# DISTRIBUTED DETECTION WITH CENSORING SENSORS UNDER DEPENDENT OBSERVATIONS

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**ABSTRACT**

Distributed detection in censoring sensor networks, where each sensor transmits "informative" observations to the Fusion Center (FC), and censors those deemed "uninformative", has been investigated by many researchers, but under the assumption of conditionally independent observations. In this paper, we consider a more realistic situation in a censoring sensor network where observations may not be independent. We derive optimal fusion rules at the FC under both Neyman-Perason (NP) and Bayesian frameworks, assuming that each sensor sends complete observations to the FC only when its observation falls out of a certain no-send region. Simulation results are provided to demonstrate the superior performance of our fusion rule compared with several other fusion rules derived in earlier work.

**Keywords: Distributed detection, Censoring, Dependent observations**

## 1. INTRODUCTION

Advances in computational capabilities of the constituent sensor nodes inspired a surge of interest in decentralized detection in which the local sensors send their decisions instead of raw observations to the FC where the final decision is made according to a certain fusion rule [1, 2]. A relatively new transmission efficient distributed detection framework is based on a send/no-send idea. The sensors "censor" their observations according to a censoring mechanism to reduce data transmission. Thus, only a subset of measurements are transmitted to the FC for decision making. It is shown in [3] that with conditionally independent sensor data, if the local likelihood ratio falls in the "no-send" interval, transmission dose not take place, under both NP and Bayesian frameworks.

The authors in [3–5] have considered distributed detection with censored observations. However, they have assumed conditionally independent sensor observations, which may not be valid in many real life situations. Since sensors that are distributed in the area of interest observe the same phenomenon, it is highly probable that their measurements are dependent, especially when the sensors are geographically close to each other and thus their measurements are likely to be contaminated by the same noise source. The effect of dependence on the performance of distributed detection has been investigated in the literature [6, 7].

In this paper, we consider detection with censoring sensors under dependent observations and focus on the design of the fusion rule at the FC for a given censoring scheme at local sensors. We derive the optimal fusion rule under both NP and Bayesian frameworks and compare the performance of our fusion rule with other strategies in a censoring sensor network. Our fusion rule, by taking the dependence among sensors' observations into consideration, can improve the detection performance of a censoring sensor network without violating the communication constraints.

In [8], the authors analyzed the distributed detection problem in a censoring sensor network with correlated observations and proposed a modified Generalized Likelihood Ratio Test (mGLRT). However, they made the assumption that when no sensor sends their data, the FC decides $H_0$, which may not be a good strategy. This is because sensors censor their data only when their observation is not "informative", and neither $H_1$ or $H_0$ is implied. In addition, their analysis ignores local sensors' censoring scheme in fusion rule design.

The idea of censoring has also been applied for data reduction in Wireless Sensor Networks (WSNs) for estimation application in [9]. The canonical decentralized detection problem with each sensor employing an on/off signaling scheme is considered in [10], integrating fading transmission channels in the fusion algorithm design. In [11], a new framework for sequential Bayesian estimation in a censoring sensor network is proposed.

The outline of this paper is as follows. In Section 2, the measurement model as well as the detection problem is described. In Section 3, the problem of detection with a subset of measurements is identified as a composite hypothesis problem in the NP framework. In Section 4, we derive an optimal fusion rule which minimizes the probability of error in the Bayesian sense. Simulation results are provided in Section 5. Section 6 concludes the paper and discusses the future work.

