

# Decision Fusion for Wireless Sensor Networks over the Multi-Access Channel

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## Abstract

The decision fusion for multi-route and multi-hop Wireless Sensor Networks (WSNs) is studied, wherein a discrete memoryless channel model, i.e., the Binary Symmetric Channel (BSC), is considered to characterize the relay transmission of each hop from the local sensor to the fusion center. In particular, we develop the optimal log-likelihood ratio (LLR) based decision fusion rule, wherein the fusion center is assumed to have perfect knowledge of both the local sensor performance indices and the Channel State Information (CSI), i.e., crossover probability for each BSC. Our result show that our optimum fusion detectors require less or no a priori information about crossover probability and/or the local sensor performance indices, and thus are easy to implement. We also show that the simple decision fusion statistic, i.e., the counting-based statistic, can be directly derived from the optimal LLR-based statistic for both cases. We uniformly quantize the equivalent crossover probability into discrete status, and thus give a optimum but more computationally practical scheme. The performance evaluation is finally developed both analytically and through simulation.

## Keywords

Decision Fusion, Multi-route and Multi-hop, Binary Symmetric Channel, Channel State Information.

## 1. INTRODUCTION

Much concentrations have been recently achieved on wireless sensor networks (WSNs) especially because of its appropriate application in “edge access” of future “Internet of Things (IoT)”. In such distributed networks, the the fusion center (FC) gathers the decisions from the local sensors, and the global decision is then declared by the FC using a particular fusion rule [1]. To the best of our knowledge, several decision fusion schemes have been proposed in recent years [2].

Local sensor decision rules based on an energy detector is introduced in [3], and the performance characteristics is also given. By ordering sensor transmissions, an energy-efficient counting rule for distributed detection is proposed in [4], wherein the sensors transmit their unquantized statistics to the fusion center in a sequential manner.

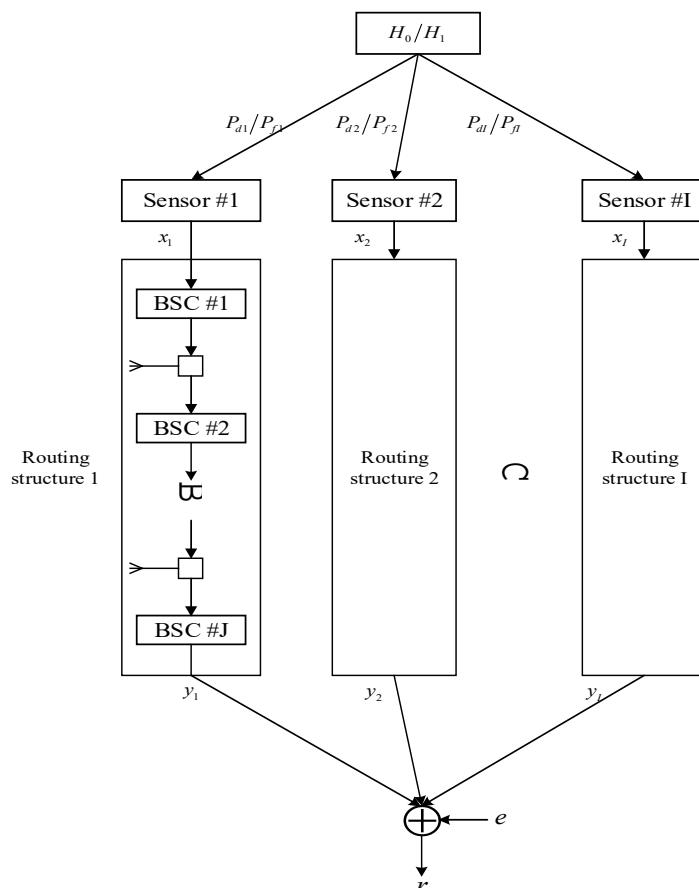
Unlike like those who were researching ways to develop decision fusion unders single-hop WSNs, substantial work has also been devoted to optimize the fusion process over multi-hop WSNs[5]. Note that, multi-hop transmission is of value for some resource-constrained WSNs. In this context, the multi-hop transmission is needed to relay the binary decisions from local sensors to reach a fusion center for minimal energy consumption. In a heterogeneous WSN (HWSN), an iterative decision fusion algorithm is studied in [6], wherein the multi-hop transmission is needed to relay the sensed information from N heterogeneous access points to M heterogeneous FCs. Distributed detection of sparse signals with censoring sensors in

clustered multi-hop sensor networks is presented in [7]. Taking parameters of energy consumption balance, environmental metrics and reliability into consideration, [8] introduces a fusion-based routing algorithm, which is environment-aware as well as reliable.

