Hindawi Publishing Corporation
International Journal of Distributed Sensor Networks
Volume 2016, Article ID 8613149, 9 pages
http://dx.doi.org/10.1155/2016/8613149

Research Article

A Fault-Tolerant Detection Fusion Strategy for Distributed Multisensor Systems

Shengli Zhao and Jie Zhou

College of Mathematics, Sichuan University, Chengdu, Sichuan 610064, China

Correspondence should be addressed to Jie Zhou; jzhou@scu.edu.cn

Received 29 October 2015; Accepted 5 January 2016

Academic Editor: George P. Efthymoglou

The distributed detection fusion formulation (DDFF) in ideal multisensor systems has been studied over the last two decades. If some local sensors cannot work normally, the detection performance of system may reduce significantly. It is meaningful to design fault-tolerant detection fusion rules which can guarantee the performance of system no matter whether the fusion center and local sensors work well or not. A new distributed detection fusion strategy is thus proposed by minimizing a weighted sum of risk at the fusion center and risks at the local sensors, and then a fault-tolerant distributed detection fusion formulation (FT-DDFF) is derived. Some numerical examples illustrate the performance of the proposed formulation. If the whole system is perfect, compared with the DDFF, the FT-DDFF has both small risks of local sensors and a little small risk of fusion center with an appropriately selected parameter. While some local sensors cannot work, the FT-DDFF would perform better than the DDFF at fusion center in average.

1. Introduction

In the past, more than two decades, multisensor information fusion techniques have received significant attentions in practice (see, e.g., [1–9]). In distributed architectures, the local decisions or estimates using the observations from individual processors are made and then transmitted to a fusion center where the final global decision or estimate is made in terms of some criterions. Such distributed multisensor architecture has many advantages, such as more capability, reliability, robustness, and survivability than the centralized architecture.

For a parallel distributed multisensor system, the optimal detection fusion formulation was addressed (see, e.g., [3, 4, 7, 10, 11]). In [3], a distributed detection fusion formulation (DDFF) was provided in ideal conditions. It seeks a detection fusion rule for whole system and information compression rules for all local sensors. Some necessary conditions of an optimal fusion rule and optimal sensor decision rules are derived using a person-by-person optimization (PBPO) methodology. The desired PBPO solution consists of a fusion rule and some sensor decision rules. For distributed detection fusion systems with correlated noises, the fusion rule and sensor decision rules were formulated to the fixed points of some equations and an iterative algorithm was developed in [4, 7]. It provides the approximate solutions to the necessary conditions for optimum sensor decision rules. An algorithm to simultaneously search for an optimal fusion rule and the corresponding optimal sensor decision rules was derived in [12]. In [13], a computationally efficient iterative algorithm to simultaneously and alternately search for a fusion rule and sensor decision rules was proposed. All of the above works are to minimize the Bayesian risk at the fusion center, and the solutions were derived when the system is perfect.

As the local sensors are just to serve for the fusion center, when the optimal performance of fusion center is attained, the performances of some local sensors may be ignored. If the fusion center is destroyed, each local sensor would use its own decision rule to make the final decision for the two hypotheses. Then, the performance of the whole system would be reduced. If some local sensors are destroyed, or the communications between fusion center and those sensors are cut off, the fusion center can only use the available local decisions so that its performance would not be guaranteed. Thus, it is meaningful to design fault-tolerant fusion rule and sensor decision rules.

The fault-tolerance capability is an important factor in many applications, such as designing classification systems in wireless sensor networks (WSN). Several researchers have considered the design of fault-tolerant distributed detection fusion systems [14–16]. However, they only designed the system based on a known a priori failure probability and considered the binary detection problem. The extension from binary detections for fault-tolerant detection to multihypothesis detections was also considered in WSN [17]. The authors proposed a classification fusion approach which was implemented via error correcting codes to incorporate fault-tolerance capability. In [18], a fusion rule that combined both soft-decision decoding and sensor decision rules was proposed in WSN with fading channels. Besides the error correcting codes which provide good sensor fault-tolerance capability, the soft decoding scheme is utilized to combat channel fading. In [19], the optimal sensor decision rules with channel errors for a given fusion rule were proposed in which sensor observations are not necessarily independent of each other. Furthermore, the results on the unified fusion rules for network decision systems with ideal channels were extended to systems with channel errors.

In this paper, for a general parallel distributed detection fusion system, we extend the idea of existing DDFF by employing a new detection fusion strategy so as to find a fault-tolerant formulation. It can guarantee the performances of both fusion center and local sensors whether the system is perfect or imperfect. Under Bayesian criterion, the risks at local sensors (local risks) are defined similar to the risk at fusion center (system risk). The new detection fusion strategy is adopted to minimize the total risk, that is, the weighted sum of system risk and local risks. A new fault-tolerant distributed detection fusion formulation (FT-DDFF) is obtained by the PBPO methodology as the DDFF.

The rest of this paper is organized as follows. A statement of the problem and a brief review of the DDFF are given in Section 2. In Section 3, we model the fault-tolerant detection fusion under a new strategy and derive an FT-DDFF by PBPO methodology. Some numerical examples are provided in Section 4, and a conclusion is given in Section 5.

2. Problem Statement

Consider a distributed detection fusion system depicted in Figure 1 which has N local sensors and a fusion center.

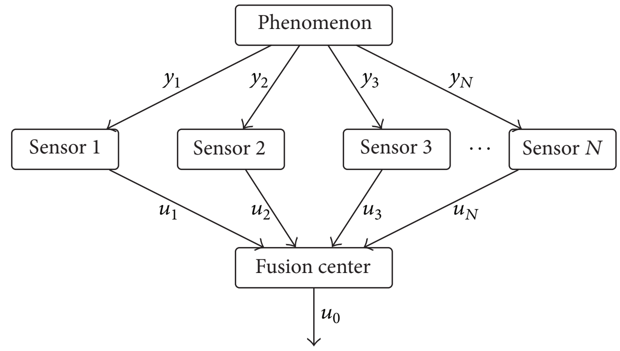

FIGURE 1: Distributed detection fusion system.

