Collaborative Wireless Sensor Networks for Target Detection Based on the Generalized Approach to Signal Processing

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Abstract: Collaboration in wireless sensor networks must be fault-tolerant due to the harsh environmental conditions in which such networks can be deployed. This paper focuses on finding signal processing algorithms for collaborative target detection based on the generalized approach to signal processing in the presence of noise that are efficient in terms of communication cost, precision, accuracy, and number of faulty sensors tolerable in the wireless sensor network. Two algorithms, namely, value fusion and decision fusion constructed according to the generalized approach to signal processing in the presence of noise, are identified first. When comparing their performance and communication overhead, decision fusion is found to become superior to value fusion as the ratio of faulty sensors to fault free sensors increases. The use of the generalized approach to signal processing in the presence of noise under designing value and decision fusion algorithms in wireless sensor networks allows us to obtain the same performance, but at low values of signal energy, as under the employment of universally adopted signal processing algorithms widely used in practice.

Keywords: Collaborative target detection, generalized detector, decision fusion, value fusion, wireless sensor network.

1. INTRODUCTION

Recent advances in computing hardware and software are responsible for the emergence of wireless sensor networks capable of observing the environment, processing the data, and making decisions based on the observations. In particular, the development of technologies such as Bluetooth [1] or the IEEE 802.11 standard [2] enables us to connect the sensor nodes together wirelessly. This allows for deployment of ad hoc wireless sensor networks that do not require backbone infrastructure. This, together with progress in signal processing and sensing and computer technology, give rise to many new applications. Such wireless sensor networks can be used to monitor the environment, detect, classify, and locate specific events and track targets over a specific region. Examples of such systems are in military, surveillance, monitoring of pollution, traffic, agriculture, or civil infrastructures.

The essence of wireless sensor networks is to have sensor nodes within a region, make local observations of the environment, and collaborate to produce a global result that reflects the status of the region covered [3]. This collaboration requires local processing of the observed data, communication between different sensor nodes, and information fusion. For many applications, the wireless sensor network is deployed in a harsh environment and some of the sensor nodes may be faulty or may fail during the wireless sensor network's lifetime, thus requiring collaboration to be robust to sensor node failures. Two other constraints in wireless networks of autonomous sensor nodes come from the limited bandwidth and power source of these elements, requiring collaboration to be communication and power efficient.

Thus, the challenges of wireless sensor networks include distributed signal processing that makes use of the processing power of all the sensor nodes, ad hoc routing, and communication protocols that enable information sharing among sensor nodes and fault tolerance that accounts for the possible misbehaviors of a subset of the sensor nodes. All these challenges need to cope with the power constraint of the wireless sensor network. This paper focuses on finding and analyzing signal processing algorithms for robust collaborative target detection based on the generalized approach to signal processing in the presence of noise [4-8]. Therefore, it addresses both the distributed signal processing and fault tolerance challenges. This work continues a preliminary study presented in [9].

The basic premise of target detection is that sensor nodes are deployed over a region of interest and are required to determine if a target is present in that region. In general, targets emit signals characterizing their presence in the region that can be measured by the sensors. Therefore, sensor nodes need to collaborate by exchanging and fusing their local information to produce a result global to the region. The presence of faulty sensor nodes affects this fusion process and can potentially corrupt the detection result. Target detection algorithms need to specify a way to fuse the signals measured at each sensor node to produce one consistent and useful result characterizing the whole region. These target detection algorithms can be evaluated for their performance in terms of accuracy, communication overhead, and robustness to sensor node failure.

2. PROBLEM STATEMENT AND MODEL

This section formulates the target detection problem being investigated. We consider the model for the wireless sensor network presented in [10]. The wireless sensor network is assumed to be composed of a set of nodes connected to sensor, called sensor nodes or simply nodes. A model is developed for each sensor node in fault-free and faulty mode and for the collaboration among nodes. The target is modeled by the signal it emits.

Sensor nodes, with possibly different sensing modalities, are deployed over a region $\mathscr{X}$ to perform target detection. Sensors measure signals at a given sampling rate to produce time series that are processed by the nodes. The nodes fuse the information obtained from every sensor according to the sensor type and location to provide an answer to a detection query. We assume that the nodes have the ability to communicate with each other. The node peer-to-peer communication is assumed to be realizable with appropriate communication techniques [11].

