

# Decision Fusion: Sparse Network vs. Dense Network

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**Abstract** – Wireless sensor networks have found many applications because of their facility for remote information monitoring and processing. One of the main applications of sensor networks is detection of an event occurrence. In these applications, a fusion center decides about an event occurrence based on the data of sensors. Here, the goal is to detect event occurrence correctly while avoiding its false detections. To reach this, either a sparse network of expensive precise sensors or a dense network of cheap sensors may be used. This paper attempts to examine these cases. It is shown that using a relatively dense network of cheap sensors may satisfy design parameters. In addition, it is shown that how a suitable decision fusion rule can reduce design costs.

**Key words** – wireless sensor networks, decision fusion, distributed detection.

## I. INTRODUCTION

Wireless sensor networks (WSN) are networks of wireless nodes capable of sensing, processing and communication. The flexibility nature of such networks makes them suitable for implementing many applications. However, energy and processing limitations of wireless nodes impose design restrictions. Implementation of classical problems – such as detection, estimation and target tracking – in a distributed manner while considering WSN limitations has been a hot research topic during recent decades [1, 2].

Detection is either the main task or one of the main tasks of WSNs in many applications. In detection applications, sensors observe a region of interest (ROI) and send either raw or processed data to a fusion center (FC) in which the final decision is taken. The final result of such network would be either event occurrence – referred to as hypothesis  $H_1$  – or no event occurrence – referred to as hypothesis  $H_0$ .

Due to energy limitations and wireless medium, sensors have to send less data. Rago et. al. in [3] have suggested sensors to send data only when it is informative. The extreme limit is the distributed detection scheme where sensors decide about the even occurrence locally and send their decisions to the FC just upon event detection. Thus, sensors may inform the FC about their decision during only one bit. Then, the FC takes the final decision by fusing the received decisions from sensors. There are many practical issues; however, the two basic problems are optimum local decision rules and optimum decision fusion rule.

Assuming that sensors' observations are statistically independent given each hypothesis, the local decision rules are shown to be a likelihood ratio test (LRT) [4, 5]. Chair and Varshney in [6] have obtained an optimal decision fusion rule where each sensor's decision is weighed based on its detection

performance. Since computing each sensor's detection performance is practically very challenging, sensors' decisions may be treated equally and hence the counting fusion rule – proposed by Niu et. al. in [7] – may be exploited. In counting rule, the number of positive decisions (i.e. decisions implicating event occurrence) are counted and compared to a threshold. The threshold is computed based on the desired system's false alarm rate. It has been shown that the counting rule is a robust fusion rule even when considering effects of communication channels [8].

Recently, the weighted decision fusion (WDF) rule has been proposed in [9] in which the bandwidth is used more efficiently. In WDF, sensors estimate their sensing signal-to-noise ratio (SNR) after detecting the desired event and inform the FC about that if the measured SNR is more than a pre-specified value. In counting rule, receiving a bit from a node means event detection by that node. In WDF, the value of that bit is meaningful as well. For example, when network nodes are forced to send only one bit upon event detection, a '1' bit may be used to inform the FC about detecting the event with a high SNR value while a '0' bit means detection with low SNR (low confidence). Hence, the FC would weigh more on the '1' bits and sensors' decision wouldn't be treated equally anymore.

From the view of design costs, a common dilemma is choosing between a dense network of low-cost sensors and a sparse network of expensive precise sensors. In this paper, this issue is addressed. Note that the problem of nodes deployment is not considered here, though it affects the network performance [10].

The paper is organized as follows. The problem and its solutions are discussed in section II. In section III, simulation results are shown. Finally, the paper is concluded in section 0.

## II. PRECISION AND DECISION FUSION RULES

One of the main challenges of WSN implementations is to select appropriate sensors. Each sensor type covers an extensive range of prices. As an instance of WSN applications, the quality of agricultural crops as well as water consumption could be significantly improved by exploiting WSNs. In this application of WSNs – often referred to as precision agriculture –, soil moisture sensors are required. However, there are several kinds of soil moisture sensors in market ranging their prices from just 1\$ (several unbranded in market) to over hundreds of dollars (e.g. the products of Acclima and Enviroscan).

On the other hand, it is shown that distributed detection performs optimally in large network sizes [11-13]. In other words, one may use large number of nodes in order to reach the optimal performance. This paper attempts to address the

following question: which one is better: a dense network of low-cost sensors or a sparse network of expensive precise sensors?

