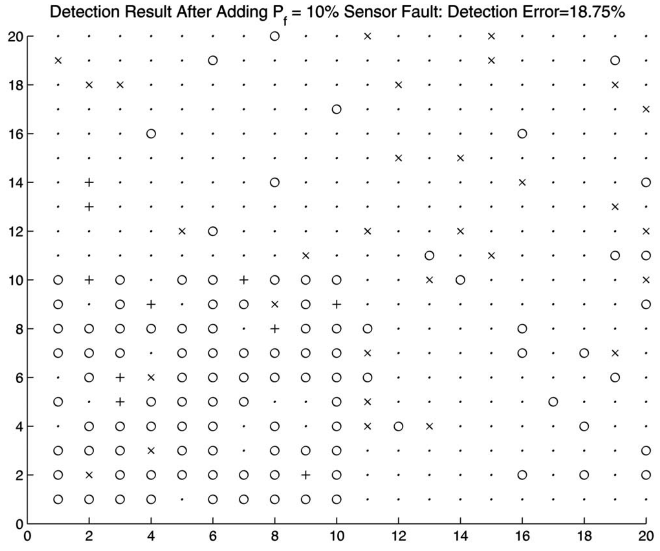

Fig. 9. Detection results after adding $P_f = 10\%$ sensor fault.

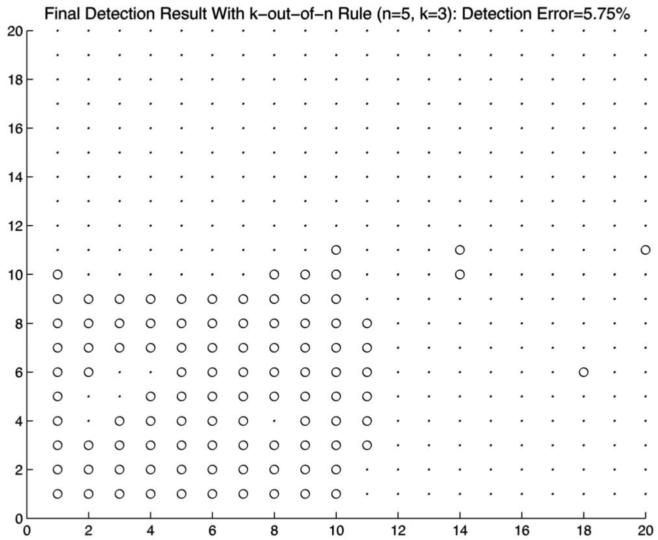

Fig. 10. Final detection results with k-out-ot-n rule ($n = 5,\ k = 3$).

7.2.1 *Bayesian Detection*

Fig. 8 shows the initial detection results (Step 2 of the proposed detection scheme) with 400 sensors in total and 100 sensors in the event region. The log-likelihood ratio threshold τ is set at $\tau = 0.4064$, based on (17). If the event is detected by a sensor node, it is marked by a circle "$\circ$" in the corresponding location; otherwise, the location is marked by a dot "$\cdot$". We can see that the overall probability of detection error is 11.75 percent. We simulated 10 percent sensor faults by reversing the sensor decisions in Fig. 8 randomly, as shown in Fig. 9. A "$+$" indicates that, originally, an event is detected at the location and the decision is converted to no-event due to sensor fault, while a "$\times$" represents the case of no-event detected originally. The probability of detection error is increased to 18.75 percent after introducing sensor fault. The final detection result (Steps 3 and 4 of the proposed detection scheme) with $n = 5$ and $k = 3$ (computed based on (17)) is presented in Fig. 10.

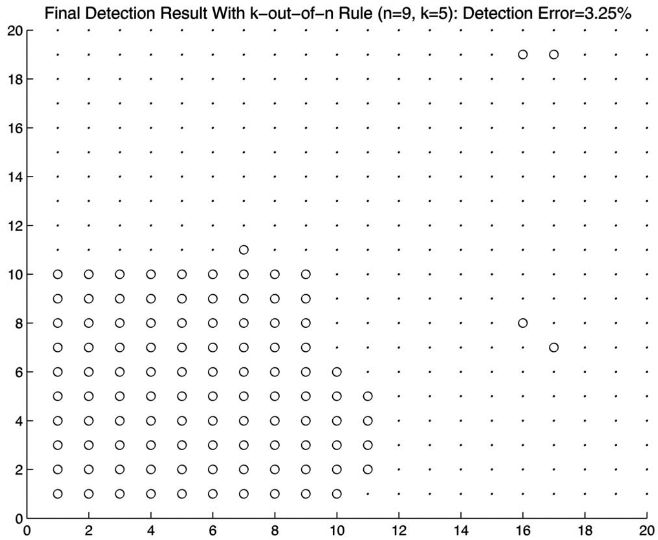

Fig. 11. Final detection resuls with k-out-of-n rule ($n = 9,\ k = 5$).