We assume that the sensor nodes obtain a target energy measurement after T seconds while a target was at a given position inside or outside the region $\mathcal{X}$. Obtaining that energy requires preprocessing of the time series measured during period T and, possibly, fusion of data from different sensors by each node. The detection procedure consists of exchanging and fusing the energy values produced by the sensor nodes to obtain a detection query answer. Note that a more accurate answer can be obtained in a general if the sensors exchange their time series rather than energies; however, that would require high communication bandwidth that may not be available in a sensor network. The performance of fusion is partly defined by the accuracy that measures how well sensor decisions represent the environment.

We assume that detection results need to be available at each node. The reason for such a requirement is that the results can be needed for triggering other actions such as localization of the target detected. This requirement can be fulfilled by having a central node make a decision and disseminate that decision to all the nodes in the wireless sensor network. The correctness of such a scheme relies on the central node's correctness, therefore, central node-based schemes have low robustness to sensor failure. Distributing the decision making over several or all the nodes improves reliability at the cost of communication overhead.

The wireless sensor network considered is likely to contain faulty sensor nodes due to harsh environmental conditions. Faults include misbehaviors ranging from simple crash faults, where a node becomes inactive, to Byzantine faults [10], where the node behaves arbitrarily or maliciously. Faulty nodes are assumed to send inconsistent and arbitrary values to other nodes during information sharing. An example of such behavior, where four nodes, A, B, C, and D, measure energy values to determine if a target is in region $\mathcal{X}$, is given in Fig. 1.

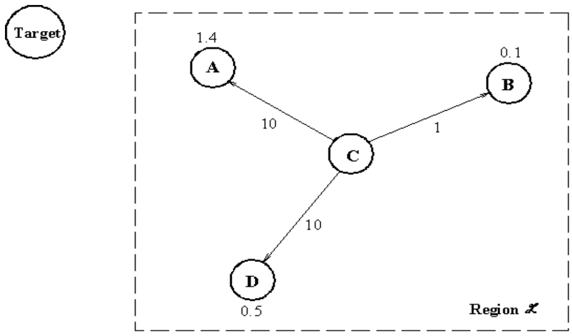

Fig.1. Byzantine faulty behavior.

As the target is outside region $\mathcal{X}$, sensor A measures an energy level of 1.4 (including noise), whereas sensors B and D measure an energy level of 0.1 and 0.5, respectively. Sensor C is assumed faulty and sends different measurements to the other sensors (10, 1, and 10 to A, B, and D, respectively). As a result, non-faulty sensors obtain different global information about the region and may conclude differently on the presence of the target, i.e., sensors A and D may conclude that a target is present while sensor B concludes that no target is present.

The target detection algorithm needs to be robust to such inconsistent behavior that can jeopardize the collaboration in the wireless sensor networks. For example, if the detection results trigger subsequent actions at each node, then inconsistent detection results can lead each node to operate in a different mode, resulting in the wireless sensor network going out of service. The performance of fusion is therefore also defined by precision [12,13]. Precision measures the closeness of decisions from each other, the goal being that all nodes obtain the same decision.

A target at location l emits a signal, which is measured by sensors deployed at locations $s_i, i = 1,..., n$. The strength of the signal emitted by the target decays as a polynomial of the distance. If the decay factor is k, the signal energy of a target at location l measured by a sensor at location s_i is given by

$$S_i(l) = \begin{cases} PT, & \text{if} \quad r < r_0 \,; \\ \dfrac{PT}{(\frac{r}{r_0})^k}, & \text{otherwise}, \end{cases} \tag{1}$$

where P is the power emitted by the target during time T and

$$r = \| l - s_i \| \tag{2}$$

is the geometric distance between the target and the sensor and r_0 is a constant that accounts for the physical size of the sensor and the target. Depending on the environment, i.e., atmospheric conditions, the value k typically ranges from 2.0 to 5.0 [14]. The energy $S_i(l)$ also depends on the possible presence of obstacles lying between the target and the sensors. However, we assume no such obstacles to be present in the region considered.