## 2. PROBLEM FORMULATION

We consider a distributed detection network consisting of two sensors where the FC also makes its own observations. The FC combines messages from the sensors and its own observations to determine the true state of nature $H$ as $H_0$ (null) or $H_1$ (target). We denote the complete set of sensors' observations as $\mathbf{X} = [X_1, X_2]$ and FC's observations as $X_0$. Observations are not independent, given $H_i, i = 0, 1$, namely, $p(\mathbf{x}, x_0|H_i) \neq p(x_1|H_i)p(x_2|H_i)p(x_0|H_i)$, where $p(\cdot|H_i)$ is the conditional probability density function (pdf) under hypothesis $H_i$. The joint distribution $p(x_1, x_2, x_0|H_i)$ is known at the FC. Each sensor node computes a local output $g_n(x_n)$ based on its observations $x_n, n = 1, 2$ and a predefined censoring scheme which takes the following form:

$$\begin{aligned} g_n(x_n) &\in R_n^{'} \quad g_n(x_n) \text{ is sent} \\ g_n(x_n) &\in \overline{R_n^{'}} \quad \text{nothing is sent} \end{aligned} \tag{1}$$

where the no-send region $\overline{R_n^{'}}$ satisfies a communication constraint under $H_0$, i.e., $P(g_n(X_n) \in \overline{R_n^{'}}|H_0) = k$, where $k \in (0, 1)$

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in the NP framework and satisfies an average communication constraint, i.e., $P(g_n(X_n) \in \overline{R_n'}|H_0)P(H_0) + P(g_n(X_n) \in \overline{R_n'}|H_1)P(H_1) = k$, in the Bayesian framework. It is proved in [3] that given conditionally independent observations, the optimal $g_n(\cdot)$ is the likelihood ratio function in both NP and Bayesian frameworks, i.e., $g_n(x_n) = l_n(x_n) = p(x_n|H_1)/p(x_n|H_0)$ and $\overline{R_n'}$ is a single interval, i.e., $\overline{R_n'} = [t_{n,l}, t_{n,u}]$, where $t_{n,l}$ and $t_{n,u}$ are respectively the lower limit and the upper limit of the censoring region. The intuition behind this censoring scheme is that the larger or smaller the $l_n(x_n)$ is, the more confidence one has about $H_1$ or $H_0$, thus $l_n(x_n) \in [t_{n,l}, t_{n,u}]$ does not indicate a strong preference for either $H_1$ or $H_0$ and is deemed "uninformative".

For the case of dependent sensor observations, we assume that the censoring scheme at the local sensors takes the following form

$$\begin{aligned} x_n \in R_n & \quad x_n \text{ is sent} \\ x_n \in \overline{R_n} & \quad \text{nothing is sent} \end{aligned} \tag{2}$$

where $\overline{R_n} = l_n^{-1}(\overline{R_n'})$ and $R_n = l_n^{-1}(R_n')$. Recall that if the ratio of two pdfs is non-decreasing in the argument $x_n$, we say that they have Monotone Likelihood Ratio Property (MLRP) in $x_n$. For distributions satisfying MLRP, $\overline{R_n}$ preserves the single interval property.

We assume that the censoring scheme in (2) is known at the FC. We are interested in finding the optimal fusion rule $\phi_0$ under NP and Bayesian criteria. Note that $\phi_0$ is a binary valued function of the received data and the censoring scheme. The design of the fusion rule includes consideration of inter sensor dependence and the censoring mechanism.

## 3. NEYMAN-PEARSON FRAMEWORK

Let the probability of detection and probability of false alarm be defined as $P_D = E[\phi_0|H_1], P_F = E[\phi_0|H_0]$, where $E[\cdot|H_i]$ denotes conditional expectation under $H_i$. The optimal fusion rule in the NP sense would be the one that maximizes the probability of detection $P_D$ subject to the constraint that $P_F$ is no greater than $\alpha$, i.e., $\max P_D$ subject to $P_F \leq \alpha$.

In a two sensor network, at the FC, depending on which sensor's observations are received, there are four possible situations:

$$H_i : \{(0,0,x_0), (0,x_2,x_0), (x_1,0,x_0), (x_1,x_2,x_0)\}, i = 0,1 \tag{3}$$

where $x_0$ is the observation at the FC, $x_1, x_2$ are the received data at the FC from sensor 1 and sensor 2, respectively and a 0 represents the fact that the sensor's observation is in the no-send region and thus not available at the FC. We apply the Neyman-Pearson theorem [12, see Section 6.4] to each of the four cases. For the cases when not all sensors' observations are received at the FC, we convert this simple binary hypothesis testing problem to a composite hypothesis testing problem in which the observations that are not received are treated as the unknown parameters, as in [8]. The authors in [8] modeled the unknown parameters as deterministic and developed a modified Generalized Likelihood Ratio Test (mGLRT) for this problem.