Let H_0 and H_1 be two hypotheses with associated prior probabilities P_0 and P_1, respectively. All local sensors observe the same phenomenon. The observations of local sensors are denoted by y_i, $i = 1, \ldots, N$, and their joint conditional probability density functions $p(y_1, \ldots, y_N \mid H_j)$, $j = 0, 1$, are assumed to be known. For all $i = 1, \ldots, N$, based on its own observation y_i, the ith local sensor makes a local decision u_i as follows:

$$u_i = \begin{cases} 0, & H_0 \text{ is declared present,} \\ 1, & H_1 \text{ is declared present.} \end{cases} \tag{1}$$

Then, the fusion center yields a global decision u_0 based on the received decision vector $\mathrm{u} = (u_1, \ldots, u_N)^T$. Note that the local decisions are transmitted over bandlimited channels to the fusion center and there is no communication among local sensors.

The distributed detection fusion problem is to seek an optimal set of rules:

$$\Gamma = \{\gamma_0, \gamma_1, \ldots, \gamma_N\}, \tag{2}$$

where γ_0 and γ_i, respectively, denote the fusion rule and decision rule at the ith sensor for $i = 1, \ldots, N$, which map from observation space to decision space as follows:

$$\begin{aligned} u_0 &= \gamma_0(u_1, \ldots, u_N), \\ u_i &= \gamma_i(y_i), \quad i = 1, \ldots, N. \end{aligned} \tag{3}$$

Denote the probabilities of false alarm, miss, and detection at fusion center by P_F^0, P_M^0, and P_D^0, respectively.

In [3], the distributed detection fusion is modeled by minimizing the following system risk:

$$R^0 = \sum_{i=0}^{1} \sum_{j=0}^{1} C_{ij}^0 P_j P(u_0 = i \mid H_j), \tag{4}$$

where C_{ij}^0 is the cost of global decision being H_i when H_j is present. Using the PBPO methodology, the sensor decision rules and fusion rule can be obtained from the following DDFF:

$$\frac{p(y_k \mid H_1)}{p(y_k \mid H_0)} \underset{u_k=0}{\overset{u_k=1}{\gtrless}} \frac{\sum_{\mathrm{u}^k} \int_{\mathrm{Y}^k} A(\mathrm{u}^k) C_F^0 P(\mathrm{u}^k \mid \mathrm{Y}^k) p(\mathrm{Y}^k \mid y_k, H_0) \, d\mathrm{Y}^k}{\sum_{\mathrm{u}^k} \int_{\mathrm{Y}^k} A(\mathrm{u}^k) C_D^0 P(\mathrm{u}^k \mid \mathrm{Y}^k) p(\mathrm{Y}^k \mid y_k, H_1) \, d\mathrm{Y}^k}, \tag{5}$$

$$\frac{P(\mathrm{u}^* \mid H_1)}{P(\mathrm{u}^* \mid H_0)} \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \frac{C_F^0}{C_D^0}, \tag{6}$$

where u^* denotes one out of 2^N possible values of u and

$$\begin{aligned}
C_F^0 &= P_0\left(C_{10}^0 - C_{00}^0\right),\\
C_D^0 &= \left(1-P_0\right)\left(C_{01}^0 - C_{11}^0\right),\\
C^0 &= C_{01}^0\left(1-P_0\right) + C_{00}^0 P_0,\\
\mathrm{u}^k &= \left(u_1,\ldots,u_{k-1},u_{k+1},\ldots,u_N\right)^T,\\
\mathrm{Y}^k &= \left(y_1,\ldots,y_{k-1},y_{k+1},\ldots,y_N\right)^T,\\
\mathrm{u}^{kj} &= \left(u_1,\ldots,u_{k-1},u_k=j,u_{k+1},\ldots,u_N\right)^T,\\
&\qquad j = 0,1,\\
A\left(\mathrm{u}^k\right) &= P\left(u_0 = 1 \mid \mathrm{u}^{k1}\right) - P\left(u_0 = 1 \mid \mathrm{u}^{k0}\right).
\end{aligned} \tag{7}$$

Thus, the DDFF consists of N equations given by (5) and 2^N equations given by (6). It provides us a way to find a stable solution to the detection fusion problem. Note that the DDFF derived by PBPO methodology cannot ensure providing a globally optimal solution in general.

The purpose of Bayesian criterion in [3] is to optimize the performance of fusion center. As the optimal performance of fusion center is attained, the performances of some local sensors may be ignored. From (5) and (6), the sensor decision rules and fusion rule are coupled with each other. If the system is imperfect, for example, some local sensors fail or the joint conditional probability density functions of observations vary; the performance of fusion center would become very poor. In addition, it is also important to guarantee the performances of local sensors in many practical applications.

3. The Fault-Tolerant Detection Fusion Formulation

The local risk of the kth local sensor is expressed as

$$R^k = \sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij}^k P_j P\left(u_0 = i \mid H_j\right), \tag{8}$$

where C_{ij}^k denotes the cost of the kth local sensor decision being H_i when H_j is present. It is easy to see that the local risk R^k can be expressed as

$$R^k = C_F^k P_F^k - C_D^k P_D^k + C^k, \tag{9}$$

where

$$\begin{aligned}
C_F^k &= P_0\left(C_{10}^k - C_{00}^k\right),\\
C_D^k &= \left(1-P_0\right)\left(C_{01}^k - C_{11}^k\right),\\
C^k &= C_{01}^k\left(1-P_0\right) + C_{00}^k P_0.
\end{aligned} \tag{10}$$

In order to design a fault-tolerant formulation which could guarantee the performances of both fusion center and local sensors, we will consider the total risk, that is, the weighted sum of system risk and local risks:

$$R = \sum_{k=0}^{N} w^k R^k = \sum_{k=0}^{N}\sum_{i=0}^{1}\sum_{j=0}^{1} w^k C_{ij}^k P_j P\left(u_0 = i \mid H_j\right), \tag{11}$$

where $\mathrm{w} = (w^0, w^1, \ldots, w^N)^T$ is the weighting vector such that $w^i \geq 0$, $i = 0, 1, \ldots, N$ and $\sum w^i = 1$. For the given weighting vector w, we consider the following unconstrained optimization problem:

$$\min_{\Gamma} \quad R. \tag{12}$$

Theorem 1. *The solution Γ of problem (12) by the PBPO methodology can be obtained from the following FT-DDFF:*

(a) *The formulation for fusion rule at fusion center as the DDFF is*

$$\frac{P\left(\mathrm{u}^* \mid H_1\right)}{P\left(\mathrm{u}^* \mid H_0\right)} \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \frac{C_F^0}{C_D^0}. \tag{13}$$