TABLE 1
Averaged Detection Errors of Sensor Networks with 400 and 10,000 Sensor Nodes with $P_f = 10\%$ Using the Bayesian Scheme

N	τ	n, k	$I.E$	$FT.E$	$F.E$
400	0.5964	$3, 2$	13.35%	20.57%	12.52%
400	0.4064	$5, 3$	13.98%	21.14%	8.35%
400	0.3082	$7, 4$	14.39%	21.46%	6.01%
400	0.2482	$9, 5$	14.53%	21.70%	4.46%
$10,000$	0.5964	$3, 2$	13.30%	20.67%	11.68%
$10,000$	0.4064	$5, 3$	13.91%	21.13%	7.29%
$10,000$	0.3082	$7, 4$	14.28%	21.46%	4.81%
$10,000$	0.2482	$9, 5$	14.55%	21.67%	3.22%

$N =$ number of sensors, $I.E =$ initial detection error rate, $FT.E =$ detection error rate after adding sensor fault, and $F.E =$ final detection error rate.

After applying the k-out-of-n rule, many incorrect detections (including false alarm and missing detection) have been corrected. The probability of detection error is reduced to 5.75 percent. Fig. 11 shows final detection results with a larger neighborhood ($\tau = 0.2482,\ n = 9,\ k = 5$, and $P_f = 10\%$). As expected, the probability of detection error is reduced more (3.25 percent) as n increases. However, we could still offer more than 94 percent detection accuracy by choosing $n = 5$ if energy conservation is our top priority. Notice that the detection accuracy in our simulation is lower than the theoretical estimation, which is mainly caused by the confusions along the boundary of the event region (see Figs. 10 and 11). As mentioned in Section 2.1, how to identify the sensor nodes near the boundary and process their information accordingly are still challenging problems in event detections. We leave it for future research.

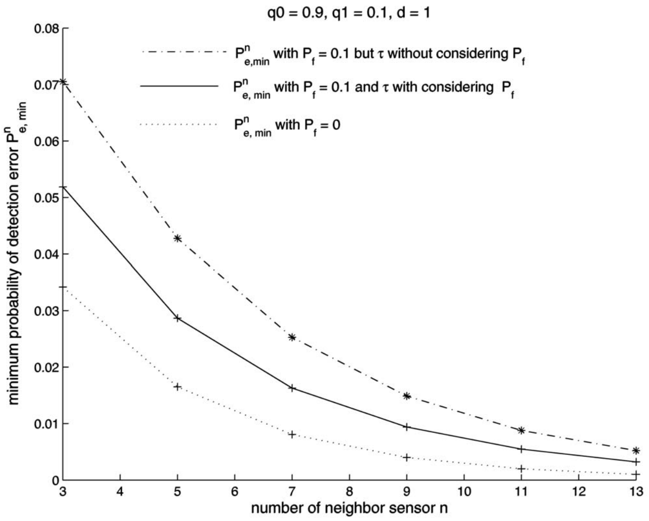

Fig. 12. Minimum probability of detection error $P^n_{e,min}$ versus the neighborhood size n for the case of $q_0 = 0.9,\ q_1 = 0.1,\ d = 1$, and $P_f = 0, 0.1$.

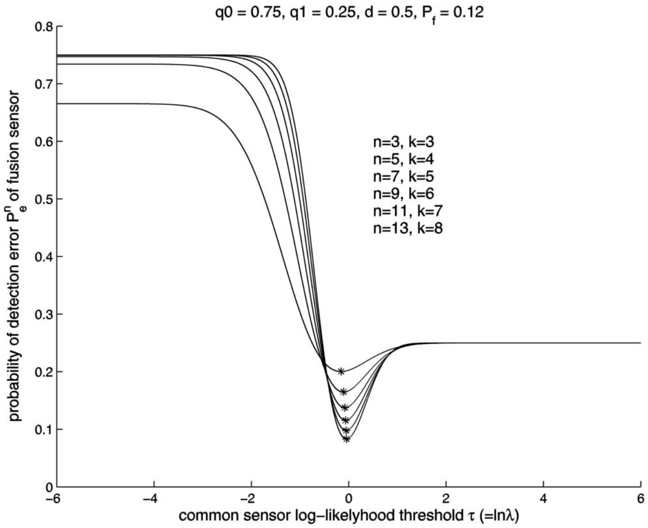

Fig. 13. Probability of detection error P_e^n versus the neighborhood size n for the case of $q_0 = 0.75$, $q_1 = 0.25$, $d = 0.5$, and $P_f = 0.12$.