#### A. Precision and accuracy

Precision and accuracy are two barely distinguishable terms. However, they are technically different. Accuracy refers to the closeness of the measurement to the true value while precision is the degree to which repeated measurements under unchanged conditions show same results [14]. In other words, a sensor measurement drift from its true value could be considered as its accuracy while its measurement statistical standard deviation (i.e. its sigma) could be considered as its precision.

This paper studies the effect of sensors precision on detection performance of a network. Effects of sensors' drift and the necessity to calibrate sensors will be studied as a future work.

#### B. Counting fusion rule

In counting fusion rule, network nodes decide locally and send a bit to the FC when they detect the target event. The FC makes the final decision using the decision fusion rule given by:

$$\Lambda = \sum_{i=1}^N u_i \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} T \quad (1)$$

where  $u_i$  is the binary decision of node  $i$ ,  $N$  is the total number of network nodes and  $T$  is the threshold of the FC which is computed based on a desired false alarm rate of the system. If all nodes maintain a same false alarm rate (i.e.  $p_{f_i} = p_f, i = 1, 2, \dots, N$ ), then the network's false alarm probability,  $P_F$ , when using the counting fusion rule, is given by:

$$P_F = \Pr(\Lambda \geq T | H_0) = \sum_{i=\lfloor T \rfloor}^N \binom{N}{i} p_f^i (1 - p_f)^{N-i} \quad (2)$$

in which the operator  $\lfloor x \rfloor$  gives the largest integer number less than  $x$ . Thus, system design involves computing the threshold  $T$  which is a constant.

#### C. Weighted Decision Fusion (WDF)

In counting rule, all decisions are treated equally. However, the decisions of nodes which are in the neighborhood of event are more important. In fact, it has been shown in [15] that the optimal decision fusion rule would be based on the decision of the nearest node to the event.

In WDF, a simple method of weighting has been proposed. Under AWGN with variance  $\sigma^2$  in sensors performing binary hypothesis test based on  $M$  observations, the decision rule is given by [16]:

$$\Lambda_i = \sum_{j=1}^M y_{ij} \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \tau_i$$

with  $y_{ij}$  being the  $j$ th observation of sensor  $i$  and  $\tau_i$  is the detection threshold of sensor  $i$ . Then, nodes estimate the SNR of their measurements,  $S_i$ , using the maximum likelihood estimation (MLE) method:

$$S_i = \frac{\Lambda_i^2}{M^2 \sigma^2} \quad (3)$$

At the next step, nodes quantize their estimated SNRs and send them to the FC if they detect the target event and also if the estimated SNR is more than a pre-specified value. Finally, the FC makes the final decision based on the following fusion rule:

$$\Lambda = \sum_{i=1}^{n_A} \hat{S}_i \begin{matrix} H_1 \\ > \\ < \\ H_0 \end{matrix} \tau \quad (4)$$

where  $\tau$  is the detection threshold of the FC,  $\hat{S}_i$  is the quantized SNR of sensor  $i$ ,  $A$  is the set of nodes that have already transmitted data to the FC and  $n_A$  is the cardinality of  $A$ . Here, the detection threshold of the FC is a function of  $n_A$  (i.e.  $\tau = a_1 n_A + a_2$ ,  $a_1, a_2 \in R$ ).

Clearly, the number of quantization levels of SNR is a function of the number of bits used for sending data. After having the quantization levels specified, designing a decision fusion system based on WDF involves setting  $a_1$  and  $a_2$  for a desired system's false alarm rate and optimum detection performance. The required relations for calculating WDF detection performance have been obtained in [9]. One may use either a full space search or an evolution algorithm such genetic algorithm (GA) for obtaining optimum values of  $a_1$  and  $a_2$ .

### III. SIMULATION RESULTS

In this section, detection performance of a WSN in an area of  $100 m^2$  in different number of nodes – ranging from sparse to dense network – and with different sensor precisions is simulated. The simulations are performed using both counting rule and WDF decision methods. In simulations,  $P_F \leq 0.01$  is considered and the optimum design parameters for the optimum detection performance are chosen. Communication channels are modeled as binary symmetric channels (BSC). Nodes are assumed to be uniformly randomly deployed in the ROI. Also, nodes decide based on 10 measurements, i.e.  $M = 10$ .

