Decentralized Detection in Clustered Sensor Networks

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We investigate decentralized detection in clustered sensor networks with hierarchical multi-level fusion. We focus on simple majority-like fusion strategies, leading to closed-form analytical performance evaluation. The sensor nodes observe a binary phenomenon and transmit their own data to an access point (AP), possibly through intermediate fusion centers (FCs). We investigate the impact of uniform and nonuniform clustering on the system performance, evaluated in terms of probability of decision error on the phenomenon status at the AP. Our results show that, under a majority-like fusion rule, uniform clustering leads to the minimum performance degradation, which depends only on the number of decision levels rather than on the specific clustered topology. We then extend our approach, taking into account the impact of spatial variations of the phenomenon, noisy communication links, and weighed fusion rules. Finally the proposed distributed detection schemes are characterized with simulation and experimental results (relative to IEEE 802.15.4-based networks), which confirm the analytical predictions.

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I. INTRODUCTION AND MOTIVATION

Distributed detection has been an active research field for a long time [1]. The increasing interest in sensor networks has spurred significant activity in the design of efficient distributed detection techniques [2–6]. In the last years, a larger and larger number of civilian applications based on this technology have been developed [7], e.g., for environmental monitoring [8].

While in typical sensor network scenarios all sensors communicate directly to an access point (AP), which acts as a collector and processes the received information, this configuration might not be feasible in scenarios with a large number of nodes or scenarios where the nodes are spread over a wide surface. In this case, the information collected by a sensor can be transferred to the AP through multiple hops, i.e., by exploiting intermediate nodes as relays. Besides the need to support multiple communications, in several scenarios the information received by a relay from sensors placed in a specific region might be redundant. For example, a sensor network could be used to monitor the average temperature of an industrial plant: each industrial machinery could be monitored by a group of sensors connected to an intermediate relay. In this case, the relay does not need to forward the information received by all sensors, but can extract a concise "picture" of the status of the monitored machinery.

The goal of this paper is the investigation of the impact of clustering on the performance of distributed detection schemes with multi-level fusion. In particular, a simple majority-like rule is used at each fusion level. This choice is motivated by the fact that we consider scenarios where the AP does not know the exact distribution of the sensors among the clusters. This is meaningful, for instance, in large networks where only local topology knowledge is feasible and where the AP might assume that all clusters have the same dimension. Moreover in dynamic sensor networking scenarios, sensors might die, and the clusters might become unbalanced. In this case, intelligent reclustering techniques can be used to improve the system performance [9]. On the other hand, if the distribution is very unbalanced (e.g., most of the sensors concentrate inside one cluster) and the AP knows the exact network topology, more refined fusion rules can be applied. The key performance indicator considered here is the probability of decision error (at the AP) on the status of the phenomenon under observation.

In order to carry out the analysis outlined in the previous paragraph, we consider network scenarios where sensors, which observe a binary phenomenon, are grouped into clusters and directly connected with local fusion centers (FCs) (one per cluster), denoted as first-level FCs. In most of this paper, we assume that the observed phenomenon is spatially constant. This is meaningful, for example, when it is of interest to detect if the phenomenon under observation (e.g., temperature, humidity, pressure) overcomes a critical threshold. However, we also investigate the impact of spatial variations of the phenomenon under observation. Each first-level FC makes a local information fusion based on the data collected from its associated sensors and then transmits its decision to the AP. Both uniform and nonuniform clustering configurations are analyzed.

The main contributions of this paper can be summarized as follows. We first introduce an analytical framework for the evaluation of the probability of decision error in a clustered sensor network scenario. While we first consider a network scenario with ideal communication links between sensors and first-level FCs, we then extend our analysis to encompass the presence of noisy communication links between sensors and first-level FCs. For simplicity, a noisy link is modeled as a binary symmetric channel (BSC) [10–14]. In general a BSC might not be the best modelling choice for a wireless communication link, which might experience (block) fading [15–18]. However in the presence of memoryless communication channels, the use of a crossover probability p is accurate. More precisely, p can be given a precise expression depending on the type of channel (with additive white Gaussian noise (AWGN) or bit-by-bit independent fading). The use of a more refined channel model is expedient to devise joint detection/decoding/fusion strategies, which can avoid the information loss due to the presence of hard-detection before fusion [19]. The analytical framework proposed here can be extended to incorporate these strategies. Through an OPNET-based simulator [20], we obtain performance results in more realistic Zigbee [21] clustered network scenarios. These simulation results confirm the theoretical performance results, which are further verified by experimental results based on the use of MicaZ nodes [22]. Our findings suggest that uniform clustering techniques, combined with simple majority-like (intermediate and final) fusion rules, are to be preferred in terms of robustness against spatial variations of the phenomenon and observation/communication noises. On the other hand, weighed fusion strategies can improve the system performance, provided that the observation/communication quality are jointly taken into account.

This paper is structured as follows. In Section II we comment on the literature related to the material presented in this paper. In Section III we propose, after a few preliminaries on decentralized detection, an analytical framework for the evaluation of the probability of decision error at the AP in various clustered scenarios. In Section IV simulation and experimental results relative to realistic (IEEE 802.15.4-based) clustered wireless networks with data fusion are presented. In Section V, the main results obtained in this paper are discussed, and concluding remarks are given.

II. RELATED WORK

Several communication-theoretic approaches to decentralized detection have been proposed [23, 24]. In [25], the author considers minimum mean-square error (MMSE) parameter estimation in sensor networks. In [26], the authors analyze, according to the same MMSE criterion, the problem of joint decoding of correlated data in sensor networks. They show that an MMSE decoder is not feasible for large-scale sensor networks and propose an approach based on decoding over factor graphs [27]. In [28], MMSE-based algorithms to estimate a spatially nonconstant phenomenon are proposed. Use of censoring algorithms at the sensors has also been studied for the design of decentralized detection schemes [29]. In [30], the authors analyze aspects related to compression of observed data (using distributed source coding) and data transmission. In [31], the authors follow a Bayesian approach for the minimization of the probability of decision error and study optimal fusion rules. Most of the proposed approaches are not immediately applicable to realistic sensor networks because of the common assumption of ideal communication links between the sensors and the AP. However in a realistic (e.g., wireless) sensor network scenario, the communication links are likely to be noisy [32]. The impact of noisy communication links on the design of optimal fusion rules is evaluated in [10–14]. Information-theoretic approaches have also been proposed for the study of sensor networks with decentralized detection. In [33], the authors propose a framework to characterize a sensor network in terms of its entropy and false alarm/missed detection probabilities [34]. Other information-theoretic-based approaches can be found in [35, 36].

III. ANALYTICAL FRAMEWORK

We consider a network scenario where N sensors observe a common binary phenomenon whose status is defined as follows:

$$H = \begin{cases} H_0 & \text{with probability } p_0 \\ H_1 & \text{with probability } 1 - p_0 \end{cases}$$

where $p_0 \triangleq P(H = H_0)$. The sensors are clustered into $n_c < N$ groups, and each sensor can communicate only with its local first-level FC. The first-level FCs collect data from the sensors in their corresponding clusters and make local decisions on the status of the binary phenomenon. In a scenario with two levels of information fusion, each local FC transmits to the AP, which makes the final decision. A logical

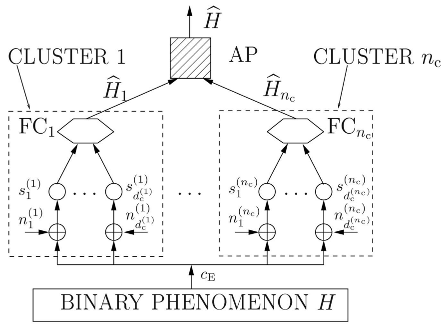

Fig. 1. Block diagram of clustered sensor network with decentralized binary detection and two decision levels.