Energy measurements at a sensor are usually corrupted by noise. If N_i denotes the noise energy at sensor i during a particular measurement, then the total energy measured at sensor i when the target is at location l is

$$E_i(l) = S_i(l) + N_i \ . \tag{3}$$

3. DISTRIBUTED DETECTION

Classical multisensor detection assumes that all local sensors communicate their data to a central processor performing optimal or near optimal detection using conventional statistical techniques [15]. Later investigations, however, focused on decentralized processing in which some preliminary processing of data is performed at each sensor node so that compressed information is gathered at the fusion center [16]. Decentralizing the detection results in a loss of performance compared to the performance of centralized systems since the fusion center of a decentralized system has only part of the information collected by the sensor nodes. However, decentralized schemes require reduced communication bandwidth and it will be shown in this paper that they may achieve increased reliability. Further, the performance loss of decentralized schemes may be reduced by optimally processing the information at each sensor.

Wireless sensor network parallel topology where N sensors measure a signal y_i produced by a phenomenon $\mathcal{H}$ is shown in Fig. 2 [17]. Each sensor S_i processes its signal y_i to generate a quantized information l_i and all the $l_i, i = 1,..., N$ are then fused into l_0 at the fusion center. In the binary hypothesis testing problem, the observations at all the sensors either correspond to the presence of a target (the hypothesis $\mathcal{H}_1$) or to the absence of a target (the hypothesis $\mathcal{H}_0$). The performance of detection is measured by the probability of false alarm P_F and the probability of miss P_M. The P_F is the probability of concluding that a target is present when the target is absent, i.e.,

$$P_F = P\{l_0 = 1 \mid \mathcal{H}_0) \quad . \tag{4}$$

The P_M is the probability concluding that a target is absent when a target is actually present, i.e.,

$$P_M = P\{l_0 = 0 \mid \mathcal{H}_1) \quad . \tag{5}$$

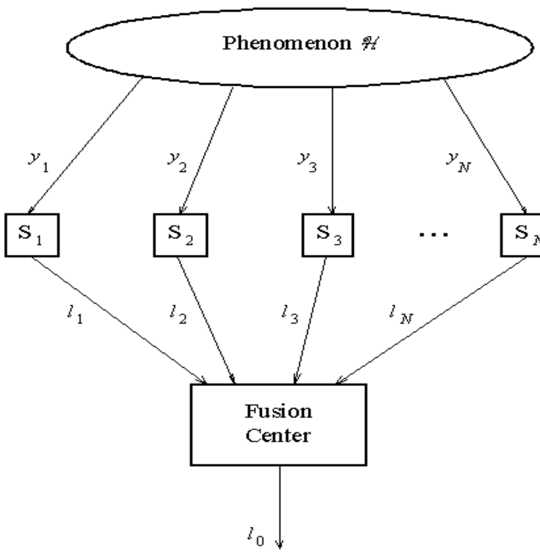

Fig.2. Parallel topology.

The Neyman-Pearson criterion can be used to find optimum local and global decision rules that minimize the global probability of miss P_M assuming that the global probability of false alarm P_F is below a given bound α [16]. For this criterion, the mapping rules used at the nodes to derive l_i and the decision rule at the fusion center are threshold rules based on likelihood ratios [18].

The thresholds used at each sensor and at the fusion center need to be determined simultaneously to minimize the probability of miss P_M under the constraint $P_F \le \alpha$. This is a difficult optimization problem since the number of fusion rules to be considered, i.e., the number of choices for thresholds, is large. The problem becomes somewhat tractable when assuming conditional independence of sensor observations and when limiting the number of quantization levels used for values of l_i . Although many studies assume l_i to be binary values, design of multilevel quantizers for distributed hypothesis testing has also been considered [16]. Increasing the number of levels improves the system performance and coding quantized values into 3 bits was shown to give a near-optimum solution, i.e., performance close to the one of the centralized system [19].

The Neyman-Pearson criterion is applicable when observation statistics under each hypothesis are completely known *a priori*. This is often not the case and probability distribution may be known approximatively or very coarsely. When detecting a target in a region, the probability distribution depends on the noise, the target emitted energy, and its position, which are unknown *a priori*. If only very coarse information about the observation is available, detection performance can be guaranteed only by nonparametric techniques. Such techniques usually make some general assumptions about observation statistics, such as symmetry of the probability density functions or continuity of the cumulative distribution functions.

4. DETECTION ALGORITHMS

Consider two target detection algorithms based on the generalized approach to signal processing in the presence of noise: value fusion and decision fusion.

