# Selection-Based Detectors and Fusion Centers for Cooperative Cognitive Radio Networks in Heavy-Tailed Noise Environment

Iickho Song, Dongjin Kim, Seungwon Lee, and Seokho Yoon

*Abstract:* **In this paper, nonlinear schemes are proposed and analyzed for the spectrum sensing in cooperative cognitive radio networks under the influence of impulsive (heavy-tailed) noise. By jointly employing the order statistics, generalized likelihood ratio test, and counting rule in the framework of spectrum sensing according to the noise environment, the proposed scheme is shown to exhibit a better performance than the conventional counterparts. Through computer simulations, the performance characteristics of the proposed cooperative spectrum sensing scheme are investigated and analyzed in various noise circumstances. It is confirmed from numerical simulation results that the proposed scheme, under various noise circumstances which might be different from one cognitive radio to another, can provide significant improvements of performance over the conventional schemes.**

*Index Terms:* **Cognitive radio, cooperative network, impulsive noise, nonlinear schemes, spectrum sensing.**

## I. INTRODUCTION

THE radio spectrum has gradually become a scarce resource in wireless communications because of the advent of many new applications, growing demands for higher data rates, and explosive increase in the number of subscribers [1]. As a consequence, it is one of the imminent issues in wireless communications to elevate the efficiency of spectrum usages.

Employing dynamic spectrum allocations, the cognitive radio (CR) is one of the plausible solutions to the problem of spectrum deficiency [2], [3]. In the CR systems, the spectrum sensing is a prime function for the flexible and efficient allocation of spectrum, with which secondary users may be allowed to use a spectrum band without interference to the primary user (PU) until the activation of the communication of the PU is sensed. In essence, the CRs are expected to operate spectrum sensing reliably under shadowing, fading, and impulsive noise circumstances, while satisfying the allowed level of interference which impacts on the PU.

In most cases, the CRs do not have sufficient information on the transmission specification (such as pilots and synchronization messages) of the signals of the PU. Naturally, non-coherent spectrum sensing schemes, not requiring signal information on the PU, are commonly employed in most problems of spectrum sensing: Specifically, the energy detector is widely adopted for spectrum sensing because of its reliable performance even with the minimum knowledge on the transmission environment, in addition to its low requirements for computation and implementation complexities [4].

In the meantime, the concept of cooperative (or collaborative) spectrum sensing (CSS) has been introduced to overcome the effects of fading and shadowing without incurring excessive processing time for detection [5], [6]. By sharing and combining the spectrum sensing information (SSI) among a multiple of CRs, a CSS system can successfully compensate for the effects of shadowing and fading as a consequence of spatial diversity. Yet, CSS schemes inevitably require overhead data traffic for transmitting the SSI such as the observed data, local test statistics, and decision results to a fusion center (FC), in which the SSI is combined and a final decision is made on whether a signal of the PU is present or not. As the amount of data traffic should be minimized to save power consumption in mobile and low power communications, transmitting quantized SSI has quite often been adopted at the cost of an additional noise and a loss of the signal-to-noise ratio (SNR) at the FC. More recently, a novel cooperative spectrum sensing technique for cognitive radio networks is proposed, which is robust to the impact of realistic errors such as phase and synchronization errors [7]. In [8], motivated by the simplicity of energy detector and capability of higher order and fractional lower order statistics in non-Gaussian signal processing, a new spectrum sensing method, referred to as kernelized energy detector, is proposed based on kernel theory, which exhibits a moderate complexity and easiness to implement. In addition, a log-likelihood ratio based cooperative spectrum sensing scheme [9], a double threshold-based detection technique to make a local decision [10], an optimal normalized energy detection-based cooperative sensing scheme [11], and a sub-Nyquist wideband spectrum sensing scheme [12] have also been studied.