representation of this architecture is shown in Fig. 1. The observed signal at the ith sensor can be expressed as

$$r_i = c_E + n_i, \qquad i = 1, \ldots, N \tag{1}$$

where

$$c_E \triangleq \begin{cases} 0 & \text{if} \quad H = H_0 \\ s & \text{if} \quad H = H_1 \end{cases}$$

and $\{n_i\}$ are additive noise samples. Note that s is considered as a known parameter. Assuming that the noise samples $\{n_i\}$ are independent with the same Gaussian distribution $\mathcal{N}(0, \sigma^2)$, the common signal-to-noise ratio (SNR) at the sensors, denoted as $\text{SNR}_{\text{sensor}}$, can be defined as [31]

$$\text{SNR}_{\text{sensor}} \triangleq \frac{s^2}{\sigma^2}.$$

Each sensor makes a decision comparing its observation r_i with a threshold value τ_i and computes a local decision $u_i = U(r_i - \tau_i)$, where $U(\cdot)$ is the unit step function. In order to optimize the system performance, the thresholds $\{\tau_i\}$ need to be optimized. In particular, in a more general scenario where the type of event perceived by the sensor might vary, a more refined per-cluster optimization of the sensor decision threshold could be considered. However since we are interested in monitoring a spatially constant binary phenomenon, we consider a simpler optimization approach where the same threshold is used at all sensors. While in a scenario with no clustering and ideal communication links between the sensors and the AP the relation between the optimized value of τ and s is well known [31], in the presence of clustering it is not. In the following, the value of τ is optimized in all considered scenarios, for given SNR and clustering configuration, in order to minimize the probability of decision error.

In a scenario with noisy communication links, modeled as BSCs, the decision u_i sent by the ith sensor can be flipped with a probability corresponding to the crossover probability of the BSC model and denoted as p [14]. The received bit at the fusion point (either an FC for clustered networks or directly the AP in the absence of clustering), referred to as $u_i^{(r)}$, can be expressed as

$$u_i^{(r)} = \begin{cases} u_i & \text{with probability } 1 - p \\ 1 - u_i & \text{with probability } p. \end{cases}$$

In the presence of noisy links, the value of the optimized local threshold τ, fixed for all sensors, might be different from that in a scenario with ideal communication links. Therefore a different optimized value of τ is needed, as outlined at the end of the previous paragraph.

We point out that the specific topologies of the considered networks are not explicitly taken into account. For instance, the distances between nodes are not explicitly mentioned. This corresponds to the assumption of modelling all noisy communication links as BSCs with the same crossover probability. In order to extend our analytical framework while still keeping the simple BSC-based link modelling, one can consider different crossover probabilities (they could be associated with a specific network topology). This motivates the use of weighing fusion schemes, where the decisions to be fused together are weighed by the corresponding link qualities. The impact of this weighing fusion strategy is investigated in Section IIIE.

A. Uniform Clustering

In Fig. 2(c), the logical structure of a sensor network with three decision levels is illustrated. For comparison, in the same figure the schemes with (a) no clustering and (b) two-decision-level uniform clustering are also shown. One should note that Fig. 2(b) is logically equivalent to the network schemes shown in Fig. 1. We focus our analytical derivation on a three-level scenario. However, our approach can be easily extended to a generic number of decision levels.

In a three-decision-level scenario, the N sensors observe a common binary phenomenon H and send their decisions $\{u_i\}$ to the n_{c_1} first-level FCs. Each of the n_{c_1} first-level clusters contains d_{c_1} ($N = n_{c_1} \cdot d_{c_1}$) sensors connected to the associated first-level FC. We preliminarily define the majority-like fusion rule as

$$\Gamma(x_1, \ldots, x_M, k) \triangleq \begin{cases} 0 & \text{if} \quad \sum_{m=1}^{M} x_m < k \\ 1 & \text{if} \quad \sum_{m=1}^{M} x_m \geq k \end{cases} \tag{2}$$

where $x_1, \ldots, x_M$ are the M binary data ($x_m \in \{0, 1\}$) to be fused together, and $k \in \{0, \ldots, M\}$ is the decision threshold.

The jth ($j = 1, \ldots, n_{c_1}$) first-level FC makes a first information fusion and computes the following local decision:

$$h_j = \Gamma(u_1^{(j)}, \ldots, u_{d_{c_1}}^{(j)}, k_1) \tag{3}$$

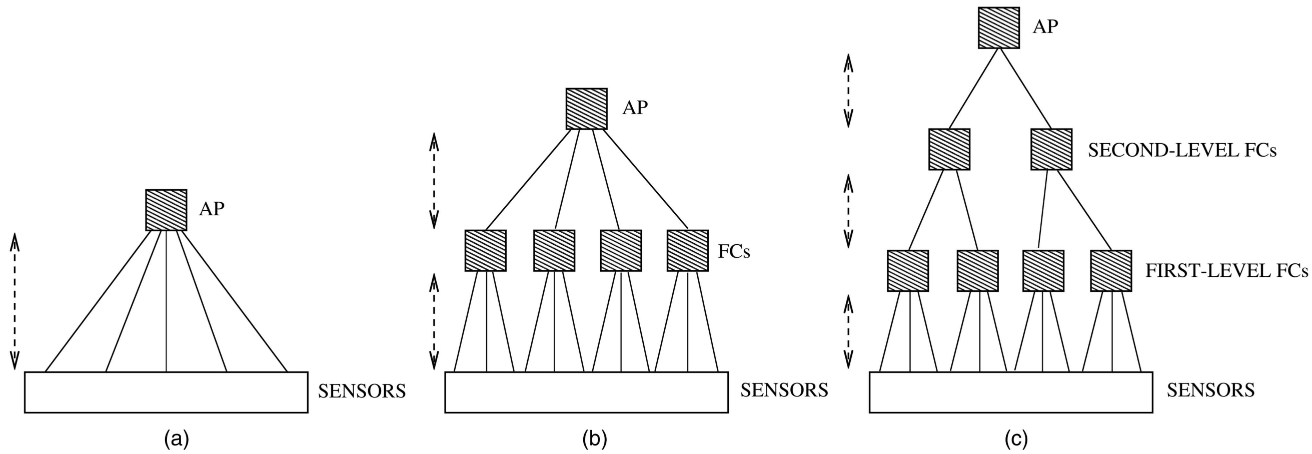

Fig. 2. Basic structures for sensor networks with decentralized detection. Three cases are shown. (a) Absence of clustering. (b) Uniform clustering with two levels of information fusion. (c) Uniform clustering with three levels of information fusion.

where $k_1 = \lfloor d_{c_1}/2 \rfloor + 1$ is the decision threshold at the first-level FCs. After the decisions at the first-level FCs are made, they are sent to the n_{c_2} second-level FCs, each of which is connected to d_{c_2} first-level FCs, with $n_{c_1} = n_{c_2} \cdot d_{c_2}$. We point out that the majority fusion rule (2) with decision threshold $k = \lfloor M/2 \rfloor + 1$ is exact for odd values of M. For even values of M, the proposed fusion strategy tends to favor a final decision equal to '0.' However for sufficiently large values of N, this unbalancing is negligible.