We study the optimal decision fusion over MAC, wherein the multi-hop relay transmission is considered from the local sensor to the fusion center, and the explicit and exact form of the decision metric is given. Our results show that the fusion center needs to achieve the perfect CSI of each relay channel and MAC, as well as the local sensor performance indices, namely, detection probability and false alarm probability. The implementation process of the decision metric also involves a large number of logarithmic and multiplication operations. The final simulation results are consistent with our theoretical analysis conclusions.

We organized the content of the article as follows. Section 2 gives the system transmission model of MAC. Then the optimal decision fusion method used by the fusion center and the statistical analysis of its received data are presented in Section 3. The simulation results are given in Section 4. Finally, some conclusions and future work are presented in Section 5.

## 2. SYSTEM MODEL



**Figure 1.** Parallel distributed detection with multi-hop relay structure

The MAC system model we consider is shown in Fig. 1. The binary information  $H_0$  and  $H_1$  generated by the source are observed independently by  $I$  sensors, where  $P_{di}$  and  $P_{fi}$  are the detection probability and false alarm probability of the local sensor respectively. It is used to characterize the quality of the channel from the source to the local sensor. The sensor decodes the observed data samples through the maximum a posteriori probability quasi test and decides to the information sequence  $x_i$ . Then each sensor forwards the information sequence to the next relay node, and the information sequence forwarded through a total of  $J$  relay nodes is

recorded as  $y_i$ . The value  $z$  is obtained by modulo two addition of  $y_i$  sent from each link, and then it is forwarded again. After passing through the binary channel with the error vector  $e$ , the receiving end finally receives the information  $r$ .

In order not to lose generality, we assume that the forwarded channels are binary symmetric channels. Considering that the energy of the relay node is limited, the forwarding method we use is amplification forwarding, and the amplification factor is set to 1.

### 3. OPTIMAL LLR-BASED DECISION FUSION

The analysis of each transmission link shows that  $y_1 \oplus y_2 \oplus y_3 \oplus \dots \oplus y_l \oplus e = r$ . According to the log likelihood ratio criterion, we derive the expression of the optimal fusion decision metric as

$$\begin{aligned} \Lambda &= \log \frac{P(H_1 | r)}{P(H_0 | r)} = \log \frac{P(r | H_1)P(H_1)/P(r)}{P(r | H_0)P(H_0)/P(r)} = \log \frac{P(r | H_1)}{P(r | H_0)} \\ &= \log \frac{P(y_1 \oplus y_2 \oplus y_3 \oplus \dots \oplus y_l \oplus e = 1 | H_1)}{P(y_1 \oplus y_2 \oplus y_3 \oplus \dots \oplus y_l \oplus e = 1 | H_0)} \end{aligned} \quad (1)$$

In the following section, we will discuss the explicit and exact form of the decision metric when different  $r$  value is received.

The crossover probability matrix of relays BSC can be written as

$$\begin{aligned} \begin{bmatrix} 1 - \varepsilon_i & \varepsilon_i \\ \varepsilon_i & 1 - \varepsilon_i \end{bmatrix} &= \begin{bmatrix} P(y_i = 0 | x_i = 0) & P(y_i = 1 | x_i = 0) \\ P(y_i = 0 | x_i = 1) & P(y_i = 1 | x_i = 1) \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{2} \left[ 1 + \prod_{j=1}^J (1 - 2\varepsilon_{i,j}) \right] & 1 - \frac{1}{2} \left[ 1 + \prod_{j=1}^J (1 - 2\varepsilon_{i,j}) \right] \\ 1 - \frac{1}{2} \left[ 1 + \prod_{j=1}^J (1 - 2\varepsilon_{i,j}) \right] & \frac{1}{2} \left[ 1 + \prod_{j=1}^J (1 - 2\varepsilon_{i,j}) \right] \end{bmatrix} \end{aligned} \quad (2)$$