Building a robust wireless sensor network for target detection requires an understanding of the agreement problem in unreliable distributed systems. As processors in such a system cooperate to achieve a specified task, they often have to agree on a piece of data that is critical to subsequent computation. Although this can be easily achieved in the absence of faulty processors, for example, by simple message exchange and voting, special protocols need to be used to reach agreement in the presence of inconsistent faults. Three problems have drawn much attention in trying to develop these protocols, namely, the consensus problem, the interactive consistency problem, and the general problem [20,21]. The consensus problem considers n processes with initial values x_i and these processes need to agree on a value

$$y = f(x_1,...,x_n) \quad , \tag{6}$$

with the goal that each non-faulty process terminates with a value $y = y_i$. The protocols for consensus need to be nontrivial, i.e., the consensus value y must depend on the initial values x_i and should not be just a constant. They also need to meet the unanimity requirement, i.e., the consensus value is $y = x$ if all non-faulty processes have the same initial value x. The interactive consistency problem is like the consensus problem with the goal that the non-faulty processes agree on a vector

$$\mathbf{y} = (y_1,...,y_n) \tag{7}$$

with $y_i = x_i$ if process y_i is non-faulty. The general problem considers one specific processor, named "general", trying to broadcast its initial value x to other processors with the requirement that all non-faulty processes terminate with identical values y and $y = x$ if the general is non-faulty.

The problem of target detection differs from previously studied problems in distributed signal detection because of the presence of faults that require special processing of the data. The problem also differs from previously studied problems in agreement in the sense that nodes sharing information may contain local information that can be totally different from one node to another. In target detection, nodes close to the target report high energy measurements, while nodes far from target report low energy measurements. Thus, in fusion, there is a lack of common truth in the measured values. Yet, it is desirable to arrive at a common value or common values and determine the impact of faults in the methods developed to arrive at consensus.

The algorithms considered are nonparametric detection algorithms based on the generalized approach to signal processing in the presence of noise, which let the nodes share their information and use a fusion rule to arrive at a decision. They use exact agreement to reach consensus, although other agreement types such as inexact agreement might be appropriate. Exact agreement guarantees that all the non-faulty nodes obtain the same set S of data and the data sent by the non-faulty nodes are part of this set. Different fusion algorithms can be derived by varying the size of the information shared between sensor nodes. Two extreme cases are explored: a) value fusion where the nodes exchange their raw energy measurements and

b) decision fusion where the nodes exchange local detection decisions based on their energy measurement [10].

Let N be the total numbers of sensors; n is the number of maximum and minimum values dropped in fault tolerant fusion; m is the number of faulty sensors in the wireless sensor network; K_v and K_d are the thresholds for value and decision fusion; P_F is the probability of false alarm; P_D is the probability of detection. According to the generalized approach to signal processing in the presence of noise [4-8], the probability distribution function of the background noise is given by

$$f(z) = \frac{1}{2\pi\sigma^2} K_0\Big(\frac{z}{2\sigma^2}\Big) \ , \tag{8}$$

where $K_0(z)$ is the modified second kind Bessel function of an imaginary argument; $z = \eta^2 - \xi^2$; ξ is the noise at the output of preliminary filter of the generalized detector and η is the noise at the output of additional filter of the generalized detector, which is uncorrelated with the noise ξ and has the same statistical parameters as the noise ξ, since the noise ξ and η are obtained at the input of the generalized detector from the common noise; in a general case, the statistical parameters of the noise ξ and η may be differed. The thresholds K_v and K_d are defined using the probability distribution function given by (8).

4.1 Value fusion

For non-fault-tolerant value fusion, false alarms occur when the average of the N values measured by the sensors is above the threshold K_v in the absence of target. The measured values contain noise and the probability of false alarm is given by

$$P_F = P\Big[\frac{1}{N}\sum_{i=1}^{N} N_i > K_v\Big] = 1 - P\Big[\frac{1}{N}\sum_{i=1}^{N} N_i \le NK_v\Big] = 1 - \Phi(NK_v) \ , \tag{9}$$