The second-level FCs perform another information fusion, and compute local decisions using the following majority-like rule:

$$\hat{H}_r = \Gamma(h_1^{(r)}, \ldots, h_{d_{c_2}}^{(r)}, k_2) \tag{4}$$

where $r = 1, \ldots, n_{c_2}$, and $k_2 = \lfloor d_{c_2}/2 \rfloor + 1$ is the decision threshold at the second level FCs. Finally the decisions are sent to the AP, which makes the final decision

$$\hat{H} = \Gamma(\hat{H}_1, \ldots, \hat{H}_{n_{c_2}}, k_f) \tag{5}$$

where $k_f = \lfloor n_{c_2}/2 \rfloor + 1$ is the AP decision threshold. Using a combinatorial approach (based on the repeated trials formula [37]) and taking into account the decision rules (3)–(5), the probability of decision error at the AP can be expressed as follows:

$$\begin{aligned} P_e = {} & p_0 \text{bin}(k_f, n_{c_2}, n_{c_2}, \text{bin}(k_2, d_{c_2}, d_{c_2}, \text{bin}(k_1, d_{c_1}, d_{c_1}, Q(\tau)))) \\ & + (1-p_0)\text{bin}(0, k_f - 1, n_{c_2}, \text{bin}(k_2, d_{c_2}, d_{c_2}, \\ & \times \text{bin}(k_1, d_{c_1}, d_{c_1}, Q(\tau - s)))) \end{aligned} \tag{6}$$

where $Q(x) \triangleq \int_x^\infty (1/\sqrt{2\pi}) \exp(-y^2/2) dy$ and

$$\text{bin}(a, b, n, z) \triangleq \sum_{i=a}^{b} \binom{n}{i} z^i (1-z)^{(n-i)} \tag{7}$$

where $a, b, n \in \mathbb{N}$ and $z \in (0,1)$. If $n_c = k_f = 1$ and $d_c = N$, i.e., there is no clustering, the probability of decision error (6) reduces to that derived in [14].

B. Nonuniform Clustering

Assuming for the sake of simplicity a two-level sensor network topology, the probability of decision error in a generic scenario with nonuniform clustering can be evaluated as follows. Define the cluster size vector $\mathcal{D} \triangleq \{d_c^{(1)}, d_c^{(2)}, \ldots, d_c^{(n_c)}\}$, where $d_c^{(i)}$ is the number of sensors in the ith cluster ($i = 1, \ldots, n_c$) and $\sum_{i=1}^{n_c} d_c^{(i)} = N$. Furthermore define also the following two probability vectors:

$$\mathcal{P}^{1|1} \triangleq \{p_1^{1|1}, p_2^{1|1}, \ldots, p_{n_c}^{1|1}\}$$

$$\mathcal{P}^{1|0} \triangleq \{p_1^{1|0}, p_2^{1|0}, \ldots, p_{n_c}^{1|0}\}$$

where $p_\ell^{1|1}$ ($p_\ell^{1|0}$, respectively) is the probability that the ℓth FC decides for H_1 when H_1 (H_0, respectively) has happened. We still consider the use of a common threshold τ at the sensors. The elements of $\mathcal{P}^{1|1}$ (equivalently, the elements of $\mathcal{P}^{1|0}$) are, in general, different from each other and depend on the particular distribution of the sensors among the clusters. In Appendix I, it is shown that the probability of decision error can be expressed as follows:

$$\begin{aligned} P_e = {} & p_0 \sum_{i=k_f}^{n_c} \sum_{j=1}^{\binom{n_c}{i}} \prod_{\ell=1}^{n_c} \{c_{i,j}(\ell) p_\ell^{1|0} + (1 - c_{i,j}(\ell))(1 - p_\ell^{1|0})\} \\ & + (1-p_0) \sum_{i=0}^{k_f - 1} \sum_{j=1}^{\binom{n_c}{i}} \prod_{\ell=1}^{n_c} \{c_{i,j}(\ell) p_\ell^{1|1} + (1 - c_{i,j}(\ell))(1 - p_\ell^{1|1})\} \end{aligned} \tag{8}$$

where $\mathbf{c}_{i,j} = (c_{i,j}(1), \ldots, c_{i,j}(n_c))$ is a vector which designates the jth configuration of the decisions from the first-level FCs in a case with i 1s (and, obviously, $n_c - i$ 0s). In Table I, the possible configurations of $\mathbf{c}_{i,j}$ are shown in the presence of $n_c = 3$ clusters. For example, $\mathbf{c}_{1,2}$ is the second possible configuration with one 1 (and two 0s): the 1 is the decision of the second FC. The proposed approach can be extended to a scenario with a generic number of fusion levels.

TABLE I
Possible Configurations of $\mathbf{c}_{i,j}$ in a Scenario with $n_c = 3$ Clusters

i	j	$\mathbf{c}_{i,j}$
0	1	000
1	1	100
	2	010
	3	001
2	1	110
	2	101
	3	011
3	1	111

We remark that a scenario with uniform clustering can be interpreted as a special case of a generic nonuniform scenario. In this case, in fact, the elements of the three vectors $\mathcal{D}$, $\mathcal{P}^{1|1}$, and $\mathcal{P}^{1|0}$ become equal, i.e.,

$$d_c^{(i)} = d_c$$
$$p_i^{1|1} = \mathrm{bin}(k, d_c, d_c, Q(\tau - s))$$
$$p_i^{1|0} = \mathrm{bin}(k, d_c, d_c, Q(\tau))$$

$\forall i = 1, \ldots, n_c$. It can be shown that (8) reduces to (6) in the presence of uniform clustering and two decision levels.

C. Scenarios with Noisy Communication Links

In a scenario with nonuniform clustering and two decision levels, the probability of decision error can be derived from (8) by replacing the probabilities $\{p_\ell^{1|i}\}_{\ell=1,\ldots,n_c}^{i=0,1}$ with the probabilities $\{p_{\ell,\mathrm{noisy}}^{1|i}\}_{\ell=1,\ldots,n_c}^{i=0,1}$, which take into account the noise in the communication links between sensors and first-level FCs and are defined as

$$p_{\ell,\mathrm{noisy}}^{1|0} \triangleq \sum_{m=k_\ell}^{d_c^{(\ell)}} \binom{d_c^{(\ell)}}{m} P_{c_0}^m P_{e_0}^{d_c^{(\ell)}-m} \qquad (9)$$

$$p_{\ell,\mathrm{noisy}}^{1|1} \triangleq \sum_{m=k_\ell}^{d_c^{(\ell)}} \binom{d_c^{(\ell)}}{m} P_{c_1}^m P_{e_1}^{d_c^{(\ell)}-m}. \qquad (10)$$

In (9), $P_{c_0} = 1 - P_{e_0}$ is the probability that a sensor decision sent to a first-level FC is in favor of H_1 when H_0 has happened; it can be expressed, according to the BSC model for a noisy communication link, as

$$P_{c_0} = Q(\tau)(1-p) + [1 - Q(\tau)]p. \qquad (11)$$

Similarly in (10), $P_{c_1} = 1 - P_{e_1}$ represents the probability that a decision sent by a sensor to a first-level FC is in favor of H_1 when H_1 has happened; it can be given the following expression:

$$P_{c_1} = Q(\tau - s)(1-p) + [1 - Q(\tau - s)]p. \qquad (12)$$

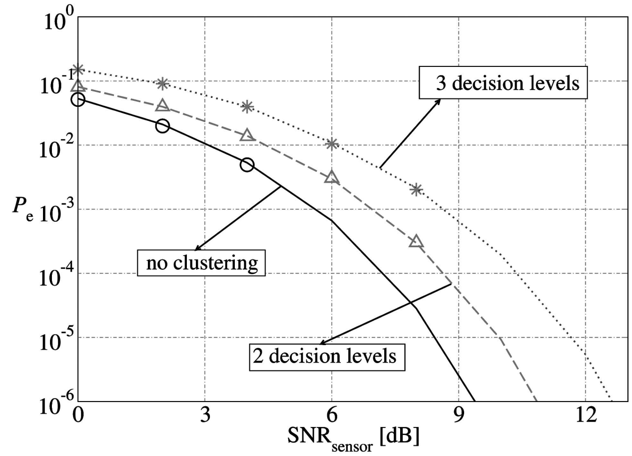

Fig. 3. Probability of decision error as function of sensor SNR in scenario with equal a priori probabilities of phenomenon ($p_0 = p_1 = 1/2$), $N = 16$ sensors, and uniform clustering.