It can be easily obtained from Fig. 1 that

$$\begin{cases} P(y_i = 1 | H_1) = P_{di}(1 - \varepsilon_i) + (1 - P_{di})\varepsilon_i = P_{11}^i \\ P(y_i = 0 | H_1) = P_{di}\varepsilon_i + (1 - P_{di})(1 - \varepsilon_i) = P_{01}^i \end{cases} \quad (3)$$

$$\begin{cases} P(y_i = 1 | H_0) = P_{fi}(1 - \varepsilon_i) + (1 - P_{fi})\varepsilon_i = P_{10}^i \\ P(y_i = 0 | H_0) = P_{fi}\varepsilon_i + (1 - P_{fi})(1 - \varepsilon_i) = P_{00}^i \end{cases} \quad (4)$$

Let  $P(e = 1) = \alpha$ , and the conditional probabilities of the fusion center receiving the  $r$ , value by (3) are

$$\begin{aligned}
 P(r = 1 | H_1) &= P(y_1 \oplus y_2 \oplus y_3 \oplus_B y_I \oplus e = 1 | H_1) \\
 &= \frac{1}{2} \left( 1 - (1 - 2\alpha) \prod_{i=1}^I (1 - 2P(y_i = 1 | H_1)) \right) \\
 &= \frac{1}{2} \left( 1 - (1 - 2\alpha) \prod_{i=1}^I (1 - 2P_{di})(1 - 2\varepsilon_i) \right)
 \end{aligned} \tag{5}$$

$$\begin{aligned}
 P(r = 0 | H_1) &= P(y_1 \oplus y_2 \oplus y_3 \oplus_B y_I \oplus e = 0 | H_1) \\
 &= \frac{1}{2} \left( 1 + (1 - 2\alpha) \prod_{i=1}^I (1 - 2P(y_i = 1 | H_1)) \right) \\
 &= \frac{1}{2} \left( 1 + (1 - 2\alpha) \prod_{i=1}^I (1 - 2P_{di})(1 - 2\varepsilon_i) \right)
 \end{aligned} \tag{6}$$

Then combining (4), we can get

$$P(r = 1 | H_0) = \frac{1}{2} \left( 1 - (1 - 2\alpha) \prod_{i=1}^I (1 - 2P_{fi})(1 - 2\varepsilon_i) \right) \tag{7}$$

$$P(r = 0 | H_0) = \frac{1}{2} \left( 1 + (1 - 2\alpha) \prod_{i=1}^I (1 - 2P_{fi})(1 - 2\varepsilon_i) \right) \tag{8}$$

Substituting (5) and (7) into (4) when the receiving value of the fusion center  $r = 1$ , we have

$$\begin{aligned}
 \Lambda &= \log \frac{P(y_1 \oplus y_2 \oplus y_3 \oplus_B y_I \oplus e = 1 | H_1)}{P(y_1 \oplus y_2 \oplus y_3 \oplus_B y_I \oplus e = 1 | H_0)} \\
 &= \log \frac{1 - \frac{1}{2} \left( 1 + \prod_{i=1}^I [1 - 2(P_{di}(1 - \varepsilon_i) + (1 - P_{di})\varepsilon_i)](1 - 2\alpha) \right)}{1 - \frac{1}{2} \left( 1 + \prod_{i=1}^I [1 - 2(P_{fi}(1 - \varepsilon_i) + (1 - P_{fi})\varepsilon_i)](1 - 2\alpha) \right)} \\
 &= \log \frac{1 - \frac{1}{2} \left( 1 + \left[ \prod_{i=1}^I (1 - 2P_{di})(1 - 2\varepsilon_i) \right] (1 - 2\alpha) \right)}{1 - \frac{1}{2} \left( 1 + \left[ \prod_{i=1}^I (1 - 2P_{fi})(1 - 2\varepsilon_i) \right] (1 - 2\alpha) \right)} \\
 &= \log \frac{1 - \left[ \prod_{i=1}^I (1 - 2P_{di})(1 - 2\varepsilon_i) \right] (1 - 2\alpha)}{1 - \left[ \prod_{i=1}^I (1 - 2P_{fi})(1 - 2\varepsilon_i) \right] (1 - 2\alpha)}
 \end{aligned} \tag{9}$$

Where  $\varepsilon_i = 1 - \frac{1}{2} [1 + \prod_{j=1}^J (1 - 2\varepsilon_{i,j})]$ .