We model the unknown parameter as a random variable and use the Bayesian approach [12] to deal with the composite hypothesis testing problem. The likelihood ratio is calculated in the following way:

$$\frac{p(\mathbf{x}\,|H_1)}{p(\mathbf{x}\,|H_0)} = \frac{\int p(\mathbf{x}\,|\boldsymbol{\theta_1}; H_1) p(\boldsymbol{\theta_1}) d\boldsymbol{\theta_1}}{\int p(\mathbf{x}\,|\boldsymbol{\theta_0}; H_0) p(\boldsymbol{\theta_0}) d\boldsymbol{\theta_0}} \tag{4}$$

where $p(\mathbf{x}\,|\boldsymbol{\theta_i}; H_i), i = 0,1$ are the pdfs of data $\mathbf{x}$ given the parameter $\boldsymbol{\theta_i}$. We treat the received $x_n, n = 0,1,2$ as the sample data $\mathbf{x}$ in (4), and the censored random variables as the unknown parameters with a different prior pdf under each hypothesis. The likelihood ratio in (6) for decision making is obtained by letting $\mathbf{x} = \{x_n : x_n \neq 0\}$ and $\boldsymbol{\theta_i} = \{X_n|H_i : x_n = 0\}$. The decision rule at the FC is

$$\phi_0 = \begin{cases} 1 & L \geq \tau \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $\tau$ is the threshold that satisfies $P_F = \alpha$ and the likelihood ratio $L$ at the FC for the four cases is:

$$L = \begin{cases} \frac{p(x_0,x_1,x_2|H_1)}{p(x_0,x_1,x_2|H_0)} & \text{both send} \\ \frac{\int_{\overline{R_1}} p(x_2,x_0|x_1,H_1)p(x_1|H_1)dx_1}{\int_{\overline{R_1}} p(x_2,x_0|x_1,H_0)p(x_1|H_0)dx_1} & \text{only 2 sends} \\ \frac{\int_{\overline{R_2}} p(x_1,x_0|x_2,H_1)p(x_2|H_1)dx_2}{\int_{\overline{R_2}} p(x_1,x_0|x_2,H_0)p(x_2|H_0)dx_2} & \text{only 1 sends} \\ \frac{\int_{\overline{R_1},\overline{R_2}} p(x_0|x_1,x_2,H_1)p(x_1,x_2|H_1)dx_1dx_2}{\int_{\overline{R_1},\overline{R_2}} p(x_0|x_1,x_2,H_0)p(x_1,x_2|H_0)dx_1dx_2} & \text{both censor} \end{cases} \tag{6}$$

We can see from (6) that if none of the sensors' observations is censored, then the test is equivalent to a simple hypothesis testing problem and the test statistic is the likelihood ratio as that in centralized detection. When observations are independent, the test statistics becomes the product of likelihood ratios in the send region and fixed ratios of probabilities in the no-send region, which is $P(X_n \in R_n|H_1)/P(X_n \in R_n|H_0)$.

The optimality of the fusion rule $\phi_0$ in (5) over any other fusion rule $\phi_0'$ can be shown for the four cases. We demonstrate this with the case that sensor 1 transmits and sensor 2 censors. Let $\phi_0'$ be a fusion rule that also satisfies the false alarm constraint. Based on the definition of the fusion rule in (5), we have

$$\left(\int_{\overline{R_2}} p(x_1,x_2,x_0|H_1)dx_2 - \tau \int_{\overline{R_2}} p(x_1,x_2,x_0|H_0)dx_2\right) \\ [\phi_0(x_1,x_0,\overline{R_2}) - \phi_0'(x_1,x_0,\overline{R_2})] > 0, \forall x_1 \in R_1 \tag{7}$$

After integrating over $x_1 \in R_1$ and $x_0$, we get $P_D(\phi_0) \geq P_D(\phi_0')$. Similar results can be obtained for the other three cases as well, so $\phi_0$ is the optimal fusion rule with censored observation under the NP framework.