(b) *The formulation for decision rule at the kth sensor for all $k = 1, \ldots, N$ alternatively is*

$$\begin{aligned}
&\frac{p\left(y_k \mid H_1\right)}{p\left(y_k \mid H_0\right)} \underset{u_k=0}{\overset{u_k=1}{\gtrless}}\\
&\frac{w^k C_F^k + w^0 \sum_{\mathrm{u}^k}\int_{\mathrm{Y}^k} A\left(\mathrm{u}^k\right) C_F^0 P\left(\mathrm{u}^k \mid \mathrm{Y}^k\right) p\left(\mathrm{Y}^k \mid y_k, H_0\right) d\mathrm{Y}^k}{w^k C_D^k + w^0 \sum_{\mathrm{u}^k}\int_{\mathrm{Y}^k} A\left(\mathrm{u}^k\right) C_D^0 P\left(\mathrm{u}^k \mid \mathrm{Y}^k\right) p\left(\mathrm{Y}^k \mid y_k, H_1\right) d\mathrm{Y}^k}.
\end{aligned} \tag{14}$$

Proof. First, we consider the fusion rule. By the PBPO methodology, we assume that all sensor decision rules have been designed and then the local risks are fixed. Therefore, we only need to minimize the system risk function R^0 as w^0 is a constant. The fusion rule thus can be obtained using the same method in [3].

Next, we deal with the decision rule at the kth sensor by the PBPO methodology for $k = 1, \ldots, N$. Noting that the fusion rule and other sensor decision rules have been designed and fixed, we may express R as

$$\begin{aligned}
R &= w^0 C^0 + w^k C^k + \sum_{i\neq k}^{N} w^i R^i\\
&\quad + w^0 C_F^0 \sum_{\mathrm{u}} P\left(u_0 = 1 \mid \mathrm{u}\right) P\left(\mathrm{u} \mid H_0\right)\\
&\quad - w^0 C_D^0 \sum_{\mathrm{u}} P\left(u_0 = 1 \mid \mathrm{u}\right) P\left(\mathrm{u} \mid H_1\right)\\
&\quad + w^k\left[C_F^k P\left(u_k = 1 \mid H_0\right) - C_D^k P\left(u_0 = 1 \mid H_1\right)\right].
\end{aligned} \tag{15}$$

Since w, C^0, C^k, and $\sum_{i\neq k}^{N} R^i$ are constants, we only need to minimize the remaining items:

$$\begin{aligned}\overline{R} &:= w^0 C_F^0 \sum_{\mathrm{u}} P(u_0 = 1 \mid \mathrm{u}) P(\mathrm{u} \mid H_0) \\ &\quad + w^k C_F^k P(u_k = 1 \mid H_0) \\ &\quad - w^0 C_D^0 \sum_{\mathrm{u}} P(u_0 = 1 \mid \mathrm{u}) P(\mathrm{u} \mid H_1) \\ &\quad - w^k C_D^k P(u_0 = 1 \mid H_1).\end{aligned} \tag{16}$$

For $k = 1, \ldots, N$, we have

$$\begin{aligned}&\sum_{\mathrm{u}^k} P(u_0 = 1 \mid \mathrm{u}^k)\left[C_F^0 P(\mathrm{u} \mid H_0) - C_D^0 P(\mathrm{u} \mid H_1)\right] \\ &= \sum_{\mathrm{u}^k}\left\{P(u_0 = 1 \mid \mathrm{u}^{k1})\right. \\ &\cdot \left[C_F^0 P(\mathrm{u}^{k1} \mid H_0) - C_D^0 P(\mathrm{u}^{k1} \mid H_1)\right] \\ &+ P(u_0 = 1 \mid \mathrm{u}^{k0}) \\ &\cdot \left.\left[C_F^0 P(\mathrm{u}^{k0} \mid H_0) - C_D^0 P(\mathrm{u}^{k0} \mid H_1)\right]\right\} \\ &= \sum_{\mathrm{u}^k}\left\{P(u_0 = 1 \mid \mathrm{u}^{k0})\right. \\ &\cdot \left[C_F^0 P(\mathrm{u}^{k} \mid H_0) - C_D^0 P(\mathrm{u}^{k} \mid H_1)\right] \\ &+ \left[P(u_0 = 1 \mid \mathrm{u}^{k1}) - P(u_0 = 1 \mid \mathrm{u}^{k0})\right] \\ &\cdot \left.\left[C_F^0 P(\mathrm{u}^{k1} \mid H_0) - C_D^0 P(\mathrm{u}^{k1} \mid H_1)\right]\right\} = \overline{C} \\ &+ \sum_{\mathrm{u}^k}\left\{A(\mathrm{u}^k)\left[C_F^0 P(\mathrm{u}^{k1} \mid H_0) - C_D^0 P(\mathrm{u}^{k1} \mid H_1)\right]\right\},\end{aligned} \tag{17}$$

where

$$\begin{aligned}\overline{C} &= \sum_{\mathrm{u}^k}\left\{P(u_0 = 1 \mid \mathrm{u}^{k0})\right. \\ &\quad \cdot \left.\left[C_F^0 P(\mathrm{u}^{k} \mid H_0) - C_D^0 P(\mathrm{u}^{k} \mid H_1)\right]\right\}.\end{aligned} \tag{18}$$

Therefore, $\overline{R}$ can be expanded in terms of the kth local decision u_k as follows:

$$\begin{aligned}\overline{R} &= w^0 \left\{\overline{C} + \sum_{\mathrm{u}^k}\left\{A(\mathrm{u}^k)\right.\right. \\ &\quad \cdot \left.\left.\left[C_F^0 P(\mathrm{u}^{k1} \mid H_0) - C_D^0 P(\mathrm{u}^{k1} \mid H_1)\right]\right\}\right\} \\ &\quad + w^k\left[C_F^k P(u_k = 1 \mid H_0) - C_D^k P(u_0 = 1 \mid H_1)\right].\end{aligned} \tag{19}$$

The conditional density of u is given by

$$P(\mathrm{u} \mid H_j) = \int_{\mathrm{Y}} P(\mathrm{u} \mid \mathrm{Y}) P(\mathrm{Y} \mid H_j)\, d\mathrm{Y}, \tag{20}$$

where $\mathrm{Y} = (y_1, \ldots, y_N)^T$ and $\int_{\mathrm{Y}} \cdot$ represents a multifold integral over all components of Y. Since the decision of each local sensor depends only on its own observations, then

$$\begin{aligned}P(\mathrm{u} \mid \mathrm{Y}) &= \prod_{i=1}^{N} P(u_i \mid y_i), \\ P(\mathrm{u}^{ki} \mid \mathrm{Y}) &= P(u_k = i \mid y_k) P(\mathrm{u}^k \mid \mathrm{Y}^k), \quad i = 0, 1.\end{aligned} \tag{21}$$