Finally the probability of decision error in a scenario with noisy communication links becomes

$$P_e = p_0 \sum_{i=k_f}^{n_c} \sum_{j=1}^{\binom{n_c}{i}} \prod_{\ell=1}^{n_c} \{c_{i,j}(\ell) p_{\ell,\mathrm{noisy}}^{1|0} + (1 - c_{i,j}(\ell))(1 - p_{\ell,\mathrm{noisy}}^{1|0})\}$$
$$+ (1 - p_0) \sum_{i=0}^{k_f - 1} \sum_{j=1}^{\binom{n_c}{i}} \prod_{\ell=1}^{n_c}$$
$$\times \{c_{i,j}(\ell) p_{\ell,\mathrm{noisy}}^{1|1} + (1 - c_{i,j}(\ell))(1 - p_{\ell,\mathrm{noisy}}^{1|1})\}. \qquad (13)$$

In this case as well, the proposed approach can be extended to scenarios with a generic number of fusion levels.

D. Numerical Results: Ideal Communication Links

In Fig. 3, the probability of decision error is shown as a function of the sensor SNR in the case with $N = 16$ sensors, considering two and three decision levels. In the scenario with two decision levels, the following topologies are possible:

1) 8-8 (2 clusters with 8 sensors each);
2) 4-4-4-4 (4 clusters with 4 sensors each);
3) 2-2-2-2-2-2-2-2 (8 clusters with 2 sensors each).

For a three decision level scenario, the following topologies are considered:

1) 4-4-4-4/2-2 (4 first-level FCs, each connected with 4 sensors, and 2 second-level FCs, each connected with 2 first-level FCs);
2) 2-2-2-2-2-2-2-2/4-4 (8 first-level FCs, each connected with 2 sensors, and 2 second-level FCs, each connected with 4 first-level FCs);
3) 2-2-2-2-2-2-2-2/2-2-2-2 (8 first-level FCs, each connected with 2 sensors, and 4 second-level FCs, each connected with 2 first-level FCs).

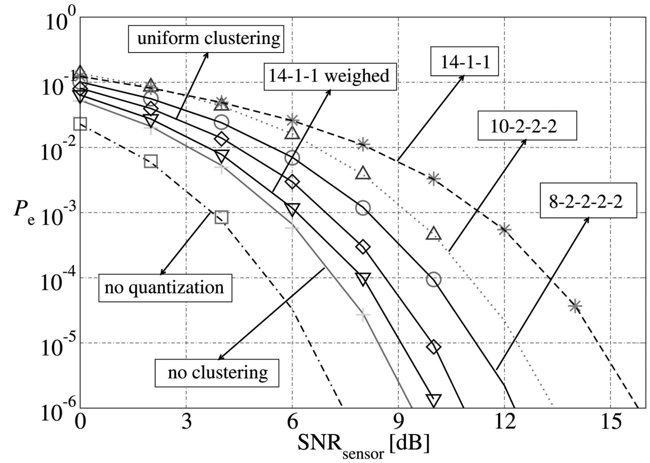

Fig. 4. Probability of decision error as function of sensor SNR in scenario with equal a priori probabilities of observed phenomenon ($p_0 = p_1 = 1/2$) and $N = 16$ sensors. Various configurations are considered.

Lines (solid, dashed, and dotted) and symbols (circles, triangles, and stars) correspond to analytical and simulation results, respectively. For comparison, the probability of a decision error with no clustering is also shown.

In Fig. 3, only one curve is shown for the scenario with two levels of information fusion since the performance curves associated with all possible configurations (i.e., 8-8, 4-4-4-4, 2-2-2-2-2-2-2-2) overlap. This implies that one can choose between a uniform network topology with a small number of large clusters and a uniform network topology with a large number of small clusters, still guaranteeing the same performance level. The intuition behind this result is the following. If one considers an architecture with small clusters, then fusion at the first-level FCs is not effective. However, many local cluster decisions are then fused together, and this allows us to recover (partially) the first-level information loss. On the other hand, considering large clusters leads to more reliable local first-level decisions. However, a few of them are then fused together, so that the supplementary (higher level) refinement is not relevant. Similar considerations also hold for a three-decision-level scenario.

Comparing the performance in the absence of clustering with that in the presence of uniform clustering (with either two or three decision levels), one can conclude that the larger the number of decision levels is, the worse the performance. This is intuitive since a larger number of decision levels corresponds to a larger number of partial information losses corresponding to the fusion operations.

In order to evaluate the impact of nonuniform clustering, we consider a scenario with $N = 16$ sensors and various nonuniform network topologies. In Fig. 4, the probability of decision error is shown as a function of the sensor SNR, considering no clustering, two-level uniform clustering, and various configurations with two decision levels and nonuniform clustering (explicitly indicated). For comparison, the curve in the absence of quantization at the sensors is also shown. The lines correspond to analytical results, whereas symbols are associated with simulations. In the scenarios with nonuniform clustering, the considered configurations are 8-2-2-2-2 (5 clusters, out of which 4 contain 2 nodes, and 1 contains 8 nodes), 10-2-2-2, and 14-1-1. As one can see from Fig. 4, in the presence of majority-like information fusion, the higher the nonuniformity degree among the clusters, i.e., the more unbalanced the clustering, the worse the system performance is. In unbalanced scenarios, however, one may use more sophisticated fusion rules. In Fig. 4, the performance for a weighed fusion scheme for the 14-1-1 case is also shown. The weighed fusion is implemented by weighing each decision with a weight proportional to the number of sensors in the corresponding cluster. More precisely, the decision from the 14-node cluster is weighed by 14/16, and the decisions from the 1-node clusters are weighed by 1/16. As one can see, using a more refined fusion rule leads to better performance: at $P_e = 10^{-4}$, a sensor SNR gain equal to 5.5 dB can be obtained. This is to be expected since the weighed fusion rule is basically equivalent to considering a nonclustered 14-node sensor network. In fact the obtained performance is between that of the nonclustered 16-node sensor network and that of a uniformly clustered scheme. However, the use of a weighed fusion rule requires that the AP know the exact distribution of the sensors among the clusters, while here, we are interested in scenarios where this does not hold.

As mentioned at the beginning of Section III, it is of interest to understand the impact of phenomenon spatial variations on the system performance. As a measure of their impact, we denote as χ the percentage of the total number of sensors which observe a "flipped" status of the phenomenon with respect to the status sensed by the other nodes. For instance, if $H = H_0$ ($H = H_1$, respectively), χ% of the N sensors (randomly chosen across all clusters) observe H_1 (H_0, respectively). In Fig. 5, the probability of decision error is shown as a function of χ in a scenario with $N = 64$ sensors, SNR$_{sensor}$ = 4 dB, and ideal communication links. The following sensor network architectures are considered: 1) no clustering, 2) uniform clustering (with 2, 4, or 8 clusters), and 3) nonuniform clustering (with the topologies 56-4-4, 40-8-8-8, or 32-8-8-8-8). Obviously the performance degrades if the number of "faulty" sensors, i.e., the number of sensors observing a different status, increases. Moreover although this performance degradation can be observed in all scenarios, it is more pronounced in the scenarios with nonuniform clustering rather than in the scenarios with uniform

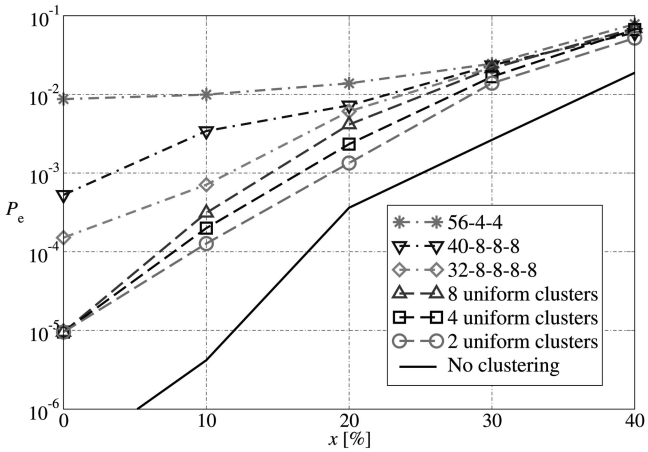

Fig. 5. Probability of decision error as function of χ in scenario with $N = 64$ sensors, $\mathrm{SNR}_{\mathrm{sensor}} = 4$ dB, and ideal communication links. Various sensor network architectures are considered.