In most studies on the CSS schemes, it is assumed that the noise distribution is Gaussian, which is one of the most important distributions in various areas of engineering and science. Although the assumption of Gaussian noise is reasonably justifiable due to the central limit theorem in most cases, communication systems could frequently be exposed to impulsive

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noise environments [13]. For example, many signal and noise sources (e.g., underwater acoustic signals, low-frequency atmospheric noise, and many types of man-made noise) in practical communication systems are obviously non-Gaussian. In addition, the noise environment of a CR, and the sum of the multiple access interference (MAI) and ambient channel noise can adequately be described with an impulsive noise model when it is influenced by near-by motors, moving vehicles, reflections from sea waves, switching transients in power line, and car ignition, where the central-limit theorem cannot be applied. At the same time, the noise environment may differ from one CR to another in the cooperative CR network (CCRN).

In this paper, when the noise environment could be impulsive and might differ from one CR to another, we consider CSS schemes for the CCRN comprised of one FC and a multiple of CRs. In the CCRN, to minimize the burden of transmission traffic, the CRs transmit the SSI in the form of binary local decision result through controller channels between the CRs and FC. The FC combines the SSI received from the CRs and makes a global decision on whether the spectrum is in use by the PU or not [14].

Unlike most of previous studies in which only Gaussian noise circumstances are considered, we assume impulsive noise environments in the investigation of the characteristics and performance of the CSS schemes. Based on the observation that nonlinear schemes (such as the Cauchy detector) have successfully been applied to mitigate the effects of impulsive noise in many signal processing applications [15]–[23], we propose to employ nonlinear schemes, which basically weight more on observations with smaller amplitudes, for the spectrum sensing in the CCRN. The novelty of this paper lies in that (1) nonlinear schemes are proposed and analyzed for CSS in impulsive noise environment and (2) the detection scenario addressed accommodates some flexibility allowing the noise environment to differ from one CR to another.

The organization of this paper is as follows. We describe the system model of the CCRN in Section II. In Section III, the detectors and combining schemes of the proposed CSS system are depicted. The detection performance characteristics of several CSS system are analyzed under Gaussian noise circumstance in Section IV. In Section V, the performance characteristics of several CSS system are investigated and discussed via Monte Carlo simulation under various noise circumstances with Rayleigh channel fading. A summary is provided in Section VI.

## II. SYSTEM MODEL

Consider a CCRN composed of one FC and a number $M$ of CRs. For $m = 1, 2, \cdots, M$ and $n = 1, 2, \cdots, N$, the low-pass discrete-time observation

$$y_m(n) = y_{m,I}(n) + jy_{m,Q}(n) \tag{1}$$

of the $m$th CR at time instant $n$ can be expressed as

$$y_m(n) = w_m(n) \tag{2}$$

when the frequency band is not being used by the PU, and as

$$y_m(n) = h_m s(n) + w_m(n) \tag{3}$$

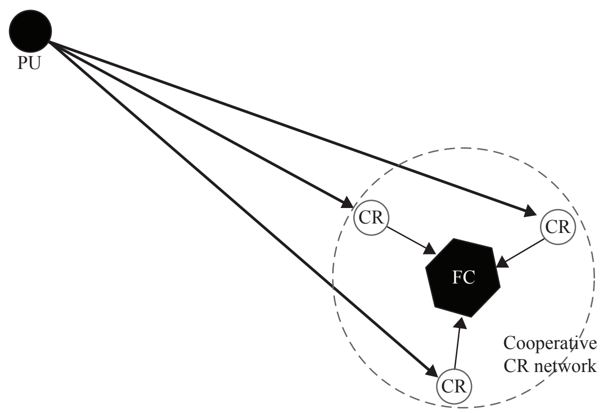


Fig. 1. The structure of a CCRN with a multiple of participating CRs and one FC.

when the frequency band is being used by the PU, where $s(n) = s_I(n) + js_Q(n)$ denotes the transmitted complex signal of the PU at time instant $n$, the complex additive noise $w_m(n) = w_{m,I}(n) + jw_{m,Q}(n)$ is independent over $m$ and $n$, and the subscripts $I$ and $Q$ represent the in-phase and quadrature components, respectively.