where $\Phi(z)$ is the tabulated function [23] given by

$$\Phi(z) = \frac{1}{2\pi}\int_{-\infty}^{z} K_0(0.5x)dx \ . \tag{10}$$

For non-fault-tolerant value fusion, detections occur when the average of the N values measured by the sensors is above the threshold K_v in the presence of target. The values measured consist of energy (function of the distance of the target from the sensor) plus noise and the P_D for a given position of target l is given by

$$P_D(l) = P\Big\{\frac{1}{N}\sum_{i=1}^{N}[E_i(l) + N_i] > K_v\Big\} = P\Big\{\sum_{i=1}^{N} N_i > NK_v - \sum_{i=1}^{N} E_i(l)\Big\} = 1 - \Phi\Big\{NK_v - \sum_{i=1}^{N} E_i(l)\Big\} \ . \tag{11}$$

For varying position of target, the P_D is given by

$$P_D = \Big\langle 1 - \Phi\Big\{NK_v - \sum_{i=1}^{N} E_i(l)\Big\}\Big\rangle \ , \tag{12}$$

where $\langle f(l)\rangle$ denotes the average of $f(l)$ over different positions l of the target in the region considered.

Now, let us consider the P_F and P_D in the presence of faults. The P_F given that m faults are present is determined in the worst-case scenario, i.e., m sensors report the maximum allowed value. In fault-tolerant value fusion, the n highest and n lowest values are dropped so that the decision is based on the $N-2n$ middle-range values. Let $d_i, 1 \le i \le N-2n$ be the $N-2n$ values that are not dropped (with $d_1 \le d_2 \le \cdots \le d_{N-2n}$ and $-\infty \le d_i \le +\infty$). False alarms occur when the average of d_i is above the threshold K_v. There are $\binom{N-m}{n}$ ways of choosing the n sensors that have lowest values, i.e., value less than d_1, and the probability for each of these sensors to have a value lower than d_1 is $\Phi(d_1)$. There are $\binom{N-n-m}{n-m}$ ways of choosing the $n-m$ non-faulty sensors that have highest values, i.e., values greater than d_{N-2n}, and the probability for each of these sensors to have a value greater than d_{N-2n} is $1-\Phi(d_{N-2n})$. The probability for remaining $N-2n$ sensors to have value $d_1, d_2, \ldots, d_{N-2n}$ is $f(d_1), f(d_2), \ldots, f(d_{N-2n})$ and there are $(N-2n)!$ possible permutations of these sensors (these permutations need to be considered since the values d_i are ordered). Therefore, the probability of false alarm is given by

$$P_F = \underbrace{\int_{d_1=0}^{\infty}\int_{d_2=d_1}^{\infty}\cdots\int_{d_{N-2n}=d_{N-2n-1}}^{\infty}}_{\frac{1}{N-2n}\sum_{i=1}^{N-2n} d_i \ge K_v} \binom{N-m}{n} \times \binom{N-n-m}{n-m}[1-\Phi(d_{N-2n})]^{n-m}(N-2n)! \times \prod_{j=1}^{N-2n} f(d_j)d(d_j) \ . \tag{13}$$

The P_D given that m faults are present is determined in the worse case scenario, i.e., m sensors report the minimum allowed value. In fault-tolerant value fusion, after dropping the n highest and n lowest values $N-2n$ values are left, $d_i, 1 \le i \le N-2n$ (with $d_1 \le d_2 \le \cdots \le d_{N-2n}$ and $-\infty \le d_i \le +\infty$). Detections occur when the average of values $d_i + E_i(l)$ is above the threshold K_v. Since the energy measured is a function of the position of the sensor, the P_D depends on which sensors are faulty and which non-faulty sensor values are dropped. The N sensors are divided into m faulty sensors with low values, $n-m$ non-faulty sensors with low values that are dropped, n non-faulty sensors with high values that are dropped, and $N-2n$ non-faulty sensors with middle values that are not dropped. Let $g \in \mathscr{F}_{N-m,N}$ be the combination that represents the non-faulty sensors, i.e., $\{g(i), 1 \le i \le N-m\}$ is the set of indices of non-faulty sensors and $\{g(i), N-m+1 \le i \le N\}$ is the set of indices of faulty sensors. Similarly, let $h \in \mathcal{F}_{N-m-n,N-m}$ be the combination that represents the $N-m-n$ non-faulty sensors that do not have highest values. Also, let $q \in \mathcal{F}_{N-2n,N-m-n}$ be the combination that represents the $N-2n$ remaining non-faulty sensors that do not have lowest values and let $p \in \mathcal{P}_{N-2n}$ be a permutation ordering the remaining $N-2n$ non-faulty sensors. The probability that a given set of values $\{d_i\}$ is obtained for given g, h, q, and p is [10]:

$$\prod_{i=1}^{n}\{1-\Phi[\max_{g,h,q,p}(l,d)-E_{g[h(i+N-n-m)]}(l)]\}$$
$$\times\prod_{j=1}^{n-m}\Phi[\min_{g,h,q,p}(l,d)-E_{g\{h[q(j+N-2n)]\}}(l)]\prod_{k=1}^{N-2n}f(d_k), \tag{14}$$

where

$$\max_{g,h,q,p}(l,d)=\max_{1\le i\le N-2n}\{E_{g\{h[q(p(i))]\}}(l)+d_i\}\ , \tag{15}$$

$$\min_{g,h,q,p}(l,d)=\min_{1\le i\le N-2n}\{E_{g\{h[q(p(i))]\}}(l)+d_i\}\ . \tag{16}$$

Integrating (14) over the sets $\{d_i\}$ that trigger a detection and over the possible permutations p and combinations q and h, and averaging over the different combinations of faulty sensors g and different target positions l, the P_D is given by

$$P_D=\left\langle \frac{1}{\binom{N}{n}}\sum_{g\in\mathcal{F}_{N-m,N}}\ \sum_{h\in\mathcal{F}_{N-n-m,N-m}}\ \sum_{q\in\mathcal{F}_{N-2n,N-n-m}}\right.$$
$$\times\underbrace{\int_{d_1=-\infty}^{\infty}\int_{d_2=d_1}^{\infty}\cdots\int_{d_{N-2n}=d_{n-2n-1}}^{\infty}}_{\frac{1}{N-2n}\sum_{i=1}^{N-2n}d_i\ge K_v-\frac{1}{N-2n}\sum_{i=1}^{N-2n}E_{g\{h[q(i)]\}}(l)}\ \sum_{p\in\mathcal{P}_{N-2n}}$$
$$\times\prod_{i=1}^{n}\{1-\Phi[\max_{g,h,q,p}(l,d)-E_{g[h(i+N-n-m)]}(l)]\}$$
$$\times\prod_{j=1}^{n-m}\Phi[\min_{g,h,q,p}(l,d)-E_{g\{h[q(j+N-2n)]\}}(l)]$$
$$\left.\times\prod_{k=1}^{N-2n}f(d_k)d(d_k)\right\rangle\ . \tag{17}$$

4.2 Decision fusion

Consider the P_F and P_D in the absence of faults. For decision fusion, false alarms occur when more than αN sensors have a value above the threshold K_d in the absence of target, where α is the threshold used in the case of non-fault-tolerant decision fusion. The probability that i sensors have a value above K_d is $[1-\Phi(K_d)]^i$ and the probability that the remaining $N-i$ sensors have a value below K_d is $\Phi^{N-i}(K_d)$. Since there are $\binom{N}{i}$ ways of choosing the i sensors among N sensors and i can vary from αN to N for a false alarm to occur, the probability of false alarm is given by:

$$P_F=\sum_{i=\alpha N}^{N}\binom{N}{i}\Phi^{N-i}(K_d)[1-\Phi(K_d)]^i\ . \tag{18}$$

Detection occurs when $i\ge\alpha N$ sensors have a value above the threshold K_d in the presence of a target. For a given set of detecting sensors defined by the permutation h, such that the set $\{h(j), 1\le j\le i\}$ are the indices of detecting sensors, the probability of detection is given by

$$P_D=\prod_{j=1}^{i}\{1-\Phi[K_d-E_{h(j)}(l)]\}\prod_{j=i+1}^{N}\Phi[K_d-E_{h(j)}(l)]\ . \tag{19}$$

The P_D for a given position of a target is the sum of these terms for different combinations h and different number of detecting sensors, from αN to N. The probability of detection is the average of this expression over different position l of the target in the region:

$$P_D=\left\langle\sum_{i=\alpha N}^{N}\sum_{h\in\mathcal{F}_{i,N}}\left[\prod_{j=1}^{i}\{1-\Phi[K_d-E_{h(j)}(l)]\}\right.\right.$$
$$\left.\left.\times\prod_{j=i+1}^{N}\Phi[K_d-E_{h(j)}(l)]\right]\right\rangle\ . \tag{20}$$