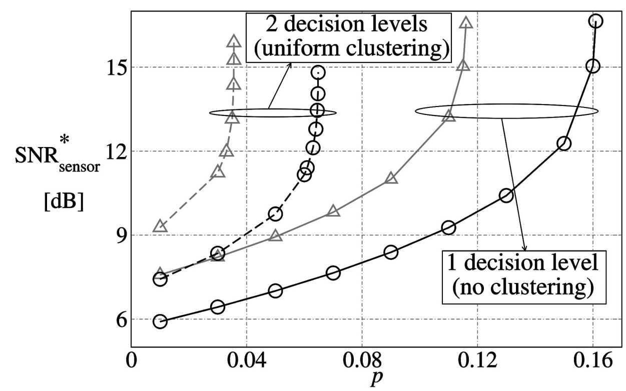

Fig. 6. Minimum sensor SNR required to obtain desired QoS in scenarios with noisy communication links in the cases 1) without clustering and 2) with uniform clustering and two decision levels. Two possible QoS are considered: 1) $P_e^* = 10^{-3}$ (lines with circles) and 2) $P_e^* = 10^{-4}$ (lines with triangles).

clustering. This is due to the fact that in nonuniformly clustered scenarios, the presence of "faulty" sensors in very small clusters has a more detrimental impact on the quality of the decisions taken at the corresponding first-level FCs.

E. Numerical Results: Noisy Communication Links

In order to investigate how the probability of decision error behaves as a function of the communication noise level, i.e., the crossover probability p, we introduce a communication-theoretic quality of service (QoS) condition in terms of the maximum tolerable probability of decision error, denoted as P_e^*. This physical layer-oriented QoS condition can be written as

$$P_e \leq P_e^*. \tag{14}$$

Since the probability of decision error is a monotonically decreasing function of the sensor SNR, the QoS condition (14) can be equivalently rewritten as

$$\mathrm{SNR}_{\mathrm{sensor}} \geq \mathrm{SNR}^*_{\mathrm{sensor}}$$

where $\mathrm{SNR}^*_{\mathrm{sensor}}$ depends on P_e^*. It is then possible to evaluate the performance under a desired QoS constraint, given by the maximum tolerable probability of decision error P_e^*.

In Fig. 6, the value of the minimum sensor SNR required to guarantee P_e^*, i.e., $\mathrm{SNR}^*_{\mathrm{sensor}}$, is shown as a function of the crossover probability p, in scenarios 1) without clustering and 2) with clustering and two decision levels, respectively. Two possible values for P_e^* are considered: 1) 10^{-3} (curves with circles) and 2) 10^{-4} (curves with triangles). As expected, when the noise level increases, the minimum sensor SNR required to guarantee the desired network performance also increases. In fact since communications become less reliable, a higher accuracy in the observation phase is needed in order to maintain the same overall performance. Besides, one can observe that there exists a vertical asymptote in each curve in Fig. 6. In other words there exists a critical value p_{crit} of the noise level such that 1) for $p < p_{\mathrm{crit}}$, the sensor network is operative, i.e., there exists a finite value of the sensor SNR which satisfies the desired QoS condition (14) and 2) for $p > p_{\mathrm{crit}}$ instead, the network is not operative, i.e., it is not possible to achieve the desired performance level regardless of the value of the sensor SNR.

In the presence of varying communication link quality, the use at the first-level FCs of weighing fusion algorithms, which take into account the qualities of the communication links, can improve the system performance. For the sake of simplicity and illustrative purposes, we assume that the BSC communication links have the same average crossover probability, denoted as $\bar{p}$, while the actual crossover probability of the ith link, denoted as p_i, is uniformly distributed in $[\bar{p} - \eta\bar{p}, \bar{p} + \eta\bar{p}]$, where[1] $\eta \in (0, \min\{1, (1/2\bar{p}) - 1\})$. At this point the first-level FC decision in a cluster containing d_c sensors, denoted as $\hat{H}_{\mathrm{level\ 1}}$, is obtained by thresholding a weighed version of the decisions received from the sensors, i.e.,

$$\sum_{i=1}^{d_c} y_i \times \frac{1 - p_i}{\sum_{j=1}^{d_c}(1 - p_j)} \underset{\hat{H}_{\mathrm{level\,1}} = H_1}{\overset{\hat{H}_{\mathrm{level\,1}} = H_1}{\gtrless}} 0 \tag{15}$$

where $y_i \triangleq 2u_i^{(\mathrm{r})} - 1$, and $u_i^{(\mathrm{r})}$ is the decision received from the ith sensor, $i = 1, \ldots, d_c$. The rationale behind (15) is that the decisions from more reliable links are taken into account with a higher weight, whereas the decisions from less reliable links are taken into account with a lower weight.

In Fig. 7, the probability of decision error is shown as a function of η in a scenario with $N = 16$ sensors and uniform clustering (with 2 or 4 clusters),

[1]The maximum allowed value for η comes from the fact that it must hold that $(\bar{p} - \eta\bar{p}) > 0$ (i.e., $\eta < 1$) and $(\bar{p} + \eta\bar{p}) < 1$ (i.e., $\eta < (1/2\bar{p}) - 1$).

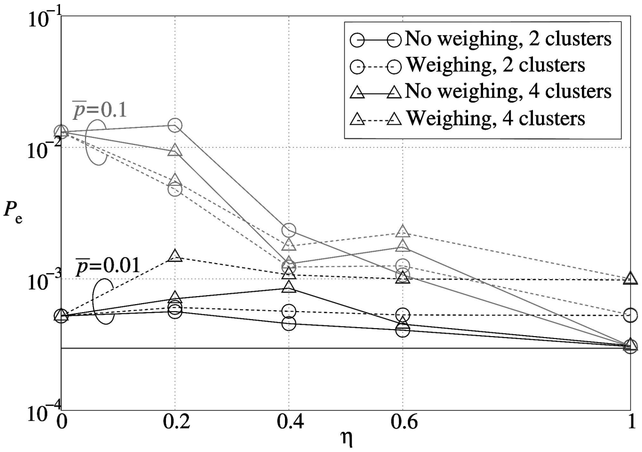

Fig. 7. Probability of decision error as function of η in scenario with $N = 16$ sensors, uniform clustering (with 2 or 4 clusters), and sensor SNR set to 8 dB. Two possible values for average crossover probability are considered: 1) $\bar{p} = 0.1$ and 2) $\bar{p} = 0.01$.

considering a sensor SNR equal to 8 dB. Two possible values for the average crossover probability are considered: 1) $\bar{p} = 0.1$ and 2) $\bar{p} = 0.01$. As a reference, a horizontal line corresponding to the probability of decision error with ideal communication links is also shown. The following comments can be carried out. One can immediately observe that various uniform clustering topologies (for the same value of N) behave differently for $\eta > 0$ (i.e., for variable quality of the communication links). Therefore the conclusion reached in Section IIID (i.e., the fact that different uniformly clustered scenarios have the same performance) holds only when a majority fusion rule is used. Moreover, while in a scenario with mild communication noise ($\bar{p} = 0.01$), the use of weighed fusion leads to a performance degradation, with respect to schemes which use a simple majority fusion rule, in a scenario with strong communication noise ($\bar{p} = 0.1$), a varying communication link quality ($\eta > 0$) leads, regardless of the fusion strategy, to a performance improvement. Finally, for $\eta = 1$ there is convergence to specific limiting values. More precisely, all clustered configurations with majority fusion are characterized by a probability of decision error equal to that in the presence of ideal communication links. In the presence of weighed fusion, the limiting probability of decision error depends on the clustering configuration, regardless of the average crossover probability.