From

$$\begin{aligned}P(\mathrm{u}^{ki} \mid H_j) &= \int_{\mathrm{Y}} P(\mathrm{u}^{ki} \mid \mathrm{Y}) P(\mathrm{Y} \mid H_j)\, d\mathrm{Y} \\ &= \int_{\mathrm{Y}} P(u_k = i \mid y_k) P(\mathrm{u}^k \mid \mathrm{Y}^k) p(\mathrm{Y} \mid H_j)\, d\mathrm{Y},\end{aligned} \tag{22}$$

for $j = 0, 1$, we have

$$\begin{aligned}\overline{R} &= w^0 \overline{C} + \int_{y_k} P(u_k = 1 \mid y_k)\, dy_k \\ &\cdot \left\{w^0 \sum_{\mathrm{u}^k} \int_{\mathrm{Y}^k} A(\mathrm{u}^k) P(\mathrm{u}^k \mid \mathrm{Y}^k)\right. \\ &\cdot \left[C_F^0 p(\mathrm{Y} \mid H_0) - C_D^0 p(\mathrm{Y} \mid H_1)\right] d\mathrm{Y}^k \\ &+ \left. w^k\left[C_F^k p(y_k \mid H_0) - C_D^k p(y_k \mid H_1)\right]\right\}.\end{aligned} \tag{23}$$

Again noting that the fusion rule and other sensor decision rules are fixed and $w^0\overline{C}$ is a constant, we obtain the following sensor decision rule:

$$P(u_k = 1 \mid y_k) = \begin{cases} 0, & \text{if } D(k) \leq 0, \\ 1, & \text{otherwise}, \end{cases} \tag{24}$$

where

$$\begin{aligned}D(k) &= w^k\left[C_F^k p(y_k \mid H_0) - C_D^k p(y_k \mid H_1)\right] \\ &+ w^0 \sum_{\mathrm{u}^k} \int_{\mathrm{Y}^k} A(\mathrm{u}^k) P(\mathrm{u}^k \mid \mathrm{Y}^k) \\ &\cdot \left[C_F^0 p(\mathrm{Y} \mid H_0) - C_D^0 p(\mathrm{Y} \mid H_1)\right] d\mathrm{Y}^k.\end{aligned} \tag{25}$$

From

$$P(\mathrm{Y} \mid H_j) = P(\mathrm{Y}^k \mid y_k, H_j)\, p(y_k \mid H_j), \tag{26}$$

we conclude that the decision rule at the kth sensor can be expressed in an alternate form as (14). □

Remark 2. Similar to the DDFF, the fusion rule and sensor decision rules of the FT-DDFF given in (13) and (14) are also coupled with each other. In addition, the FT-DDFF is derived by the PBPO methodology so that it only obtains the suboptimal solution of original optimization problem (12) in general. However, as the FT-DDFF partly optimizes the local risks, the performances of the local sensors may be better than the DDFF. More importantly, the new detection formulation has some superiorities of fault tolerance for the imperfect detection fusion system. It will be shown in Section 4.

Table 1: Ratios of average risks by the FT-DDFF to those by the DDFF.

τ	$m_1=1.0, m_2=1.0, m_3=1.4$; $\sigma_1=1.4, \sigma_2=1.0, \sigma_3=2.0$				$m_1=1.7, m_2=1.5, m_3=1.3$; $\sigma_1=1.0, \sigma_2=1.4, \sigma_3=2.0$			
	r^0	r^1	r^2	r^3	r^0	r^1	r^2	r^3
0.1	0.9532	0.9096	0.9391	0.9162	0.8642	0.9716	0.7172	0.5728
0.2	0.9551	0.9111	0.9400	0.9177	0.8890	0.9725	0.7200	0.5730
0.3	0.9579	0.9142	0.9423	0.9208	0.9006	0.9732	0.7255	0.5732
0.4	0.9611	0.9195	0.9462	0.9260	0.9202	0.9741	0.7343	0.5739
0.5	0.9639	0.9259	0.9511	0.9324	0.9437	0.9826	0.7421	0.5765
0.6	0.9670	0.9338	0.9574	0.9401	0.9840	0.9958	0.7595	0.5809
0.7	0.9709	0.9433	0.9651	0.9492	1.0048	1.0047	0.7833	0.5848
0.8	0.9757	0.9546	0.9745	0.9598	1.0077	1.0106	0.8168	0.5908
0.9	0.9827	0.9686	0.9866	0.9723	1.0041	1.0120	0.8698	0.6053
1.0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

4. Numerical Examples

In this section, some numerical simulations are provided for the binary detection fusion problem in a distributed system with three local sensors; that is, $N = 3$. The performance of the FT-DDFF is evaluated and compared with that of the DDFF. The observations at local sensors are assumed to be conditionally independent; then the sensor decision rules (14) reduce to the following threshold tests:

$$\frac{p(y_k \mid H_1)}{p(y_k \mid H_0)} \underset{u_k=0}{\overset{u_k=1}{\gtrless}} \frac{w^k C_F^k + w^0 \sum_{\mathrm{u}^k} A(\mathrm{u}^k) C_F^0 \prod_{i=1,i\neq k}^{N} P(u_i \mid H_0)}{w^k C_D^k + w^0 \sum_{\mathrm{u}^k} A(\mathrm{u}^k) C_D^0 \prod_{i=1,i\neq k}^{N} P(u_i \mid H_1)}. \tag{27}$$

Let the costs of the correct decision and mistaken decision be zero and unity, respectively; that is, $C_{00}^k = C_{11}^k = 0$, and $C_{10}^k = C_{01}^k = 1$; the system risk R^0 and the local risk R^k are just the probabilities of error decisions. Furthermore, we assume that each local sensor has equal importance; then the weighting vector can be expressed as $\mathrm{w} = (\tau, q, q, q)^T$, $q = (1-\tau)/3$, where the value of $\tau \in [0,1]$ reflects the different importance of system risk and local risks.

Assume that the observation noises at three sensors follow the Gaussian distribution. Under H_0, the conditional probability densities at three local sensors are assumed to be identical with mean zero and variance one. Under H_1, the mean and variance of observation at the kth sensor are denoted by m_k and σ_k^2, respectively, for $k = 1, 2, 3$.