Fig. 1 shows that how sensor precision affects detection performance of a network. Here, the communication error is assumed to be 0.1. The fluctuations in the curves is because of changing the FC threshold. Detection probability rises when the network size increases in a fixed FC threshold; however, the FC threshold should be changed in order to maintain the desired  $P_F \leq 0.01$ . It could be seen that using less number of more precise sensors results in better detection performance. For example, less than 20 sensors with  $\sigma^2 = 0.1$  are needed in order to reach  $P_D$  at least equal to 0.8 while more than 50 sensors with  $\sigma^2 = 5$  should be exploited for that detection

probability. Thus, selecting appropriate sensors depends on the prices of sensors as well as wireless nodes.

Another interesting result of Fig. 1 is depicting importance of clustering in WSNs. Often, network nodes are arranged in clusters in order to simplify routing. In addition, clustering suggests energy saving since a node of each cluster – referred to as the cluster head (CH) – aggregates data of other nodes of that cluster and forwards the aggregated data to the FC. Aggregating data usually results in more precision (i.e. less  $\sigma$ ). Thus, Fig. 1 introduces improving of detection performance of WSNs as another advantage of clustering.

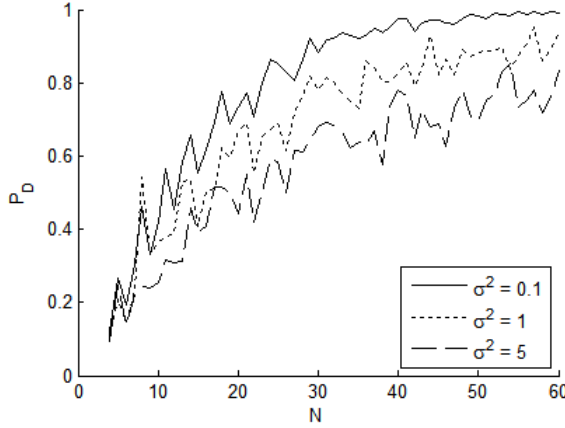


Fig. 1. The system's probability of detection vs. network size ( $N$ ) in different precision values ( $\sigma$ ) of sensors. The system's false alarm rate is 0.01. Nodes make decision based on 10 measurements ( $M = 10$ ) and the communication error probability is 0.1.

Fig. 2 shows a comparison between detection performance of counting rule and WDF in different network sizes. The simulation conditions are the same as in Fig. 1 except that here a high communication error rate of 0.2 has been considered. In simulating WDF, two quantization levels 1 and 15 have been used. If a node detects the event and its estimated SNR is less than 15, it transmits a '0' bit to the FC. If it detects the event with SNR more than 15, it sends a '1' bit to the FC.

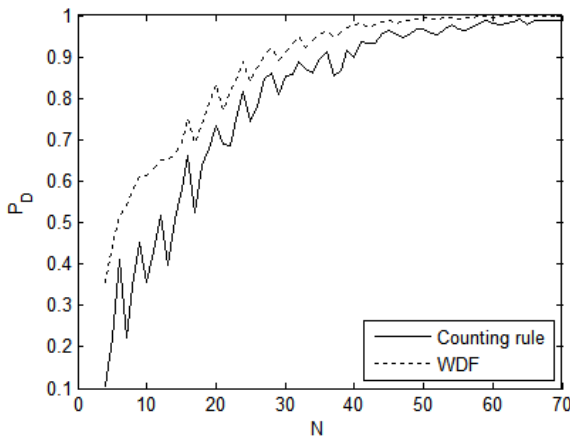


Fig. 2. Comparison of detection performance of two different decision fusion rules in different precision values ( $\sigma$ ) of sensors. The system's false alarm rate is 0.01. Nodes make decision based on 10 measurements ( $M = 10$ ) and the communication error probability is 0.2.

Fig. 2 shows how design cost is affected by decision fusion strategy. As an example, while more than 60 sensors are required for reaching  $P_D$  more than 0.96 when counting rule is used, this number decreases to less than 35 sensors when implementing WDF method. However, designing a detector network based on counting rule is very simple.

#### IV. CONCLUSION

This paper studied detection performance of WSNs in different network sizes and with different values of sensor precision. It was shown that less number of precise sensors is required for reaching a specified detection performance; however, the costs of sensors and wireless nodes define the density of network. In other words, using dense network of low-cost sensors may be more economical in many applications. On the other hand, clustering a dense network of inexpensive sensors results in improving precision in each cluster and improves detection performance of the network. In addition, it was shown that using more appropriate decision fusion rule could significantly decrease design costs.

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