IV. CLUSTERED REALISTIC NETWORKS

In this section we present simulation and experimental results which validate our analytical framework in practical sensor networking scenarios, where nodes comply with the Zigbee (simulation results) or IEEE 802.15.4 (experimental results) standards.

A. Simulations

The simulations have been carried out with the Opnet Modeler simulator [20] and a built-in Zigbee network model designed at the National Institute of Standards and Technologies (NIST) [38]. This model provides only the first two layers of the ISO/OSI stack, and we have extended it with a simple Opnet model for an FC, which, in addition to providing relaying functionalities, implements the intermediate data fusion mechanisms described in the previous sections. Our Opnet model assumes strong line-of-sight communications between the sensors and the FCs and between the FCs and the coordinator.

According to the theoretical analysis, the sensors make a noisy observation (affected by AWGN) of a randomly generated binary phenomenon H and make local decisions on the status of the phenomenon. Subsequently the sensors embed their decisions into proper data packets of length 216 bits,[2] which are sent either to the coordinator (in the absence of clustering) or to the first-level FCs (in the presence of clustering). The decisions are assumed to be either 0 (no phenomenon) or 1 (presence of the phenomenon). Obviously if some packets are lost due to medium access collisions, decisions (either at the FCs or at the AP) are made only on the received packets (this leads to a reduced reliability of the decisions). If all the packets related to a set of observations of the same phenomenon are lost instead, the final binary decision is random. Finally if half of the decisions are in favor of one phenomenon status and the other half are in favor of the other, the coordinator decides for the presence of the phenomenon. More details about the implementation of the data fusion mechanism in Opnet can be found in [39].

In both scenarios it is possible to evaluate, by simulation, the probability of decision error. Together with the probability of decision error, the simulator allows us to evaluate the 1) packet delivery fraction, denoted as ξ and defined as the ratio between the number of packets correctly delivered at the coordinator and the number of packets sent by the sensors, and 2) the delay, defined as the time interval between the transmission instant and the reception instant of a generic packet. The last parameter that we have considered is the aggregate throughput (dimension: [pck/s]), defined as $S_{agg} = N \cdot g \cdot \xi$, where N is the number of transmitting sensors and g is the packet generation rate (set to 2 pck/s in all simulation results presented in the remainder of this section). Moreover no acknowledgement (ACK) messages are used to confirm successful transmissions. Results on network performance with the use of ACK messages are presented in [39].

[2]This length corresponds to a payload of 96 bits and a header of 120 bits introduced by physical and media access control (MAC) layers.

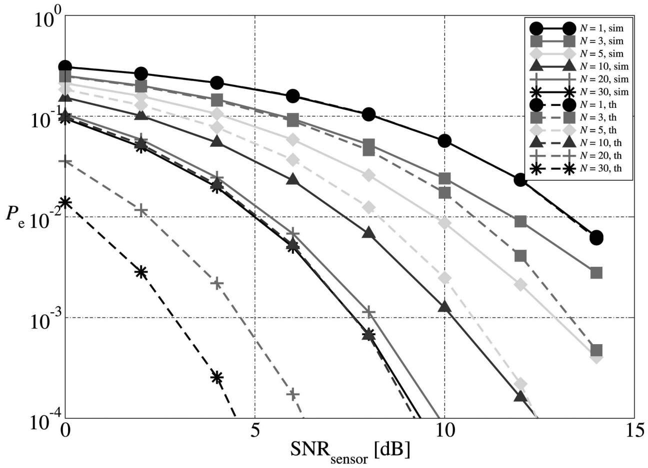

Fig. 8. Probability of decision error as function of SNR at sensors in scenarios without clustering. Results are obtained both with simulations (solid lines) and with theoretical analysis (dashed lines).

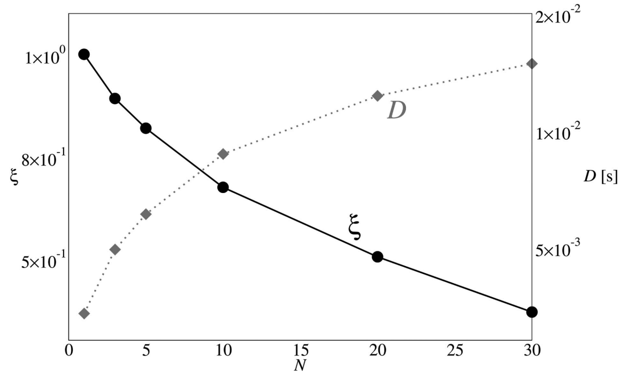

Fig. 9. Performance analysis in scenario without clustering: packet delivery fraction and delay performance as functions of number N of transmitting sensors.

TABLE II
Aggregate Throughput Performance in a Scenario without Clustering as a Function of the Number of Transmitting Sensors

N	S_{agg} [pck/s]
1	2
3	5.35156158
5	8.1906672
10	13.4860858
20	20.1639324
30	22.1357394

In Fig. 8, scenarios without clustering are considered and the probability of decision error is shown as a function of the observation SNR. In order to eliminate possible statistical fluctuations, each simulation performance point is obtained by averaging the results of ten Opnet simulation runs. For each network configuration, in the same figure we show the simulation results (solid lines) and the corresponding analytical results (dashed lines). Since the theoretical framework does not take into account the medium access strategy, analytical and simulation performance results are identical only in the scenario with $N = 1$. In the other scenarios the probability of decision error predicted by the analytical framework is better than that predicted by the simulations. This degradation becomes more and more pronounced for an increasing numbers of nodes. In the Zigbee scenarios, the performance worsens because the simulator takes into account the losses due to collisions. Since some packets may be lost, the probability of decision error is influenced by the collisions.

In Fig. 9, the packet delivery fraction and the delay are shown as functions of the number N of transmitting sensors. These curves are obtained considering a fixed observation SNR at the sensors (equal to 0 dB). Our results, however, show that the packet delivery fraction and the delay are not affected by the value of the observation SNR at the sensors. We consider, in fact, ideal communication channels so that only the observations at sensors are noisy, whereas the packets sent from the sensors to either an FC (clustered schemes) or the coordinator (nonclustered schemes) are received without error. Consequently, the performance does not depend on the considered SNR since packet delivery fraction and delay are network performance indicators and do not depend on the observation reliability. The packet delivery fraction (solid line with circles) decreases monotonically. In particular, for small values of N, it remains close to 1. When the number of transmitting nodes increases instead, the number of collisions in the channel increases as well and the packet delivery fraction reduces. In the same figure, the delay (dotted line with diamonds) is also shown. As the intuition suggests, the delay is low for small values of N. When the traffic increases instead, due to a larger number of collisions, the delay is higher, since the channel is busy for a longer period of time and the probability of finding the channel idle reduces. Finally for large values of N, the delay seems to start saturating to a maximum value. In this case, in fact, due to the increased offered traffic, at least one sensor is likely to be ready to send its packet as soon as the channel becomes idle.

In Table II, we show the aggregate throughput extracted from the results shown in Fig. 9. When the number of transmitting nodes is small, the aggregate throughput is high (close to the maximum possible for each network configuration). When the number of transmitting sensors increases instead, the aggregate throughput tends to reach a saturation value, after which the number of collisions is so large that an increase of the traffic load has no further effect.