In (2) and (3), the sample size $N$ can practically be determined [21], [24] as the time-bandwidth product

$$N \approx 2BT \tag{4}$$

assuming that $2B$ samples are acquired per second when the signal bandwidth is $B$ (Hz) and the sampling period is $T$ (sec). The transmitted signal $s(n)$ is distorted by the complex channel fading gain $h_m = h_{m,I} + jh_{m,Q}$: It is not unreasonable to assume that $\{h_m\}_{m=1}^{M}$ are independent and identically distributed (i.i.d.) when the CRs and FC are separated sufficiently far from the PU compared with the distance between any two among the $M + 1$ components, the FC and CRs of the CCRN [25] as illustrated in Fig. 1. Assuming that the observations are acquired more frequently than the rate of change of the channel fading gain, the fading gain $h_m$ can be regarded constant during the spectrum sensing interval. It should be noted that, unlike other literatures on CSS schemes, we allow the noise environment to be different from one CR to another and assume that any of the CRs may be exposed to impulsive noise.

## III. SPECTRUM SENSING SCHEMES

### A. Noise Model

The bivariate isotropic symmetric $\alpha$-stable (BIS$\alpha$S) distribution is widely employed in the modeling of impulsive noise environment [16], [26]. The probability density function (pdf) of the BIS$\alpha$S distribution can be expressed as

$$f_{\mathrm{BI}}(u_1, u_2) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp\left\{-j(u_1 t_1 + u_2 t_2) - \gamma \left(t_1^2 + t_2^2\right)^{\frac{\alpha}{2}}\right\} dt_1 dt_2 \tag{5}$$

for $-\infty < u_1, u_2 < \infty$, where $\alpha$ is the characteristic exponent with $0 < \alpha \leq 2$ and $\gamma$ is the dispersion parameter with $\gamma > 0$.

The characteristic exponent $\alpha$ represents the heaviness of the tails of the pdf, with a smaller value indicating a heavier tail. The dispersion parameter $\gamma$ is related to the spread of the pdf, with a larger value indicating a wider spread of the pdf.

It is well known that closed form expressions for the pdf (5) of the BIS$\alpha$S distribution are available only when $\alpha = 1$ and 2. Specifically, the pdf (5) is the bivariate Cauchy pdf

$$f_{BC}(u_1, u_2) = \frac{\gamma}{2\pi \left(u_1^2 + u_2^2 + \gamma^2\right)^{\frac{3}{2}}} \tag{6}$$

and the bivariate Gaussian pdf

$$f_{BG}(u_1, u_2) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{u_1^2 + u_2^2}{2\sigma^2}\right) \tag{7}$$

when $\alpha = 1$ and $\alpha > 2$, respectively, where $\sigma^2 = 2\gamma$ represents the variance.

In passing, let us mention that, from a practical point of view, estimation of the distribution for an impulsive noise is indeed rather difficult since the random variables do not even have a finite mean (for $\alpha \leq 1$) or finite variance (for $\alpha < 2$): The estimation would thus require a large number of samples to produce a faithful estimate. On the other hand, it is reported that the parameters $\alpha$ and $\gamma$ can be easily and adequately estimated using the sample mean and variance of the realizations of the S$\alpha$S process [16].

### B. Nonlinear CSS Schemes

Due to the wall behavior [27] of the SNR, the performance of non-coherent spectrum sensing schemes with noise uncertainty cannot be improved at low SNR even when the sample size is increased indefinitely. By increasing the number of participating CRs in the CCRN, the effect of the wall behavior can be reduced and the performance can be enhanced [28]. Since our concern does not lie in reducing the effect of the wall behavior in this paper, we will assume that the noise distribution is known to the detector.