Similarly, bring (6) and (8) into (1), we can get the decision metric  $\Lambda$  when the receiving value of the fusion center  $r = 0$  can be written as

$$\begin{aligned}
\Lambda &= \log \frac{P(y_1 \oplus y_2 \oplus y_3 \oplus \dots \oplus y_l \oplus e = 0 | H_1)}{P(y_1 \oplus y_2 \oplus y_3 \oplus \dots \oplus y_l \oplus e = 0 | H_0)} \\
&= \log \frac{\frac{1}{2} \left( 1 + \prod_{i=1}^l [1 - 2(P_{di}(1 - \varepsilon_i) + (1 - P_{di})\varepsilon_i)](1 - 2\alpha) \right)}{\frac{1}{2} \left( 1 + \prod_{i=1}^l [1 - 2(P_{fi}(1 - \varepsilon_i) + (1 - P_{fi})\varepsilon_i)](1 - 2\alpha) \right)} \\
&= \log \frac{1 + \left[ \prod_{i=1}^l (1 - 2P_{di})(1 - 2\varepsilon_i) \right] (1 - 2\alpha)}{1 + \left[ \prod_{i=1}^l (1 - 2P_{fi})(1 - 2\varepsilon_i) \right] (1 - 2\alpha)}
\end{aligned} \tag{10}$$

Finally, by combining (9) and (10), we get the optimal decision metric as

$$\Lambda = \log \frac{1 + (1 - 2r) \left[ \prod_{i=1}^l (1 - 2P_{di})(1 - 2\varepsilon_i) \right] (1 - 2\alpha)}{1 + (1 - 2r) \left[ \prod_{i=1}^l (1 - 2P_{fi})(1 - 2\varepsilon_i) \right] (1 - 2\alpha)} \tag{11}$$

Then, the final fusion criterion is

$$\hat{u} = \begin{cases} 1, & \text{if } \Lambda \geq \tau_1 \\ 0, & \text{if } \Lambda < \tau_1 \end{cases} \tag{12}$$

Here,  $\tau_1$  is the decision threshold.

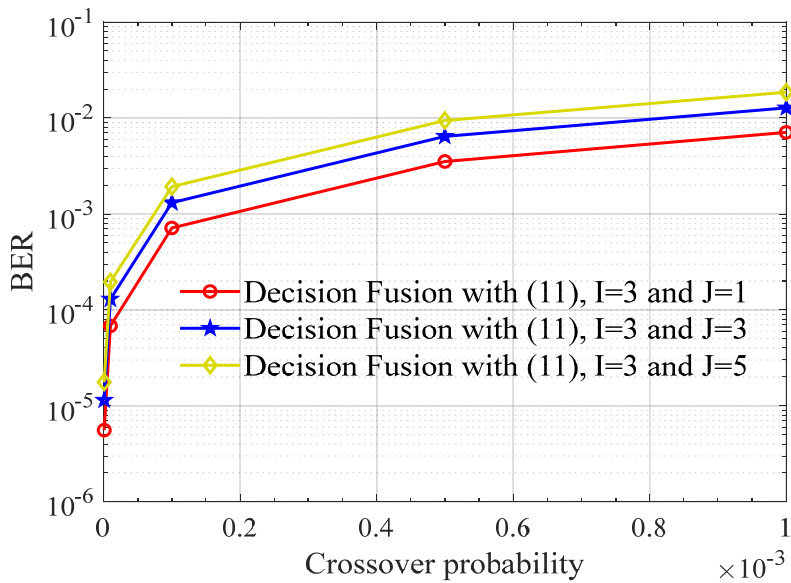
As can be seen that the accurate solution of the optimal decision metric requires a lot of complex calculations, and the CSI needs to be known. For the resource constrained relay node, this is very unfriendly. We will pay more attention to the extraction of the suboptimal decision metric with lower complexity. Before analyzing the suboptimal decision fusion strategy, the statistical characteristics of the received value  $r$  at the fusion center are given.