In Fig. 10, we analyze the impact of nonuniform clustering on the probability of decision error; as a performance benchmark, the probability of decision error in the case with uniform clustering is also shown. We consider scenarios with $N = 16$ sensors

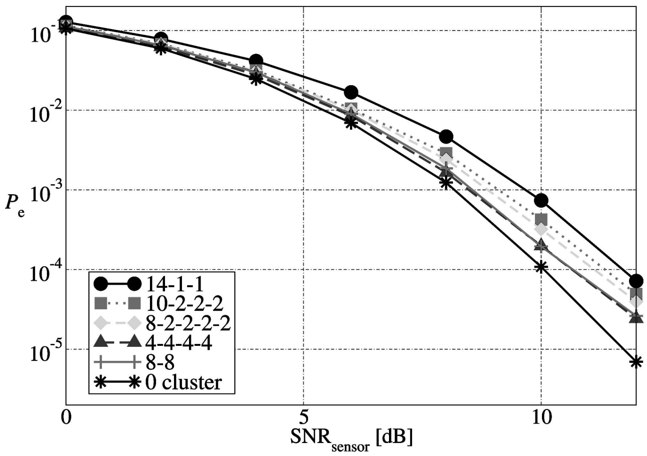

Fig. 10. BER performance in scenarios with $N = 16$ sensors both in case of uniform and nonuniform clustering. Various topologies (indicated in figure) are considered.

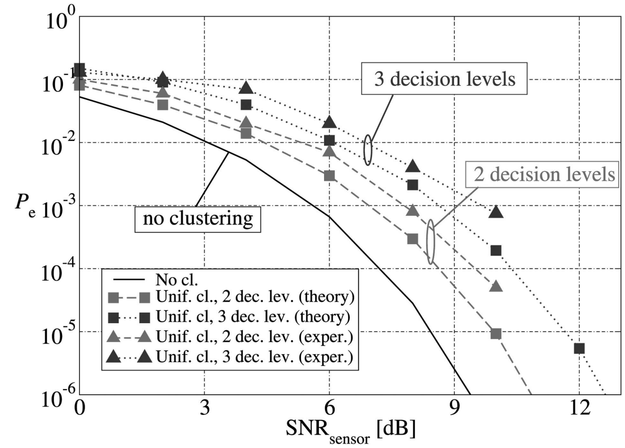

Fig. 11. Experimental BER performance in scenarios with $N = 16$ sensors and uniform clustering. Two and three decision levels are considered.

and the following network configurations: 1) no clustering, 2) 8-8, 3) 4-4-4-4 FCs, 4) 14-1-1, 5) 10-2-2-2, and 6) 8-2-2-2-2. According to the results in Fig. 10, the best performance is obtained in the absence of clustering, whereas the worst performance is obtained in the 14-1-1 scenario, i.e., with three FCs and nonuniform clustering. From Fig. 10, one can conclude that, in the presence of nonuniform clustering, the performance improves for relatively balanced clusters (as also predicted by the analytical framework). In this case, in fact, decisions made by intermediate FCs are more reliable, so the final decision made by the coordinator is more likely to be correct. In the case of uniform clustering, instead, the probability of decision error is not affected by the number of clusters in the network, as long as the total number of sensors remains the same. In this case in fact, observing Fig. 10, one can note that the curves relative to the scenarios with 4 4-sensor clusters and 2 8-sensor clusters are almost overlapped. This is due to the fact that a smaller number of clusters is compensated by a higher quality of the intermediate decisions. This result is in agreement with the theoretical conclusions reached in Section IIID.

B. Experiments

In order to verify the predictions of the theoretical framework from an experimental perspective, we consider a networking setup formed by MicaZ nodes [22]. MicaZ platforms include an ATmega128L 7.3 MHz micro-controller [40], FLASH and EEPROM memories, and a 2.4 GHz IEEE 802.15.4 Chipcon CC2420 RF transceiver [41]. The nodes' operating system is TinyOS. The experimental setup is characterized by $N = 16$ nodes, organized in uniform clusters, with 2 and 3 decision levels, respectively. In our implementation, each node observes a "0" phenomenon and adds a Gaussian observation noise generated through the function "random" available in the TinyOS environment. According to the local decision threshold, each source node makes a decision on the observed phenomenon and embeds it in a packet to be transmitted. Since each TinyOS packet is formed by a payload of 30 bytes (the first byte contains the dimension, and the following 29 the information data), we embed in each packet $29 \times 8 = 232$ consecutive binary decisions. This corresponds to 232 consecutive (time-wise) realizations of the observed binary phenomenon. The packets originated by the source nodes are then transmitted through the intermediate FCs to the AP. Note that a packet duration is on the order of 1 ms, and consecutive packet transmissions are separated by approximately 0.1 s. The transmit power is set to -25 dBm, and the sensitivity threshold at the receivers is -100 dBm. The distances between communicating nodes (on the order of 2 m) are such that the received power is significantly higher than the sensitivity threshold. The data fusion mechanisms at the intermediate FCs and at the AP follow the majority decision rules described in the analytical framework.

The experimental bit error rate (BER) performance is shown in Fig. 11. In the same figure, for comparison, we also show the corresponding theoretical results extracted from Fig. 3. As one can see, the experimental results are slightly worse than the theoretical ones (as observed also in Section IVA for simulation results), but confirm the trend. This discrepancy is due to the more realistic experimental scenario, where some packets may get lost because of the wireless communication links. Since the decision rules at the FCs and at the AP do not adapt to the number of received observations, this explains the performance degradation. We point out that in our experiments the packet losses are typically not due to collisions, i.e., the traffic load of the considered network scenarios is too low to create problems at the access level. On the opposite side, the performance degradation is due to losses of packets due to propagation reasons. An interesting research extension consists of incorporating these effects into our analytical framework.

V. CONCLUDING REMARKS

In this paper, we have characterized the behavior of clustered sensor networks with decentralized detection in the presence of multi-level majority-like information fusion. Upon the derivation of an analytical framework, we have shown that, in the considered scenarios, uniform clustering, i.e., balanced tree network architectures, leads to a lower probability of decision error than nonuniform clustering, i.e., unbalanced tree network architectures. In the former case, the probability of decision error depends only on the number of decision levels and not on the specific clustering configuration. In the presence of nonuniform clustering, the performance significantly improves if the AP is given knowledge of the network topology and uses proper weighed fusion rules.

Although the analytical framework has been derived in scenarios with a spatially constant phenomenon, we have also analyzed the impact of phenomenon spatial variations. Our results show that for stronger phenomenon spatial variations, the performance worsens in all considered scenarios, and this loss is more pronounced in scenarios with nonuniform clustering, where the quality of the FCs' decisions is rather low.

Ideal and noisy communication links have been considered. The presence of noise in the communication links has a strong bearing on the ultimate achievable performance. In order to combat the effects of communication noise, we have devised a simple weighed fusion strategy, which takes into account the noise level of the communication links. Our results show that the improvement is limited and that observation and communication noises should be jointly taken into account.

Finally we have presented simulation and experimental results (in terms of probability of decision error, throughput, and delay) relative to Zigbee and IEEE 802.15.4-based clustered sensor networks with information fusion. The obtained results confirm the validity of our analytical framework in realistic networking scenarios.

APPENDIX I. PROBABILITY OF DECISION ERROR IN A NONUNIFORMLY CLUSTERED SENSOR NETWORK

Consider a sensor network with a generic topology characterized by $\mathcal{D}$, $\mathcal{P}^{1|0}$, and $\mathcal{P}^{1|1}$. In Section IIIA, we derived expression (6) for the probability of decision error using a combinatorial approach based on the repeated trials formula [37]. However, this formula cannot be exploited in the derivation of the probability of decision error in a scenario with nonuniform clustering since the probabilities of correct decision are not the same for all FCs (and equivalently, the probabilities of incorrect decision). In this case, the evaluation of the probability of decision error can be framed as a properly extended repeated trials problem [37].