If the signal characteristics such as the modulation type, pulse shape, and packet format of the PU are available at the CR, the matched filter detection will provide the optimal performance [29]. Nonetheless, since the signal information of the PU is usually unavailable at the CR in practice, the generalized likelihood ratio test (GLRT) can instead be employed, in which the maximum likelihood estimate (MLE) of the distorted transmitted signal $h_m s(n)$ is adopted at the $m$th CR.

#### B.1 Generalized Likelihood Ratio Test

Now, the problem of spectrum sensing in the CCRN can be regarded as a problem of binary hypothesis testing of the null hypothesis

$$\mathcal{H}_0 : \text{ The spectrum of the PU is vacant} \tag{8}$$

versus the alternative hypothesis

$$\mathcal{H}_1 : \text{ The spectrum of the PU is occupied.} \tag{9}$$

Then, denoting the joint pdf of the observation vector

$$\underline{y_m} = [y_m(1), y_m(2), \cdots, y_m(N)] \tag{10}$$

under hypothesis $\mathcal{H}_c$ as $f_{\mathcal{H}_c}$ for $c = 0$ and 1, the test statistic $\mathcal{T}_{\mathrm{GL}}\left(\underline{y_m}\right)$ of the GLRT at the $m$th CR can be expressed as

$$\begin{aligned} \mathcal{T}_{\mathrm{GL}}\left(\underline{y_m}\right) &= \ln\left\{\frac{f_{\mathcal{H}_1}\left(\underline{y_m}\right)}{f_{\mathcal{H}_0}\left(\underline{y_m}\right)}\right\} \\ &= \sum_{n=1}^{N} \ln\left\{\frac{f_m\left(y_m(n) - \widehat{h_m s(n)}\right)}{f_m\left(y_m(n)\right)}\right\}, \end{aligned} \tag{11}$$

where $\ln(\cdot)$ and $\widehat{\cdot}$ denote the natural logarithm and MLE, respectively, and $f_m$ is the joint pdf of $w_{m,I}(n)$ and $w_{m,Q}(n)$ for $n = 1, 2, \cdots, N$.

Note that the numerator in the natural logarithm in (11) can be expressed as

$$\begin{aligned} & f_m\left(y_m(n) - \widehat{h_m s(n)}\right) = \\ & \qquad \frac{\gamma_m}{2\pi\left\{\left|y_m(n) - \widehat{h_m s(n)}\right|^2 + \gamma_m^2\right\}^{\frac{3}{2}}} \end{aligned} \tag{12}$$

and

$$\begin{aligned} & f_m\left(y_m(n) - \widehat{h_m s(n)}\right) = \\ & \qquad \frac{1}{2\pi\sigma_m^2} \exp\left\{-\frac{1}{2\sigma_m^2}\left|y_m(n) - \widehat{h_m s(n)}\right|^2\right\} \end{aligned} \tag{13}$$

in Cauchy and Gaussian noise circumstances, respectively, using (6) and (7) and that $f_m(x) = f_{BI}\left(\mathrm{Re}(x), \mathrm{Im}(x)\right)$ with $\gamma = \gamma_m$ in (5). Here, $\gamma_m$ and $\sigma_m^2$ are the dispersion parameter of Cauchy distribution and variance of Gaussian distribution, respectively, for the $m$th CR. From (12) and (13), it is easy to get the MLE

$$\widehat{h_m s(n)} = y_m(n) \tag{14}$$

of $h_m s(n)$ under both Cauchy and Gaussian noise environments. Apparently, replacing 0 for $\widehat{h_m s(n)}$ in (12) and (13), we will get the denominator of the natural logarithm in (11).

#### B.2 Nonlinear Schemes with Selection

Nonlinear signal processing schemes based on order statistics can be used to successfully mitigate the influence of impulsive noise components as evidenced in many signal processing applications. Because observations with large magnitudes in impulsive noise circumstance tend to have originated from noise component rather than from signal component, selecting some observations with smaller magnitudes via a nonlinear scheme based on order statistics would generally lead to a better performance than exploiting all of the observations in impulsive noise circumstances.