Now consider the P_F and P_D in the presence of faults. In the presence of m faults reporting a detection, only $\alpha N-m$ out of $N-m$ sensors need to detect for a false alarm to occur. Therefore, the probability of false alarms is given by:

$$P_F=\sum_{i=\alpha N-m}^{N-m}\binom{N-m}{i}\Phi^{N-m-i}(K_d)[1-\Phi(K_d)]^i\ . \tag{21}$$

In the presence of m faulty sensors reporting a non-detection, $\alpha N-m$ out of $N-m$ sensors need to locally detect for a global detection to occur. The P_D is averaged over the different possible sets of faulty sensors defined by combination g and is given by:

$$P_D=\left\langle\frac{1}{\binom{N}{i}}\sum_{g\in\mathcal{F}_{N-m,N}}\sum_{i=\alpha N}^{N-m}\sum_{h\in\mathcal{F}_{i,N-m}}\right.$$
$$\times\left[\prod_{j=1}^{i}\{1-\Phi[K_d-E_{g[h(j)]}(l)]\}\right.$$
$$\left.\left.\times\prod_{j=i+1}^{N-m}\Phi[K_d-E_{g[h(j)]}(l)]\right]\right\rangle\ . \tag{22}$$

5. SIMULATION RESULTS

The performance of the algorithms was evaluated using simulations in which sensor nodes were placed randomly in a region of size 20×20 unit length. To measure false alarm, no target is placed in the region. To measure probability of detection, the target is placed in a random position. The results presented here are averages of many random target placements. The number of placements simulated is determined, so as to obtain an 80% confidence that the mean found is within 10% of the actual mean, using the central limit theorem [22]. The target energy and noise models are the same as the analytical model. Simulations were performed for a variable number of sensors, variable target maximum power, and a variable number of faulty sensors. The number of values dropped, i.e., n, is chosen satisfying the bound $N \geq 3n + 1$ so that the number of values dropped does not exceed the number of faults the wireless sensor system can tolerate. The probability of false alarm and the probability of detection in the presence of faults are evaluated, given that the system does not fail. Algorithms are compared for their probability of detection at constant probability of false alarm, which depends on the values of the thresholds used in the fusion algorithms.

5.1 Non-faulty nodes

In this case, no values/decisions need to be dropped and n is set to zero. The P_D of both algorithms was measured for different P_F, number on nodes, maximum power, a decay factor as defined in (1). Figure 3 shows the average P_D for value and decision fusion as a function of the P_F for $N = 9$ and 100 and decay factors of 2 and 4. Comparison with results discussed in [10] allows us to note that under the use of the generalized approach to signal processing in the presence of noise [4-8] we can get the same performance, but at low values of maximum power, as under the use of universally adopted signal processing algorithms. We see that the superiority of value fusion over decision fusion decreases as the decay factor increases.

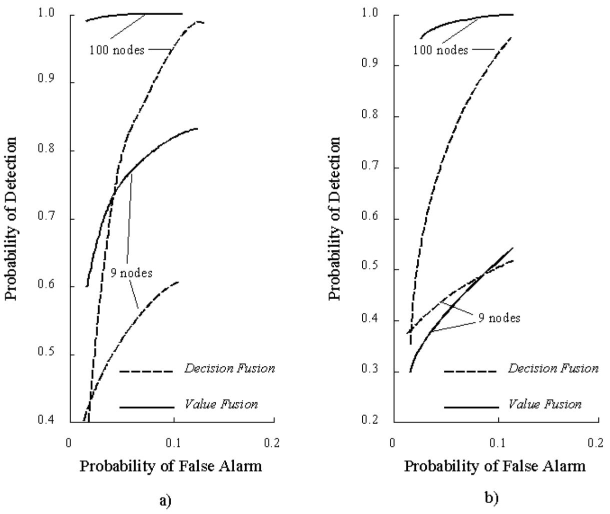

Fig. 3. Performance of value and decision fusion without faulty nodes: power 5, a) decay factor 2, and b) decay factor 4.