The purpose of this paper is to design a fault-tolerant detection fusion rule which can guarantee the performance of system no matter whether it works well or not. Therefore, we will just evaluate the performance of the FT-DDFF for perfect and imperfect distributed systems.

4.1. Perfect Distributed Systems. We will compare the performances of two formulations when the system is perfect. As mentioned before, besides the system risk, we also focus on the local risks so that the performances of local sensors and fusion center will be evaluated simultaneously.

Suppose that the prior probability P_0 follows uniformly distribution on the interval $[0, 1]$. Table 1 reports the ratios of average risks by the FT-DDFF to those by the DDFF:

$$r^k = \frac{\mathbb{E}(R^k) \text{ by the FT-DDFF}}{\mathbb{E}(R^k) \text{ by the DDFF}}, \quad k = 0, 1, 2, 3, \tag{28}$$

where the symbol $\mathbb{E}(\cdot)$ means the expectation with respect to the prior probability P_0.

In Table 1, for some different τ, we computed all average risk ratios of fusion center and local sensors. When $\tau = 1$, as the weight of each local sensor is zero, the FT-DDFF is equal to the DDFF. When $\tau < 0.7$, all the values of r^k, $k = 0, 1, 2, 3$, in Table 1 are less than 1, which means that the FT-DDFF has more significant advantages than the DDFF. How to take an appropriate τ depends on the structure of system, historical experience and subjective factors, and so forth. One way is to choose an optimal τ_{opt} by minimizing the expectation of total risk R:

$$\tau_{\text{opt}} = \arg\min_{\tau} \tau \mathbb{E}(R^0) + \frac{1-\tau}{3}\left[\mathbb{E}(R^1) + \mathbb{E}(R^2) + \mathbb{E}(R^3)\right]. \tag{29}$$

When $m_1 = 1.0$, $m_2 = 1.0$, and $m_3 = 1.4$ and $\sigma_1 = 1.4$, $\sigma_2 = 1.0$, and $\sigma_3 = 2.0$, one can obtain the optimal $\tau_{\text{opt}} = 0.17$ using an iterative algorithm. Figure 2 shows the total risk R with respect to different weight τ in this case.

If $m_1 = 1.7$, $m_2 = 1.5$, and $m_3 = 1.3$ and $\sigma_1 = 1.0$, $\sigma_2 = 1.4$, and $\sigma_3 = 2.0$, we have $\tau_{\text{opt}} = 0.3$. Next, we denote this case as

$$\text{Scenario A}: \begin{cases} \tau = 0.3, \\ m_1 = 1.7, \;\; m_2 = 1.5, \;\; m_3 = 1.3, \\ \sigma_1 = 1.0, \;\; \sigma_2 = 1.4, \;\; \sigma_3 = 2.0. \end{cases} \tag{30}$$

For Scenario A, the comparisons of probabilities of error detections for fusion center and local sensors under

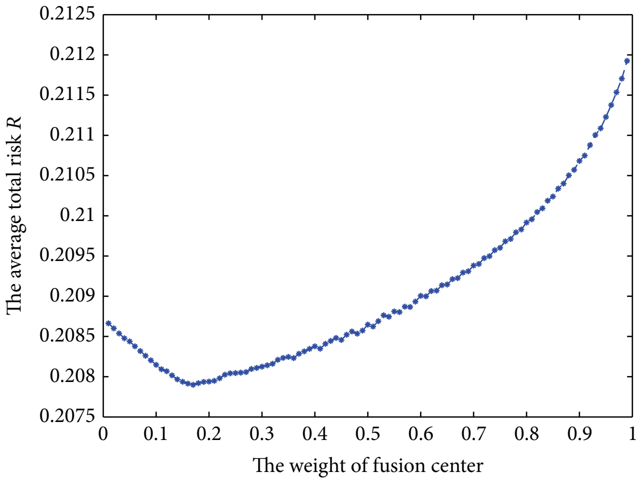

FIGURE 2: The total risk R versus the weight τ at fusion center, while $m_1 = 1.0$, $m_2 = 1.0$, and $m_3 = 1.4$ and $\sigma_1 = 1.4$, $\sigma_2 = 1.0$, and $\sigma_3 = 2.0$.

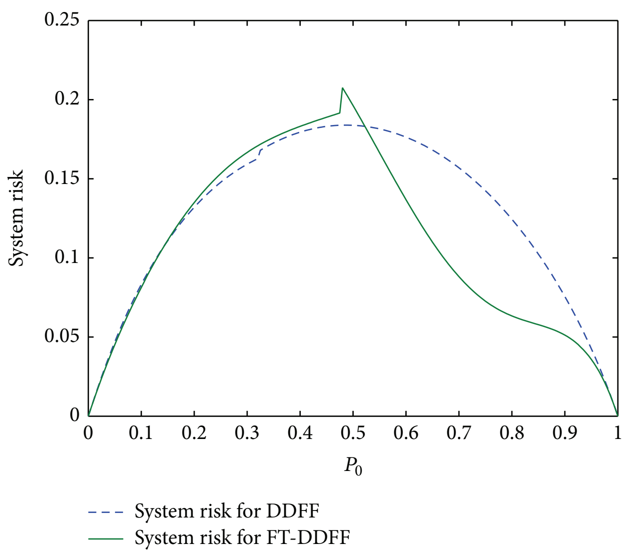

FIGURE 3: Comparison of the system risks for Scenario A.

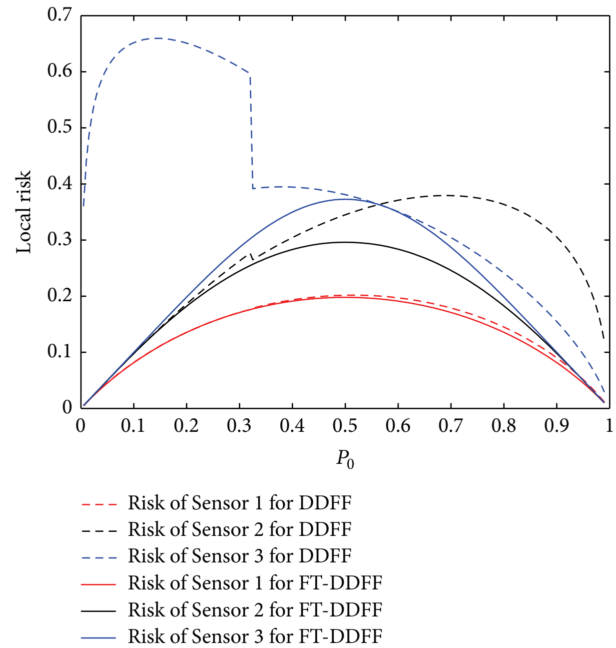

FIGURE 4: Comparison of the local risks for Scenario A.