We first produce the order statistics [26], [30], [31]

$$\left\{\underline{y_m}_{(1)}, \underline{y_m}_{(2)}, \cdots, \underline{y_m}_{(N)}\right\} \tag{15}$$

of $\underline{y_m}$, where

$$\left|\underline{y_m}_{(1)}\right| \leq \left|\underline{y_m}_{(2)}\right| \leq \cdots \leq \left|\underline{y_m}_{(N)}\right|. \tag{16}$$

Then, $J_m$ smallest observations are selected to produce the test statistic

$$\mathcal{T}_{\text{GSO}}\left(\underline{y_m}, J_m\right) = \sum_{l=1}^{J_m} \ln \left\{ \frac{f_m\left(\underline{y_m}_{(l)} - \widehat{\underline{h_m s}_{(l)}}\right)}{f_m\left(\underline{y_m}_{(l)}\right)} \right\} \tag{17}$$

of the detector for the $m$th CR, where $J_m$ is the number of observations selected in the $m$th CR. Note that we have

$$\underline{h_m s}_{(l)} = h_m s(\bar{n}) \tag{18}$$

for the integer $\bar{n}$ satisfying

$$y_m(\bar{n}) = \underline{y_m}_{(l)}. \tag{19}$$

The detector described by the test statistic (17) will be called the GLRT based on selected observations (GSO) detector.

Now, based on (11)–(17), define the generic test statistics

$$\mathcal{G}_C\left(\underline{y_m}, k\right) = \sum_{l=1}^{k} \ln \left\{ 1 + \frac{\left|\underline{y_m}_{(l)}\right|^2}{\gamma_m^2} \right\} \tag{20}$$

and

$$\mathcal{G}_G\left(\underline{y_m}, k\right) = \frac{1}{2\sigma_m^2} \sum_{l=1}^{k} \left|\underline{y_m}_{(l)}\right|^2 \tag{21}$$

in Cauchy and Gaussian noise circumstances, respectively, where $k \in \{1, 2, \cdots, N\}$. Then, it is straightforward to see that the GLRT and GSO test statistics (11) and (17) can be rewritten equivalently in terms of the generic test statistics (20) and (21): Specifically, we will have the equivalent expressions $\mathcal{T}_{\text{GL}}\left(\underline{y_m}\right) = \mathcal{G}_C\left(\underline{y_m}, N\right)$ and $\mathcal{T}_{\text{GSO}}\left(\underline{y_m}, J_m\right) = \mathcal{G}_C\left(\underline{y_m}, J_m\right)$ in Cauchy noise, and $\mathcal{T}_{\text{GL}}\left(\underline{y_m}\right) = \mathcal{G}_G\left(\underline{y_m}, N\right)$ and $\mathcal{T}_{\text{GSO}}\left(\underline{y_m}, J_m\right) = \mathcal{G}_G\left(\underline{y_m}, J_m\right)$ in Gaussian noise. Note that, when we evaluate $\mathcal{G}_C\left(\underline{y_m}, N\right)$ and $\mathcal{G}_G\left(\underline{y_m}, N\right)$, we do not need to perform the ordering of $\underline{y_m}$ to obtain $\left\{\underline{y_m}_{(\cdot)}\right\}$ since

$$\sum_{l=1}^{N} h\left(\underline{y_m}_{(l)}\right) = \sum_{l=1}^{N} h\left(y_m(l)\right) \tag{22}$$

for any function $h$.

With the GSO detector, the binary SSI $x_m$ of the $m$th CR is obtained as

$$x_m = \begin{cases} 1, & \text{if } \mathcal{T}_{\text{GSO}}\left(\underline{y_m}, J_m\right) \geq \lambda_m, \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

and then sent to the FC, where $x_m = 0$ and $1$ denote the local decision on the vacancy and occupancy of the spectrum, respectively, and $\lambda_m$ is the threshold of the $m$th CR governing the detection performance (false-alarm rate and detection rate) of the CR. One possible choice of the threshold for the $m$th CR would be $\lambda_m = J_m/2N$ for a symmetric noise.