Value fusion lets the nodes exchange more information about the target since all the nodes obtain all the energy measurements. Furthermore, for low decay factors, the target is detectable by all or most nodes over a large region and, therefore, most of the nodes collect meaningful information about the presence of the object. Sharing this information benefits the overall performance and, therefore, value fusion is superior to decision fusion. As the energy decay factor increases, only the nodes close to the target collect meaningful information and there is no benefit for other nodes to share their information. Decision fusion becomes superior since it gives more weight to the nodes closest to the target, indeed, for the threshold parameter used, the final decision is "target present" as soon as one node locally decides that the target is present.

5.2 Faulty nodes

We assume that all nodes act consistently and the faulty nodes are consistent outliers defined as follows. In the absence of a target, a faulty node reports the highest permissible value in value fusion and a local detection in decision fusion. In the presence of a target, a faulty node reports the lowest permissible value in value fusion and a "local no detection" in decision fusion. Again, the P_D of both algorithms was measured for varying P_F, numbers of nodes, maximum power, decay factor, number of values dropped, and number of faults. Only results for constant P_F of 5% are presented. Figure 4 shows the average P_D for value and decision fusion as a function of the maximum power for 9 and 100 nodes and decay factors 2 and 4. We can see again that under the use of the generalized approach to signal processing in the presence of noise [4-8] we can get the same performance as in [10], but at low values of maximum power, as under the use of universally adopted signal processing algorithms. For the simulation, the number of values dropped is taken from the condition $N \geq 3n + 1$ and the number of faults injected is $m = n$.

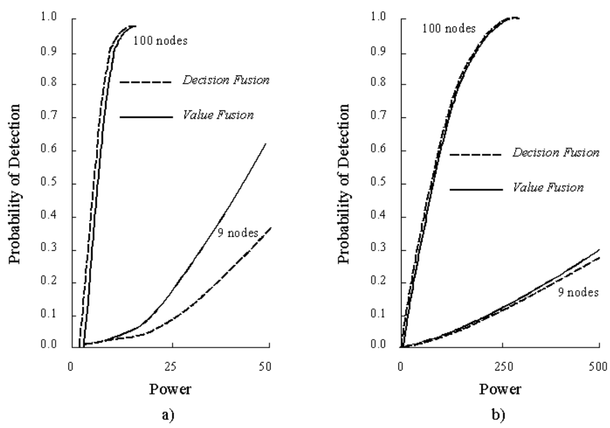

Fig. 4. Performance of value and decision fusion with faulty nodes: a) decay factor 2 and b) decay factor 4.

Analysis of performance shows that value fusion is superior to decision fusion for a small number of nodes, but decision fusion becomes superior as the number of nodes increases. For increasing decay factor, the superiority of decision fusion occurs for a large number of nodes. The difference in performance of the value and decision fusion decreases as the decay factor increases. Overall, faults have more impact on value fusion than on decision fusion. Unlike in the fault-free case, decision fusion performs better than value fusion when the P_D is 0.8 or above. This is can be explained by the fact that the value fusion algorithm often forced to discard meaningful readings from the non-faulty sensor nodes since it does not know the identity of the faulty nodes. Although decision fusion may also discard decisions by non-faulty sensor nodes, decisions contain less information than energy readings and, therefore, dropping them does not adversely impact decision fusion as much as value fusion.

6. CONCLUSIONS

We analyzed the problem of target detection by a wireless sensor network under the use of the generalized approach to signal processing in the presence of noise in a region to be monitored. A wireless sensor network model for target detection was developed, specifying the signal energy measured by the sensors, function of the target characteristics, and faulty sensor behavior. Two algorithms, value fusion and decision fusion, were identified to solve the problem. They were analyzed for their robustness to sensor nodes failure and compared for their performance and communication overhead. The use of the generalized approach to signal processing in the presence of noise allows us to obtain the same performance, but at low values of signal energy, as under the use of universally adopted signal processing algorithms. The performance comparison was performed both in the presence and in the absence of faul- ty nodes. The scope of the comparison was limited to the worst-case scenario, where all faulty nodes act consistently. Value fusion algorithms were found to perform better than decision fusion algorithms in the absence of faults. However, value fusion and decision fusion performance becomes comparable as faults are introduced in the system and decision fusion algorithm is then preferred for lower communication overhead.

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