Define the random variable S_n as follows:

$$S_n \triangleq \{\text{number of successes in } n \text{ trials}\}.$$

For a fixed value of k successes in n trials, we are interested in the probability of the event $\mathcal{E} \triangleq \{S_n = k\}$, which includes all possible combinations (with a 1 corresponding to a success and a 0 corresponding to a failure) of k "1"s in the positions $\{i_1, i_2, \ldots, i_k\}$, with $i_j \in \{1, \ldots, n\}$, $j = 1, \ldots, k$ [42]. The total number of these combinations is $\binom{n}{k}$ [43]. The probability of the event $\mathcal{E}$ is given by

$$P(\mathcal{E}) = P\left(\bigcup_{\{i_1,i_2,\ldots,i_k\}} \{\mathcal{E}_k\}\right) = \sum_{\{i_1,i_2,\ldots,i_k\}} P(\mathcal{E}_k)$$

where $\mathcal{E}_k \triangleq \{k \text{ successes in positions } i_1, i_2, \ldots, i_k\}$, and we have used the fact that all combinations are mutually exclusive. For a fixed value of k, one obtains

$$P(\mathcal{E}) = \sum_{i=1}^{\binom{n}{k}} \prod_{j=1}^{n} \{c_{i,j}(k)\bar{p}_j + (1 - c_{i,j}(k))(1 - \bar{p}_j)\} \tag{16}$$

where we have used the fact that all the combinations are independent; $c_{i,j}(k)$ is defined as in Section IIIB, and $\bar{p}_j$ is defined as

$$\bar{p}_j \triangleq P\{\text{success in position } j\}.$$

Using (16) in the derivation of the probability of decision error for a nonuniformly clustered sensor network, one obtains

$$P(\hat{H} = H_1 \mid H_0) = \sum_{i=k_{\mathrm{f}}}^{n_{\mathrm{c}}} \sum_{j=1}^{\binom{n_{\mathrm{c}}}{i}} \prod_{\ell=1}^{n_{\mathrm{c}}} \{c_{i,j}(\ell) p_\ell^{1|0} + (1 - c_{i,j}(\ell))(1 - p_\ell^{1|0})\}$$

$$P(\hat{H} = H_0 \mid H_1) = \sum_{i=0}^{k_{\mathrm{f}}-1} \sum_{j=1}^{\binom{n_{\mathrm{c}}}{i}} \prod_{\ell=1}^{n_{\mathrm{c}}} \{c_{i,j}(\ell) p_\ell^{1|1} + (1 - c_{i,j}(\ell))(1 - p_\ell^{1|1})\}$$

where $p_\ell^{1|0}$ ($p_\ell^{1|1}$, respectively) is defined as the probability that the lth sensor decides for H_1 when H_0 (H_1, respectively) has happened.

APPENDIX II. PROBABILITY OF DECISION ERROR IN A LARGE SCALE CLUSTERED SENSOR NETWORK

Although the analytical framework derived in Section III is general, the presented results refer to networks with a (relatively) small number of sensors. This is due to the fact that the evaluation of some of the formulas becomes numerically critical when the number of sensors increases. In order to apply our framework to scenarios with a large number of sensors, we propose a simple yet very accurate approximation of the derived framework based on the application of the DML theorem. We focus on scenarios with uniform clustering. The extension of the following derivation to the case with nonuniform clustering is possible.

Recall the definition (7) of the function "bin." Provided that the DML theorem applies [37], one can approximate a binomial probability mass function (with parameters n and z) with a Gaussian probability density function $\mathcal{N}(\eta_{\rm DML}, \sigma^2_{\rm DML})$, where $\eta_{\rm DML} = nz$ and $\sigma^2_{\rm DML} = nz(1-z)$. In particular one can write

$$\mathrm{bin}(a,b,n,z) \simeq \int_a^b \frac{1}{\sqrt{2\pi\sigma^2_{\rm DML}}} \exp\left(-\frac{(y-\eta_{\rm DML})^2}{2\sigma^2_{\rm DML}}\right) dy.$$

This result is not immediately applicable to the considered multi-level clustered scenarios. In fact if the dimension of the first-level clusters is too large, the dimension of higher level clusters is (relatively) small, and the condition of applicability of the DML theorem is not satisfied in the latter case. In order to avoid this problem, we consider a scenario where nodes are grouped in the largest possible clusters at the first level, whereas at the higher levels the groups have the minimum dimension, i.e., $d_{{\rm c}_i} = 2$ for $i = 2, \ldots, n_{\rm levels}$. In other words, the upper portion of the sensor network architecture corresponds to a binary tree. Consequently, it follows that the number of sensors in each cluster is $d^{\max}_{{\rm c}_1} = N/2^{n_{\rm levels}-1}$. In this case, the DML theorem can be applied at the first-level fusion centers, whereas simple binomial formulas can be used for higher level information fusions. Considering a uniformly clustered scenario with two levels of information fusion, after a few manipulations, one obtains

$$P(\hat{H} = H_1 \mid H_0) = \mathrm{bin}(k_{\rm f}, n_{{\rm c}_1}, n_{{\rm c}_1}, p^{1|0}, 1 - p^{1|0}) \quad (17)$$

$$P(\hat{H} = H_0 \mid H_1) = \mathrm{bin}(0, k_{\rm f} - 1, n_{{\rm c}_1}, p^{1|1}, 1 - p^{1|1}) \quad (18)$$

where $p^{i|j}$ $(i,j = 0,1)$ represents, as in Section IIIB, the probability that a first-level FC decides for H_i when H_j has happened. Using the DML theorem, it can be shown that

$$p^{1|0} \simeq Q(\sqrt{d_{{\rm c}_1}}\alpha), \qquad p^{1|1} \simeq 1 - Q(\sqrt{d_{{\rm c}_1}}\beta)$$

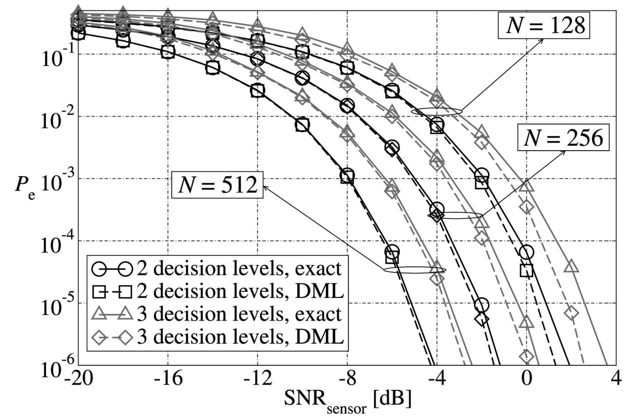

Fig. 12. Probability of decision error as function of sensor SNR in uniformly clustered scenario with two and three decision levels, respectively, and three values for number N of sensors.

where

$$\alpha \triangleq \frac{P_{\rm c0} - \frac{1}{2}}{\sqrt{P_{\rm c0}P_{\rm e0}}}, \qquad \beta \triangleq \frac{P_{\rm c1} - \frac{1}{2}}{\sqrt{P_{\rm c1}P_{\rm e1}}}$$

and $P_{\rm c0}$, $P_{\rm e0}$, $P_{\rm c1}$, $P_{\rm e1}$ are defined as in Section IIIC.

In Fig. 12, the probability of decision error is shown as a function of the sensor SNR in a scenario with uniform clustering and various values of N, namely, 128, 256, and 512. For each number of sensors, clustered scenarios with two and three decision levels are considered. One can observe that when the number of sensors increases, the curve corresponding to the asymptotic analysis (dashed line) becomes more and more accurate, i.e., the difference between exact and approximate performance becomes smaller and smaller—note that the probability of decision error predicted by the DML theorem is slightly optimistic if N is not sufficiently large. As one can see from Fig. 12, the DML theorem-based probability of decision error becomes asymptotically (for $N \to \infty$) exact. For instance, in the case with $N = 512$ sensors, the performance predicted with the proposed approximation is very accurate at almost all values of the probability of decision error.

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