It is well-known that the smallest statistic in some cases produces the optimal detector [32]. Although the choice of

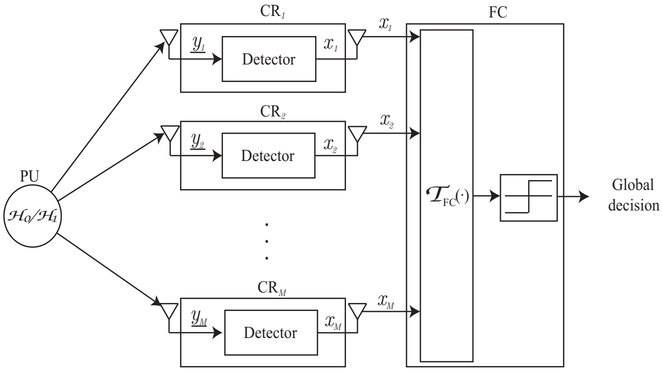


Fig. 2. A schematic representation of the CSS in the CCRN.

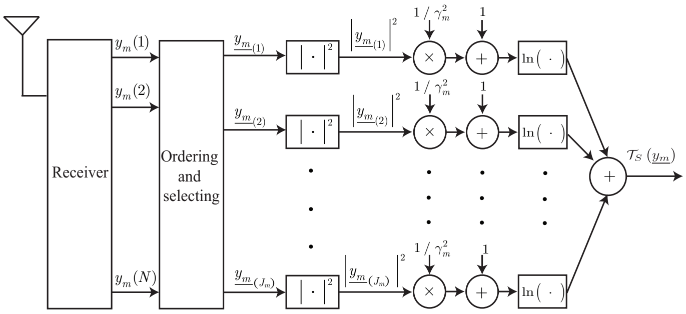


Fig. 3. A block diagram of the detector for the $m$th CR under Cauchy noise circumstance.

$J_m$ smallest observations for building the test statistic is not promptly supported by theory, we believe that such a choice in some cases (as shown in this paper) is one possible alternative for sub-optimal results. Such an effort might be useful when one tries to intuitively select a detector, without actually obtaining the performance characteristics, for sub-optimal expectations. We would like to add that there are many examples in which the combination of order statics and mean statistic produces somewhat 'robust' results: Among the numerous examples are the median-based filters [15], [33], [34] including $\alpha$ trimmed mean filters and Wilcoxon filters.

### B.3 Fusion Center

After the set $\underline{x} = [x_1, x_2, \cdots, x_M]$ of all the SSI from the $M$ CRs is collected at the FC, the SSI is combined to produce the test statistic $\mathcal{T}_{\text{FC}}\left(\underline{x}\right)$ of the FC. The procedure is illustrated in Fig. 2 and a block diagram of the detectors for the $m$th CR under Cauchy noise circumstances is shown in Fig. 3. Under Gaussian noise circumstances, a similar block diagram can be easily obtained. For simplicity, we assume that all the SSI of CRs are transmitted to the FC without any error: In other words, we do not consider the communication loss incurred due to channel fading and noise between the CRs and FC. Of course, in a wireless environment, although it is rather idealistic to assume that the channel from the sensing nodes to the FCs are perfect and noiseless, it is usual (although simplistic) to model a cooperative CR system without fading, shadowing or impulsive noise in the channel between the sensing nodes and the FC. In addition, it is easily anticipated that the 'relative' performance of the proposed detector to the conventional detectors in imperfect noisy channel (from sensing nodes to FC) will not be different very much from that in perfect noiseless channel. Let us just add that in some studies the fading/shadowing have been taken into account as in [35], [36], for example. On the other hand, we will clearly take into account the effects of channel fading and noise on the CCRN.