We repeat the above experiment 200 times. The averaged detection errors are shown in Table 1. The table also shows our experiment results for a much larger sensor network (with $10,000$ sensors). In all cases, the detection errors have been greatly reduced. The effectiveness of the proposed algorithm is obvious. Notice that the number of necessary communications during fault correction is given by $N * n$, thus more energy will be saved by choosing a smaller n for a larger sensor network (larger N).

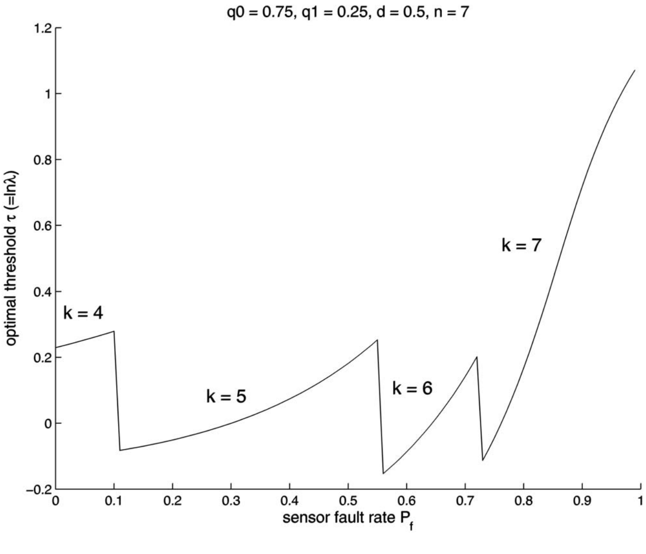

Fig. 14. Optimal log-threshold τ versus sensor fault rate P_f for the case of $q_0 = 0.75$, $q_1 = 0.25$, $d = 0.5$, and $P_f = 0.12$.

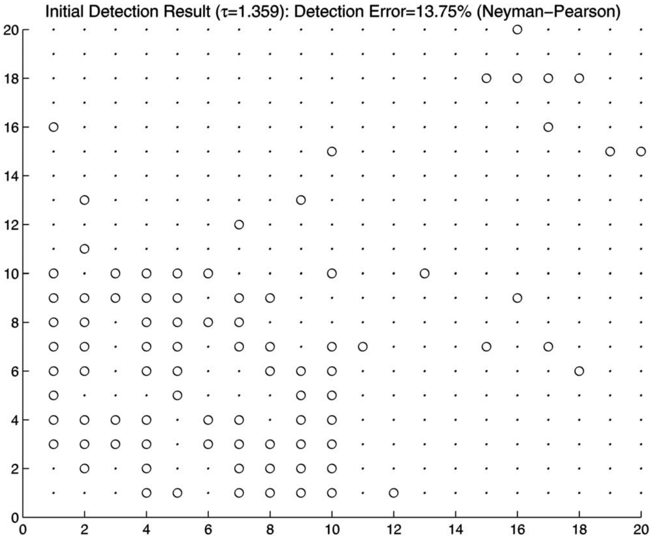

Fig. 15. Initial detection results with $\tau = 1.359$.

Fig. 12 shows that, with the same n, how sensor fault probability P_f affects the minimum detection error $\widetilde{P}_{e,min}^n$ and how an appropriate threshold obtained from (17) can improve the detection performance. The lowest curve (dotted) shows $\widetilde{P}_{e,min}^n$ versus n with $P_f = 0$. The highest curve (dash-dotted) shows $\widetilde{P}_{e,min}^n$ versus n with $P_f = 0.1$ and with the threshold τ set based on (8) (without considering sensor fault probability explicitly). The middle curve (solid) shows $\widetilde{P}_{e,min}^n$ versus n with $P_f = 0.1$, but, in this case, τ has been computed based on (17). It is clear that, by choosing the threshold pair (τ, k) with the proposed scheme, the detection performance is improved. Fig. 13 shows the probability of detection error $\widetilde{P}_e^n$ against threshold τ with unequal prior probabilities ($q_0 = 0.75$, $q_1 = 0.25$), $d = 0.5$, $P_f = 0.12$, and different neighbor size n. It is clear that the minimum detection error (marked by "*") decreases when n increases, which confirms Proposition 1. It is also interesting to notice that the optimal k (i.e., k_{min}) $= 3, 4, 5, 6, 7, 8,$ respectively, for $n = 3, 5, 7, 9, 11, 13$. The majority voting rule ($k_{min} = \frac{1}{2}n$) is NOT the optimal fusion rule, in this case, any more. Actually, our experiment shows that, when P_f is small, for example, when $P_f \leq 0.09$ in the above case ($q_0 = 0.75$, $q_1 = 0.25$, and $d = 0.5$), the majority voting is the optimal fusion rule. However, when sensor fault rate P_f becomes larger, for example, $P_f = 0.12$ in Fig. 13, the optimal k also increases and the majority voting rule loses its optimality. Our experiment also shows that, in the particular case of equal prior probabilities, majority