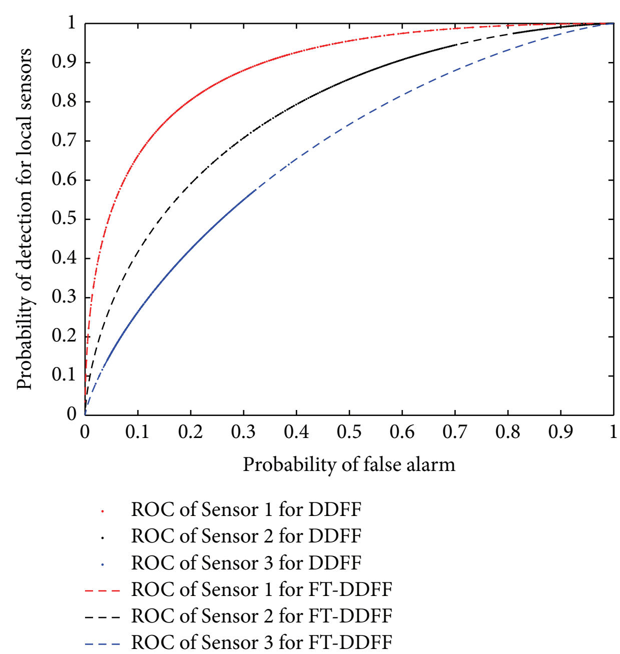

FIGURE 5: Comparison of ROCs at local sensors for Scenario A.

the DDFF and FT-DDFF are shown in Figures 3 and 4. Figure 5 shows the comparisons of the receiver operating characteristics (ROCs) of local sensors.

Figure 3 shows the system risks of two fusion formulations. Although the system risk of the FT-DDFF is not less than that of the DDFF uniformly, the average system risk is less certainly. Note that the curve of system risk R^0 by the FT-DDFF is not smooth because it is only a part of total risk R which is the objective function in optimization problem (12). It seems that the performances of local sensors under both formulations are the same as those in Figure 5, while Figure 4 shows that the FT-DDFF has smaller local risks than the DDFF uniformly.

4.2. Imperfect Distributed Systems. There are many kinds of deteriorations for a distributed fusion system. The fusion center may be destroyed or could not work normally; some of local sensors may be destroyed or the communications between fusion center and some local sensors may be cut off, which means that some local sensors are missing from the standpoint of fusion center; some of local sensors may be interfered and then the conditional distributions of observations or some parameters of the distributions may be changed. Next, we will consider the above deteriorations, respectively. More complicated situations, such as some

Table 2: Ratios of average system risk for missing local sensors with different noise variances.

σ_1	σ_2	σ_3	ρ_1	ρ_2	ρ_3	$\overline{\rho}$
1.0	1.4	1.4	0.9679	0.9844	1.0029	0.9851
1.0	2.0	1.4	0.9606	1.0138	0.9756	0.9833
1.0	2.5	1.4	0.9084	1.0287	0.9789	0.9720
1.4	1.0	1.4	0.9562	0.9851	1.0399	0.9937
1.4	1.0	2.0	0.9513	0.9062	1.0832	0.9802
1.4	1.0	2.5	0.9435	0.8756	1.0962	0.9718
1.4	2.0	1.0	0.9392	1.0879	0.9414	0.9895
2.0	2.0	1.0	0.9732	1.0214	0.9843	0.9929
2.5	2.0	1.0	0.9913	0.9935	1.0019	0.9956

combination of above deteriorations, could be processed similarly.

(1) The Fusion Center Is Destroyed. If the fusion center is destroyed, each local sensor has to use its own decision rule to make the final decision for the two hypotheses. Owing to the absence of fusion center, we only compare the performances of the local sensors. As shown in Section 4.1, if an appropriate τ is taken, the FT-DDFF can outperform the DDFF at all local sensors.

(2) Some of Local Sensors Are Missing. If some of local sensors are missing, the fusion center has to make a final decision using the available local decisions. We suppose that only one local sensor will be missing without loss of generalization. Table 2 reports the ratios of average system risk by the FT-DDFF to that by the DDFF for $\tau = 0.3$, $m_1 = 1.7$, $m_2 = 1.5$, and $m_3 = 1.3$, where ρ_k is r^0 given by (28), while the kth local sensor is missing, $k = 1, 2, 3$, and $\overline{\rho}$ is the average of ρ_1, ρ_2, and ρ_3.

From Table 2, we can see that, compared with the DDFF, the FT-DDFF decreases the average system risks, while some special sensors are missing and increase the average system risks if the remaining sensor is missing. Specifically, we have the following observations.

(i) For all kinds of situations, every $\overline{\rho}$ is less than 1. For every situation, two of ρ_1, ρ_2, and ρ_3 are less than 1, while the remaining is larger than 1. It shows that although the FT-DDFF cannot uniformly decrease the system risks, it will decrease the average system risk if one local sensor is missing.

(ii) If Sensor 1 is missing, every ρ_1 is less than 1, which shows that the FT-DDFF does decrease the system risks for different parameters.

(iii) Combining the above with results in Table 1, we conclude that, compared with the DDFF, if the system is perfect, the FT-DDFF has better performances of both fusion center and local sensors; if one local sensor is missing, the FT-DDFF has a little improvement in average; in particular, the performance of fusion center uniformly has a little improvement if Sensor 1 is missing.