#### 4. NUMERICAL RESULTS AND DISCUSSION

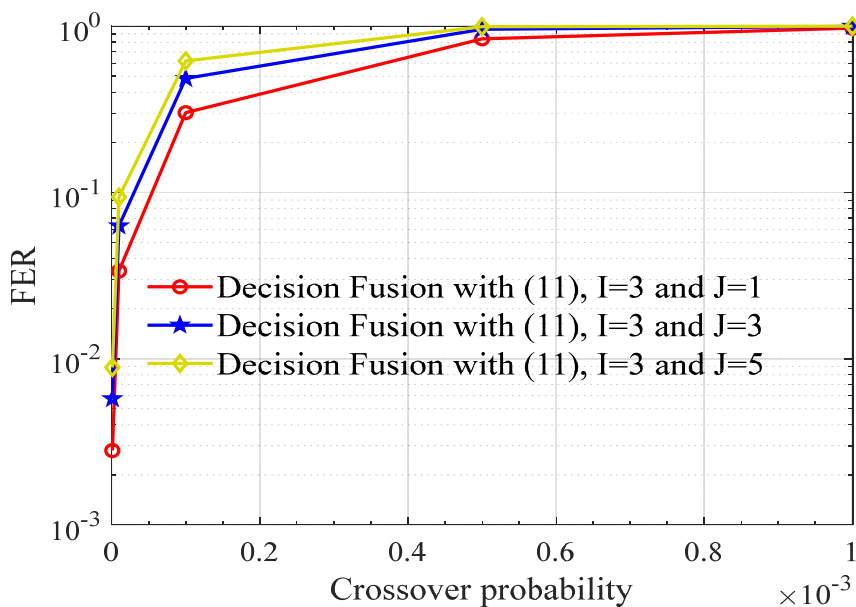
In this part, we analyze the fusion performance from many different aspects, including bit error rate (BER), frame error rate (FER), complexity analysis. In the simulation, the crossover probability of the relay channel varies from  $10^{-5}$  to 0.3. We model the crossover probability for each hop of the BSC channel using  $\varepsilon_{i,j+1} = \varepsilon_{i,j} + \Delta_{i,j}$ , where  $\Delta_{i,j}$  is an independent Gaussian random variable with known variance  $\sigma_{i,j}^2$  and mean 0. For initial crossover probability  $\varepsilon_{i,1}$ , the uniform distribution in 0.001 to 0.3 is considered. We collected at least 3000 frames of errors in each simulation process. Detailed simulation parameters are shown in Table 1. The simulation results are shown in Figures 2 to 5.

**Table 1.** Parameters used in simulations

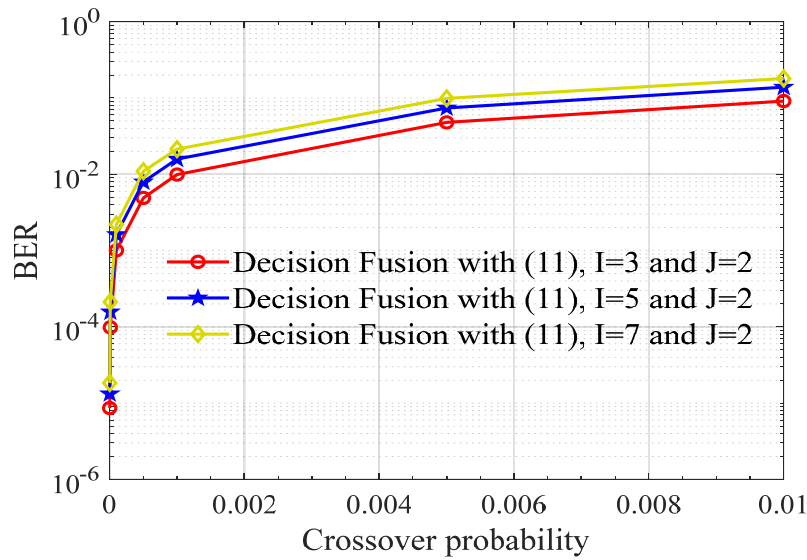
Parameter	Detailed Description
Channel condition	BSC
Channel parameters	Uniform reduction in interval 1e-5 to 0.3
Information sequence length	504 bits
Noise condition	Obey Wiener distribution
Number of sensors	3,5,7
Number of hops	1,2,3,4,5
Channel conditions of difference path	Obey the same crossover probability
Number of cycles	Get at least 3000 frame errors