This fusion rule can be easily extended to a network with $N(N > 2)$ sensors. Let the random vector $\mathbf{X}_{\mathbb{N}} = [X_1, \ldots, X_N]$ denote observations from the set of sensors $\mathbb{N} = \{1, \ldots, N\}$. For the censoring scheme given in (2), we define a new random variable $Z_n = \mathbb{I}(x_n \in R_n)$, which takes binary values $\{1, 0\}$, to indicate whether a certain observation $x_n$ is available or not at the FC. We further define two sets: $\mathbb{C} = \{n : Z_n = 0\}$ and $\mathbb{S} = \{n : Z_n = 1\}$, to represent respectively the set of sensors whose observations are censored and the set of sensors whose observations are sent to the FC. The optimal fusion rule is in the form (5) with the likelihood ratio given by:

$$L = \frac{\int \cdots \int_{x_n \in R_n, \forall n \in \mathbb{C}} p(x_0, \mathbf{x}_{\mathbb{S}}\,|\,\mathbf{x}_{\mathbb{C}}, H_1) p(\mathbf{x}_{\mathbb{C}}\,|H_1) d\,\mathbf{x}_{\mathbb{C}}}{\int \cdots \int_{x_n \in R_n, \forall n \in \mathbb{C}} p(x_0, \mathbf{x}_{\mathbb{S}}\,|\,\mathbf{x}_{\mathbb{C}}, H_0) p(\mathbf{x}_{\mathbb{C}}\,|H_0) d\,\mathbf{x}_{\mathbb{C}}} \tag{8}$$

where $\mathbf{x}_{\mathbb{C}} = [x_n : n \in \mathbb{C}]$ and $\mathbf{x}_{\mathbb{S}} = [x_n : n \in \mathbb{S}]$.

In (8), $\mathbf{X}_{\mathbb{C}}$ is viewed as the unknown parameter with corresponding prior distributions $p(\mathbf{x}_{\mathbb{C}}\,|H_i)$ under each hypothesis. By assuming independent observations, namely $p(x_0, \mathbf{x}_N\,|H_i) =$

$\prod_{n=0}^{N} p(x_n|H_i), i = 0, 1$, (8) reduces to

$$L = \prod_{n\in\mathbb{C}} \frac{P(X_n \in \overline{R_n}|H_1)}{P(X_n \in \overline{R_n}|H_0)} \prod_{n\in\mathbb{S}} \frac{p(x_n|H_1)}{p(x_n|H_0)} \tag{9}$$

which corresponds to the optimal fusion rule derived under independent observations in [3,4].

## 4. BAYESIAN FRAMEWORK

In this section, we consider the optimal fusion rule with censoring sensors in a Bayesian framework. Let the prior probability of the two hypotheses be $\pi_i = P(H_i), i = 0, 1$. Let the probability of missed detection and probability of false alarm be defined as $P_M = 1 - E[\phi_0|H_1]$ and $P_F = E[\phi_0|H_0]$. We consider the probability of error $Pe = \pi_1 P_M + \pi_0 P_F$ which can be further expanded as the following:

$$\begin{aligned}
Pe - \pi_1 = \\
&\pi_0 P(\text{decide } H_1|H_0) - \pi_1 P(\text{decide } H_1|H_1) \\
&= \int \phi_0[\pi_0 p(x_0, x_1, x_2|H_0) - \pi_1 p(x_0, x_1, x_2|H_1)]dx_1 dx_2 dx_0 \\
&= \int_{R_1 R_2} \phi_0(x_0, x_1, x_2)\big[\pi_0 p(x_0, x_1, x_2|H_0) \\
&\quad -\pi_1 p(x_0, x_1, x_2|H_1)\big]dx_1 dx_2 dx_0 \\
&+ \int_{R_1} \phi_0(x_0, x_1, \overline{R_2})\big[\pi_0 \textstyle\int_{\overline{R_2}} p(x_0, x_1, x_2|H_0)dx_2 \\
&\quad -\pi_1 \textstyle\int_{\overline{R_2}} p(x_0, x_1, x_2|H_1)dx_2\big]dx_1 dx_0 \\
&+ \int_{R_2} \phi_0(x_0, \overline{R_1}, x_2)\big[\pi_0 \textstyle\int_{\overline{R_1}} p(x_0, x_1, x_2|H_0)dx_1 \\
&\quad -\pi_1 \textstyle\int_{\overline{R_1}} p(x_0, x_1, x_2|H_1)dx_1\big]dx_2 dx_0 \\
&+ \int \phi_0(x_0, \overline{R_1}, \overline{R_2})\big[\pi_0 \textstyle\int_{\overline{R_1},\overline{R_2}} p(x_0, x_1, x_2|H_0)dx_1 dx_2 \\
&\quad -\pi_1 \textstyle\int_{\overline{R_1},\overline{R_2}} p(x_0, x_1, x_2|H_1)dx_1 dx_2\big]dx_0
\end{aligned} \tag{10}$$

To minimize $Pe$, one can minimize each of the four terms on the right hand side. The approach is to set $\phi_0 = 1$ when the term in the bracket is less than zero and $\phi_0 = 0$, otherwise. This results in an optimal decision rule in the following form

$$\phi_0 = \begin{cases} 1 & L_B \geq \pi_0/\pi_1 \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where

$$L_B = \begin{cases} \frac{p(x_0,x_1,x_2|H_1)}{p(x_0,x_1,x_2|H_0)} & \text{both send} \\ \frac{\int_{x_2\in\overline{R_2}} p(x_0,x_1,x_2|H_1)dx_2}{\int_{x_2\in\overline{R_2}} p(x_0,x_1,x_2|H_0)dx_2} & \text{only 1 sends} \\ \frac{\int_{x_1\in\overline{R_1}} p(x_0,x_1,x_2|H_1)dx_1}{\int_{x_1\in\overline{R_1}} p(x_0,x_1,x_2|H_0)dx_1} & \text{only 2 sends} \\ \frac{\int_{x_1\in\overline{R_1},x_2\in\overline{R_2}} p(x_0,x_1,x_2|H_1)dx_1 dx_2}{\int_{x_1\in\overline{R_1},x_2\in\overline{R_2}} p(x_0,x_1,x_2|H_0)dx_1 dx_2} & \text{both censor} \end{cases} \tag{12}$$

The result can be generalized to a sensor network with $N(N > 2)$ sensors. By minimizing the probability of error at the FC, the optimal fusion rule we obtain is of the form (11) with the following likelihood ratio:

$$L_B = \frac{\int\cdots\int_{x_n\in R_n,\forall n\in\mathbb{C}} p(x_0, \mathbf{x}_N\,|H_1)d\,\mathbf{x}_{\mathbb{C}}}{\int\cdots\int_{x_n\in R_n,\forall n\in\mathbb{C}} p(x_0, \mathbf{x}_N\,|H_0)d\,\mathbf{x}_{\mathbb{C}}} \tag{13}$$

where the notations follow those in Section 3. The optimal fusion rule which minimizes the probability of error at the FC with dependent observations generalizes the fusion rule with independent sensor observations in [3,4]. We also notice that the likelihood ratio in this optimal decision rule in the Bayesian framework is of the same form as that in our proposed fusion rule in the NP framework.

## 5. RESULTS AND DISCUSSION

In this section, we compare our proposed fusion rules with other fusion methods in both NP and Bayesian frameworks through simulations. A two sensor network is considered in our simulation study. It is assumed that the joint distribution of sensors' and the FC's observations follow a multivariate Gaussian distribution under both hypotheses.

$$\begin{aligned} H_1 &: [X_0, X_1, X_2] \sim N(\boldsymbol{\mu}, \Sigma_1) \\ H_0 &: [X_0, X_1, X_2] \sim N(0, \Sigma_0) \end{aligned} \tag{14}$$

where $\boldsymbol{\mu} \neq 0$ is the mean under $H_1$ and $\Sigma_1, \Sigma_0$ are covariance matrices with non-zero off-diagonal elements (dependence among observations). Since the multivariate normal distribution satisfies the monotone likelihood ratio property, we set the no-send region to be a single interval and identical censoring schemes are employed at both sensors.