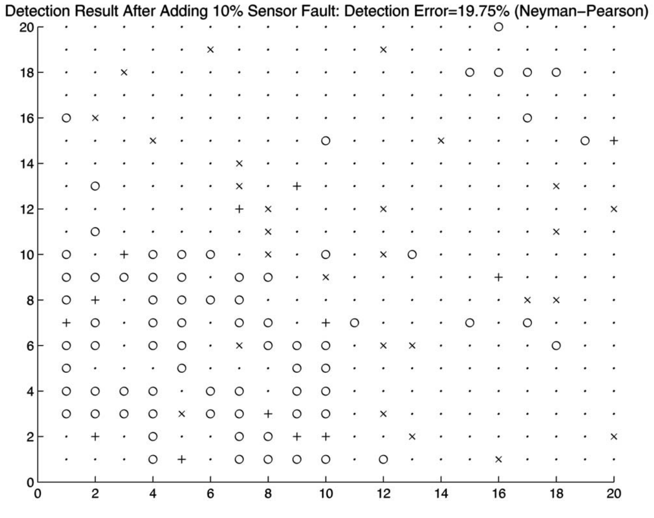

Fig. 16. Detection results after adding $P_f = 10\%$ sensor fautl.

Fig. 17. Final detection results with k-out-of-n rule ($n = 9$, $k = 4$).

voting rule is always the optimal fusion rule for all P_f. In other words, Theorem 2 in [6] is only a special case for $q_0 = q_1$ when both measurement error and sense fault are considered in fault corrections. From (17), it is clear that the optimal pair (τ k) is directly affected by P_f. Fig. 14 shows P_f versus the optimal thresholds (τ k) with unequal prior probabilities ($q_0 = 0.75$, $q_1 = 0.25$), fixed $d = 0.5$, and $n = 7$. First of all, notice that the discontinuity of τ results from the fact that k can only take an integer value in $[\frac{1}{2}n, n]$. Second, we can see clearly that, for each k, threshold τ increases with P_f. In general, the sensor fault probability P_f increases with time after the deployment. The optimal pair (τ k) should be modified to reflect the changes. It can be expected that, when the threshold τ and k are adaptively adjusted with time in a sensor network, a better detection performance can be achieved. Again, for the equal prior probability case, τ is fixed for all P_f.

7.2.2 Neyman-Pearson Detection

To compare the performance of the Neyman-Pearson approach with the Bayesian method, we conduct our experiments with the same data used for the Bayesian detection experiments. Fig. 15 shows the initial detection results with the Neyman-Pearson approach. The log-likelihood ratio threshold τ is set at $\tau = 1.359$ based on (26) and (27) with false alarm rate $\theta = 10\%$. The initial detection error is 13.75 percent. After adding 10 percent sensor fault, the detection error increases to 19.75 percent, as shown in Fig. 16. The final detection result with $n = 9$ and $k = 4$ (computed based on (26) and (27)) is presented in Fig. 17. After applying the k-out-of-n rule, the detection error is reduced to 4.75 percent. If we compare Fig. 17 (the Neyman-Pearson approach) with Fig. 11 (the Bayesian approach), it is clear that the detection performance for the Bayesian method is better than the Neyman-Pearson with the same neighborhood size $n = 9$. The underlying reason is that the Neyman-Pearson method seeks optimal detection with an accepted false alarm rate θ. In its optimization, $s = q_0/q_1$ is also optimized in (24), (25) or (26), (27) and is fixed after the optimization. It is obvious that, if actual q_0/q_1 is not the same as the optimized q_0/q_1, the performance of the Neyman-Pearson method is not as good as the Bayesian approach. However, in the case that q_0 and q_1 are unknown, the Neyman-Pearson method does provide an alternative solution. We perform the experiment 200 times. The averaged detection performance is reported in Table 2. Table 2 shows clearly that the detection error decreases as n increases, which confirms our proof in Lemma 2.