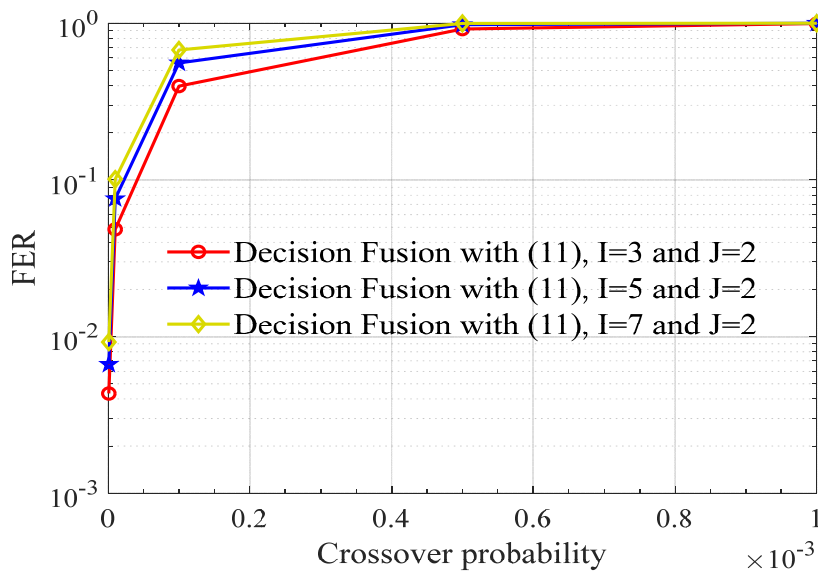
**Figure 2.** BER performance of the optimal decision fusion with (11). The number of route is set to be 3, and the relay number is 1, 3 and 5.



**Figure 3.** FER performance of the optimal decision fusion with (11). The number of route is set to be 3, and the relay number is 1, 3 and 5.



**Figure 4.** BER performance of the optimal decision fusion with (11). The number of route is set to be 3, 5, 7, and the relay number is 2.



**Figure 5.** FER performance of the optimal decision fusion with (11). The number of route is set to be 3, 5, 7, and the relay number is 2.

We can see that the curves are almost coincident. Fig. 2 and Fig. 3 respectively show the change trend of BER performance and FER performance of the system when the number of routes  $I$  is fixed to 3 and the number of relays  $J$  changes from 1 to 5. The abscissa represents the crossover probability of the transmission channel. It is obvious that there is a threshold phenomenon in the figure. When the crossover probability is lower than this threshold, the curve changes significantly, while above this threshold, the curve changes slowly. We can see that for the optimal decision fusion method, the performance of the system decreases with the increase of the number of relays.

Fig. 4 and Fig. 5 show the change trend of system performance when the number of relays  $J$  is fixed to 2 and the number of routes  $I$  changes from 3 to 7. We can see that for the optimal

decision fusion method, increasing the number of routes does not improve the system performance, but decreases.

## 5. CONCLUSIONS AND FUTURE WORK

We study the decision fusion over MAC, wherein the multi-hop relay transmission is considered from the local sensor to the fusion center, and the exact form of the decision metric is given. The optimal decision fusion method has accurate expression, This makes the system friendly and easy to implement and saves a lot of resources.

The following contents are worth studying in the future. First of all, we are committed to studying the decision fusion method of uncoded MAC in this paper. The method of deploying channel encoders in local sensors to obtain coding gain is worth studying, which can make the fusion method have better anti noise performance. Then the security problem under the MAC is also worth considering. Especially for the even transmission path scenario, the source information is eliminated by the modulo two addition of the MAC, which greatly degrades the detection performance of the fusion center. We try to apply the fusion method under the even transmission path to the communication security to fight against eavesdroppers. Finally, with the increase of the number of relays and routes in the proposed fusion method, the detection performance of the system will be degraded. Therefore, how to improve the system detection performance under MAC is also one of the research directions. For example, the stochastic resonance method, which increases the noise appropriately in the communication process to improve the detection performance of the system, is worth considering.

## ACKNOWLEDGMENTS

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