Compared with the centralized method, decentralized detection with censoring sensors has a suboptimal performance, but achieves better communication efficiency. Only when all the sensors' observations fall in their send region, the decentralized method performs as well as the centralized method. Thus, the performance of centralized detection provides an upper bound for our proposed approach. For performance comparison, we employ a simpler fusion rule assuming independent observations that uses the expression in (9) for the test. Another fusion rule for performance comparison is based on ignoring the censored observations, which uses only the received observations' likelihood ratios for decision making.

The performance of the fusion rule based on our approach is depicted in Figure 1. The ROC curve corresponding to our proposed approach is upper bounded by the centralized method. By assuming conditional independence, the performance is degraded but computation at the FC is reduced. Similarly, computation efficiency is achieved at the cost of sacrificing detection performance for the fusion rule which uses the likelihood ratios of only the received observations.

We also compare the performance of our proposed fusion rule with the mGLRT in [8], which first estimates the observations that are not received using the received data by maximum likelihood estimation (MLE), then replaces them with their ML estimates in the likelihood ratio test. For example, in a two sensor network when $x_1$ is censored and $x_2$ is transmitted, according to mGLRT the likelihood ratio at the FC is

$$\frac{\max_{x_1} p(x_1, x_2, x_0|H_1)}{\max_{x_1} p(x_1, x_2, x_0|H_0)}$$

It is shown in Figure 1 that the fusion rule based on ignoring censored observations performs even better than mGLRT. The reason is that according to [8], the test statistic for mGLRT is a function of only the received observations at the FC, which may not be the likelihood ratio, however, by NP theory, the optimal function is the likelihood ratio function, which is exactly what we get by ignoring censored observations.

Taking the prior information that once an observation is not received at the FC, it must fall in the no-send region, into consideration, we modify the mGLRT by maximizing the likelihood within no-send regions to obtain the MLEs. The test at the FC uses the following statistic

$$\frac{\max_{x_1 \in \overline{R_1}} p(x_1, x_2, x_0|H_1)}{\max_{x_1 \in \overline{R_1}} p(x_1, x_2, x_0|H_0)}$$

and we name this fusion rule the mGLRT2. The optimality of mGLRT2, compared with the method of ignoring censored observations, depends on the form and size of the no-send region $\overline{R_n}$. The optimal fusion rule we proposed in this paper has a better performance than the other fusion schemes.