TABLE 2
Averaged Detection Errors of Sensor Networks with 400 Sensor Nodes and $P_f = 10\%$ Using the Neyman-Pearson Scheme

N	τ	n, k	$I.E$	$FT.E$	$F.E$
400	1.3380	3, 2	12.75%	20.17%	13.19%
400	0.9293	5, 3	12.94%	20.39%	8.92%
400	0.7553	7, 4	13.09%	20.36%	6.38%
400	1.3590	9, 4	12.73%	20.25%	5.61%

$N =$ number of sensors, $I.E =$ initial detection error rate, $FT.E =$ detection error rate after adding sensor fault, and $F.E =$ final detection error rate.

TABLE 3
Averaged Detection Errors of Sensor Networks (400) without Enough Neighbors

	Bayesian			Neyman-Pearson		
ϕ	$I.E$	$FT.E$	$F.E$	$I.E$	$FT.E$	$F.E$
0%	14.53%	21.70%	4.46%	12.73%	20.25%	5.61%
10%	14.42%	21.26%	5.33%	12.74%	20.26%	6.37%
20%	14.42%	21.61%	6.24%	12.83%	20.37%	7.33%
30%	14.17%	21.55%	7.01%	12.77%	20.34%	7.88%
40%	14.22%	21.23%	7.79%	12.89%	20.20%	8.72%
50%	13.89%	21.11%	8.65%	12.93%	20.43%	9.67%

The required number of neighborhood sensors is nine, but ϕ sensors only have three neighborhood sensors. $P_f = 10\%$, $\theta = 10\%$, and $\phi = 0\%$, 10%, 20%, 30%, 40%, 50%, where $N =$ number of sensors, $I.E =$ inital detection error rate, $FT.E =$ detection error rate after adding sensor fault, and $F.E =$ final detection error rate.

7.2.3 Detection without Enough Neighbors

We perform additional experiments for both the Bayesian and Neyman-Pearson approaches to evaluate the detection performance when some sensors do not have enough neighbors. We assume that the minimum number of neighbors is nine for a given detection error bound. For simplicity, we also assume that each sensor can only have nine or three neighbors. Sensors with a different number of neighbors use different triples (τ, n, k). Specifically, for sensors with nine neighbors, the triples ($\tau = 0.2482$, $n = 9$, $k = 5$) and ($\tau = 1.359$, $n = 9$, $k = 4$) are used for the Bayesian and Neyman-Pearson approaches, respectively, while the triples ($\tau = 0.5964$, $n = 3$, $k = 2$) and ($\tau = 1.338$, $n = 3$, $k = 2$) are used for sensors with only three neighbors. Let ϕ denote the proportion of the number of sensors with only three neighbors. We simulate situations with $\phi = 0\%$, 10%, 20%, 30%, 40%, and 50%. The experiments are conducted 200 times for each ϕ and the averaged results are reported in Table 3. The experimental results demonstrate that the final detection performances decrease when ϕ increases for both Bayesian and Neyman-Pearson approaches. When ϕ increases from 0 percent to 50 percent, the detection error rate increases from 4.46 percent to 8.65 percent for the Bayesian method and from 5.61 percent to 9.69 percent for the Neyman-Pearson approach.

8 CONCLUSIONS AND FUTURE RESEARCH

In this paper, we study the fault correction problem for distributed event detection in a wireless sensor network. In our theoretical analysis, the sensor fault probability is formally introduced into the optimal detection process. We also mathematically show that the optimal fault-tolerant detection error (for both the Bayesian and the Neyman-Pearson performance criteria) decreases exponentially with the increase of the neighborhood size. Based on the theoretical work, a distributed fault-tolerant detection scheme is proposed to achieve the optimal detection performance. In the proposed scheme, the neighborhood size, n, of fault correction is chosen based on the given detection error bound such that better balance between detection accuracy and energy usage is obtained.

Our experiments show that, with the proposed detection algorithms, detection error could be greatly reduced even with both measurement error and sensor fault. Currently, there is no communication protocol designed specifically for sensor fault corrections. To validate our theoretical work, we plan to propose a communication protocol for fault corrections and implement the proposed detection algorithms on sensor network simulators, such as PowerTOSSIM [21].

The next step after event detection is to aggregate the detection results and transmit them to the base station, a task which typically requires fusion sensors. The number of fusion sensors needed usually depends on the area of the interested region and the communication range of an individual sensor node. Many protocols have been proposed in the literature to route the information from sensors to the base station. LEACH [22], for example, is a clustering-based protocol that utilizes randomized rotation of local cluster-heads. On the other hand, we could also divide the entire region into many spatial coherence regions (SCR) [23] and randomly select one fusion sensor in each SCR. The advantage of this approach is that we could avoid the overhead energy cost for clustering.

ACKNOWLEDGMENTS

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