For Scenario A, the performances of both formulations given in Table 2 could be furthermore revealed in Figures 6 and 7. It shows that, compared with the DDFF, the performance of fusion center by the FT-DDFF is better when

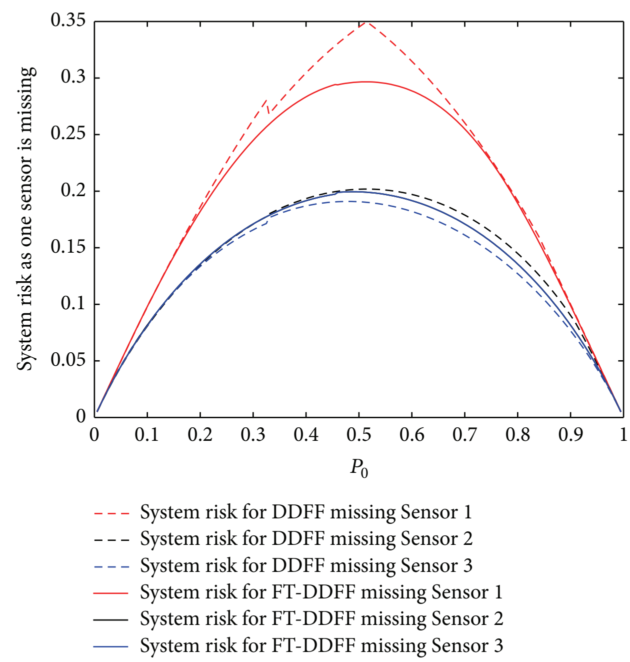

Figure 6: Comparison of system risks when one of local sensors is missing for Scenario A.

Sensor 1 or Sensor 2 is missing and worse as Sensor 3 is missing. Note that the ROCs of fusion center by the FT-DDFF and DDFF are almost identical while Sensor 2 is missing and are similar to that by the FF-DDFF while Sensor 3 is missing.

(3) Some of Local Sensors Are Interfered. If some of local sensors are interfered, the conditional distributions of observations or their parameters may be changed. We suppose that only one local sensor would be interfered and its noise variance increases. Table 3 reports the ratios of average system risks by the FT-DDFF to those by the DDFF for Scenario A, where δ_k is r^0 given by (28) while only σ_k varies, $k = 1, 2, 3$.

From Table 3, we can see that, compared with the DDFF, the FT-DDFF decreases the average system risks while the values of changed σ_1 and σ_2 become large enough and increases the average system risks while σ_3 changed. Specifically, we have the following observations.

Table 3: Ratios of average system risks for interfering local sensors with different noise variances.

σ_1	δ_1	σ_2	δ_2	σ_3	δ_3
1.5	1.0008	2.0	1.0301	2.0	1.0498
2.0	0.9788	2.5	1.0244	2.5	1.0351
2.5	0.9678	3.0	1.0164	3.0	1.0233
3.0	0.9623	3.5	1.0084	3.5	1.0139
3.5	0.9598	4.0	1.0006	4.0	1.0130
4.0	0.9588	4.5	0.9876	4.5	1.0115
4.5	0.9586	5.0	0.9866	5.0	1.0064
5.0	0.9589	5.5	0.9874	5.5	1.0063

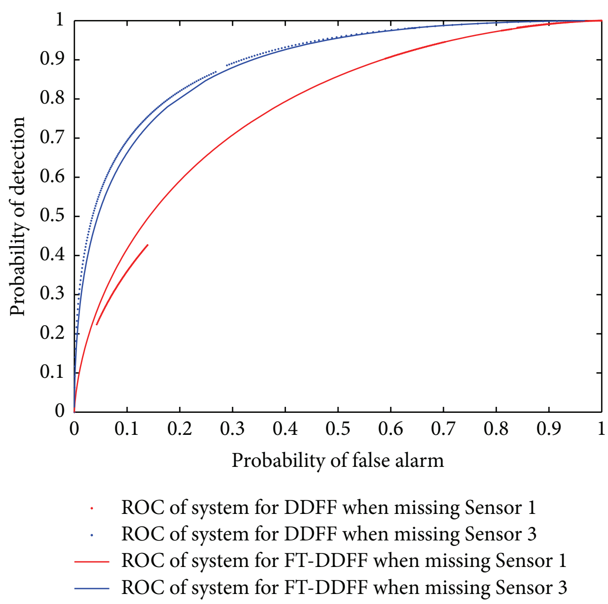

Figure 7: Comparison of detection probabilities at fusion center when one of local sensors is missing for Scenario A.

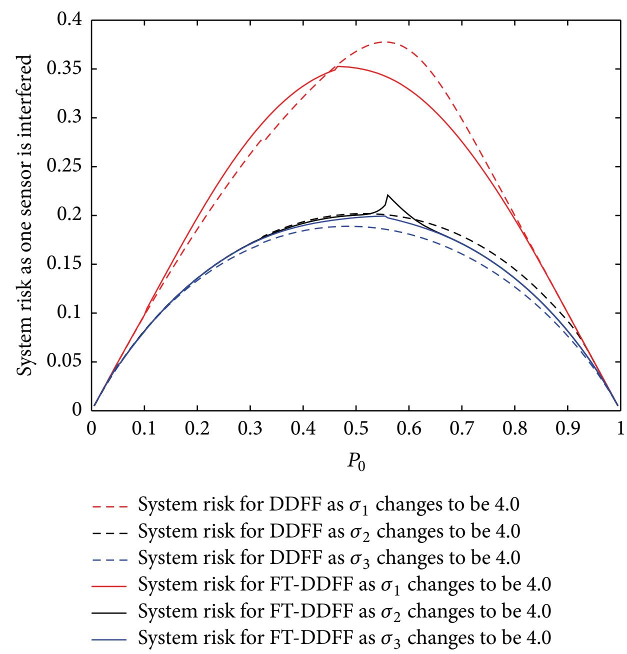

Figure 8: Comparison of system risks when one of local sensors is interfered for Scenario A.

(i) If Sensor 1 is interfered, the ratio δ_1 deceases as σ_1 increases. While $\sigma_1 > 2.0$, all the corresponding ratio $\delta_1 < 1$ which means the FT-DDFF has some superiorities of fault tolerance. Similarly, conclusion could be derived as Sensor 2 is interfered.

(ii) If σ_3 increases, the corresponding ratio δ_1 deceases. But all δ_1 are larger than 1 whatever σ_3 changes to.

(iii) The above findings are consistent with the results in Table 2. This is as σ_k becomes larger, the signal-to-noise ratio (SNR) at the kth sensor decreases. If σ_k is large enough, the corresponding SNR would be close to zero just as the kth sensor is missing.

For Scenario A, the performances for both formulations given in Table 3 with varying $\sigma_k = 4.0$, $k = 1, 2, 3$, are also revealed in Figures 8 and 9. These results show that, compared with the DDFF, the FT-DDFF has better performance at fusion center when Sensor 1 or Sensor 2 is interfered and worse performance as Sensor 3 is interfered.