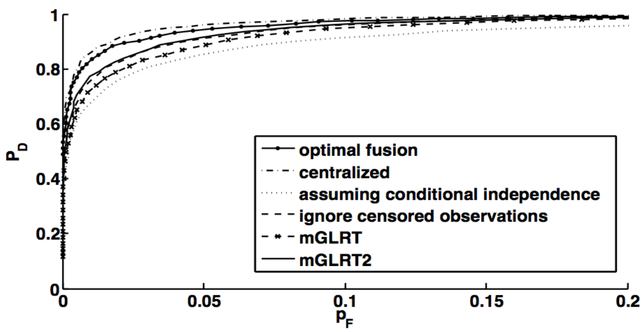


**Fig. 1**. ROC curves for different fusion rules with multivariate normal distributed data

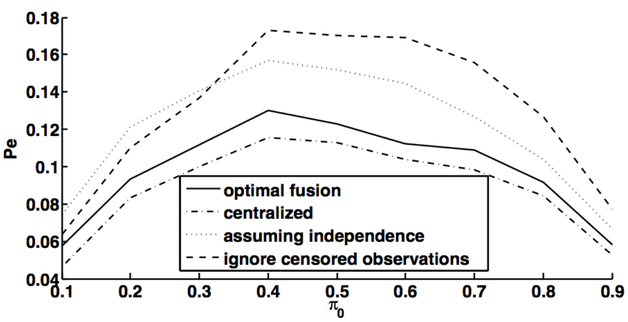


**Fig. 2**. Probability of error vs $\pi_0$ under different fusion rules with multivariate normal distributed data

In the Bayesian framework, the probability of error, as a function of $\pi_0$ is shown in Figure 2. It can be seen that the centralized method performs the best, followed by our optimal fusion rule in the censoring sensor network. The other two approaches are outperformed by our proposed fusion rule in this paper. However, in the low $\pi_0$ region, the fusion rule assuming independence has better performance than the other one which ignores unreceived data, and in the high $\pi_0$ region, the opposite happens. The reason for that is, the performance of the two fusion rules depends on which one of the four cases (case 1: both send; case 2: sensor 1 sends, sensor 2 censors; case 3: sensor 1 censors, sensor 2 sends; case 4: both censor) occurs. For the last three cases, the fusion rule which assumes independence has a better performance than the fusion rule that ignores censored data, and it is the other way around for the first case. In our experiment, the parameters are such that the probability of the last three cases decreases with $\pi_0$, thus the fusion rule assuming independence outperforms when $\pi_0$ is small and is overtaken by the other fusion rule as $\pi_0$ increases.

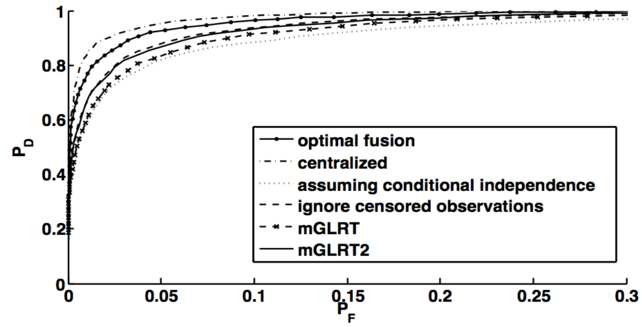


**Fig. 3**. ROC curve of different fusion rules with heterogeneous dependent data

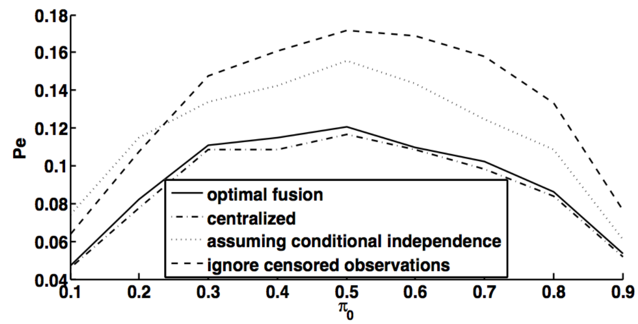


**Fig. 4**. Probability of error vs $\pi_0$ under different fusion rules with heterogeneous dependent data

We also compare the performance of different algorithms with heterogeneous dependent data. The heterogeneity comes from the fact that the observations from different sensors follow disparate pdfs and the dependence is described by a copula [13] which is a function that maps marginal density functions to a valid joint distribution. In the simulation, we assume that one sensor's observation follows exponential distribution and the other sensor's and fusion center's observations follow Gaussian distribution. And a Gaussian Copula is used to model the dependence among data. The results in Figure 3 and Figure 4 demonstrate the superior performance of our proposed fusion rule compared to other fusion rules under both frameworks.

## 6. CONCLUSION AND FUTURE WORK

In this paper, we investigated the distributed detection problem in a censoring sensor network with dependent observations. For given censoring schemes, we focused on the design of the fusion rule at the FC in both NP and Bayesian frameworks. Simulation results were also provided, showing that our proposed fusion rules in both frameworks perform better than the other methods. Since the expression of the likelihood at the FC in both frameworks involves multiple integrations, the computational complexity is prohibitive when the number of sensors is large. Our future work includes approximating the likelihood ratio in an efficient way to reduce computational complexity and designing optimal or suboptimal local censoring schemes.

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