A lot of simulations also have the similar results for different values of m_k, σ_k, $k = 1, 2, 3$, with an appropriate τ. From all of the simulations we could conclude that if the system is perfect, the FT-DDFF obviously outperforms the DDFF; if one local sensor is missing, the FT-DDFF slightly outperforms the DDFF in average; if one local sensor is interfered seriously, especially is missing, the FT-DDFF also slightly outperforms the DDFF in average.

5. Conclusion

In this paper, we deal with the distributed detection fusion having fault-tolerance capacities. A new detection fusion strategy is proposed by minimizing the weighted sum of system risk and local sensor risks. We solve this team decision problem by the PBPO methodology and provide the FT-DDFF for fault-tolerant fusion rule and sensor decision rules. Although the FT-DDFF could not ensure an optimal solution to the original detection fusion problem, it does have some superiorities compared with the DDFF in average. The numerical examples confirm the above claims and show that the new detection formulation has more fault tolerance in

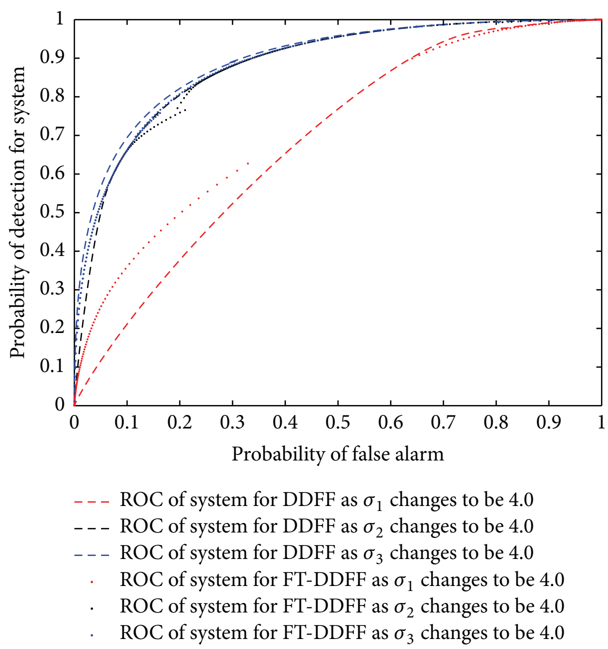

FIGURE 9: Comparison of ROCs at fusion center when one of local sensors is interfered for Scenario A.

some certain situations such as the destroy of fusion center, failure of some local sensors, and variety of distributions of sensor noises.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under Grant no. 61374027, the Specialized Research Fund for the Doctoral Program of Higher Education under Grant no. 20130181110042, and the National Key Basic Research Program of China under Grant no. 2013CB329405.

References

[1] J. Llinas and E. Waltz, *Multisensor Data Fusion*, Artech House, Boston, Mass, USA, 1990.

[2] Y. Bar-Shalom and X. R. Li, *Multitarget-Multisensor Tracking: Principles and Techniques*, YBS Publishing, Storrs, Conn, USA, 1995.

[3] P. K. Varshney, *Distributed Detection and Data Fusion*, Springer, New York, NY, USA, 1997.

[4] Y. Zhu, R. S. Blum, Z.-Q. Luo, and K. M. Wong, "Unexpected properties and optimum-distributed sensor detectors for dependent observation cases," *IEEE Transactions on Automatic Control*, vol. 45, no. 1, pp. 62–72, 2000.

[5] A. K. Hyder, E. Shahbazian, and E. Waltz, Eds., *Multisensor Fusion*, Kluwer Academic Publishers, Dordrecht, The Netherlands, 2002.

[6] G. L. Foresti, C. S. Regazzoni, and P. K. Varshney, Eds., *Multisensor Surveillance Systems: The Fusion Perspective*, Kluwer Academic Publishers, New York, NY, USA, 2003.

[7] Y. Zhu, *Multisensor Decision and Estimation Fusion*, Kluwer Academic, Boston, Mass, USA, 2003.

[8] S. Haykin and K. J. R. Liu, *Handbook on Array Processing and Sensor Networks*, John Wiley & Sons, Hoboken, NJ, USA, 2009.

[9] M. E. Liggins, D. L. Hall, and J. Llinas, Eds., *Handbook of Multisensor Data Fusion: Theory and Practice*, CRC Press, Boca Raton, Fla, USA, 2nd edition, 2009.

[10] R. Viswanathan and P. K. Varshney, "Distributed detection with multiple sensors I. Fundamentals," *Proceedings of the IEEE*, vol. 85, no. 1, pp. 54–63, 1997.

[11] R. S. Blum, S. A. Kassam, and H. Vincent Poor, "Distributed detection with multiple sensors: part II-advanced topics," *Proceedings of the IEEE*, vol. 85, no. 1, pp. 64–79, 1997.

[12] L. He, Y. Zhu, and J. Zhou, "An algorithm for simultaneously searching for optimal fusion rule and corresponding local, sensor compression rules," in *Proceedings of the 6th World Congress on Intelligent Control and Automation (WCICA '06)*, vol. 2, pp. 6929–6933, IEEE, Dalian, China, June 2006.

[13] X. Shen, Y. Zhu, L. He, and Z. You, "A near-optimal iterative algorithm via alternately optimizing sensor and fusion rules in distributed decision systems," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 47, no. 4, pp. 2514–2529, 2011.

[14] G. G. L. Meyer and H. L. Weinert, "On the design of fault-tolerant signal detectors," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 34, no. 4, pp. 973–978, 1986.

[15] A. R. Reibman and L. W. Nolte, "Optimal fault-tolerant signal detection," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 38, no. 1, pp. 179–180, 1990.

[16] S. C. A. Thomopoulos and L. Zhang, "Distributed decision fusion in the presence of networking delays and channel errors," *Information Sciences*, vol. 66, no. 1-2, pp. 91–118, 1992.

[17] T.-Y. Wang, Y. S. Han, P. K. Varshney, and P.-N. Chen, "Distributed fault-tolerant classification in wireless sensor networks," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 4, pp. 724–733, 2005.

[18] T.-Y. Wang, Y. S. Han, B. Chen, and P. K. Varshney, "A combined decision fusion and channel coding scheme for distributed fault-tolerant classification in wireless sensor networks," *IEEE Transactions on Wireless Communications*, vol. 5, no. 7, pp. 1695–1705, 2006.

[19] Q. Ren, Y. Zhu, X. Shen, and E. Song, "Optimal sensor rules and unified fusion rules for multisensor multi-hypothesis network decision systems with channel errors," *Automatica*, vol. 45, no. 7, pp. 1694–1702, 2009.