If all the detection performance (i.e., the false-alarm and detection probabilities) of the CRs are known to the FC, we can exploit the Chair-Varshney scheme [37] in the combining of the SSI $\underline{x}$ for the best possible (global) detection performance. However, the detection performances of CRs are usually not available at the FC in practice. In such a case, a counting rule, which often provides satisfactory detection performance characteristics in many instances, is commonly adopted [2], [37] in the combining stage: With a counting rule, the number of 1's in $\underline{x}$ is simply counted and is then compared with a threshold of the FC. In this paper, we consider three types of counting rules to combine the SSI. In short, based on the test statistic

$$\mathcal{T}_{\text{FC}}\left(\underline{x}\right) = \sum_{m=1}^{M} x_m, \tag{24}$$

the global (or final) decision of the FC is obtained from

$$\mathcal{T}_{\text{FC}}(\underline{x}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda_{\text{FC}}. \tag{25}$$

The threshold $\lambda_{\text{FC}}$ in (25) is set to 1, $\lceil M/2 \rceil$, and $M$ when we adopt the 1-out-of-$M$ (OR), $\lceil M/2 \rceil$-out-of-$M$ (majority: MJ), and $M$-out-of-$M$ (AND) counting rules, respectively [2], [38], where $\lceil x \rceil$ denotes the smallest integer greater than or equal to $x$.

## IV. PERFORMANCE ANALYSIS IN GAUSSIAN NOISE

### A. *Performance of a CR*

Let us first address the detection performance of the $m$th CR employing the GSO detector with $J_m = N$ (i.e., the GLRT detector) under i.i.d. Gaussian noise circumstance. Ignoring the constant term $1/2$ in (21), the test statistic $\mathcal{G}_G\left(\underline{y_m}, N\right)$ can be viewed as the sum of the squares of $2N$ independent unit-variance Gaussian random variables. The distribution of $\mathcal{G}_G\left(\underline{y_m}, N\right)$ is therefore the central chi-square distribution $\chi^2\left(2N\right)$ and non-central chi-square distribution $\chi^2\left(2N, \nu_m\right)$ under the null and alternative hypotheses, respectively, where

$$\nu_m = \frac{|h_m|^2}{\sigma_m^2} \sum_{n=1}^{N} |s(n)|^2 \tag{26}$$

is the non-centrality parameter. Note that both of the channel fading gain $h_m$ and non-centrality parameter $\nu_m$ are constants and random variables in non-fading and fading channels, respectively.

In non-fading channels, the channel fading gain $h_m$ of the CR can be set to 1 and the non-centrality parameter $\nu_m$ becomes $(1/\sigma_m^2) \sum\limits_{n=1}^{N} |s(n)|^2$. Then, the false-alarm rate $P_{\text{FA,NF}}(\lambda_m)$ in non-fading channels is expressed as [6], [21]

$$\begin{aligned} P_{\text{FA,NF}}(\lambda_m) &= \Pr\left\{\mathcal{G}_G\left(\underline{y_m}, N\right) > \lambda_m | \mathcal{H}_0\right\} \\ &= \frac{\Gamma\left(N, \frac{\lambda_m}{2}\right)}{\Gamma(N)}, \end{aligned} \tag{27}$$

where

$$\Gamma(u) = \int_0^{\infty} x^{u-1} e^{-x} dx \tag{28}$$

for $u > 0$ and

$$\Gamma(u, v) = \int_v^{\infty} x^{u-1} e^{-x} dx \tag{29}$$

for $u > 0$ and $v > 0$ are the complete gamma function and upper incomplete gamma function, respectively. In addition, the miss rate $P_{\text{M,NF}}\left(\lambda_m, \nu_m\right)$ in non-fading channels is evaluated as [6]

$$\begin{aligned} P_{\text{M,NF}}\left(\lambda_m, \nu_m\right) &= \Pr\left\{\mathcal{G}_G\left(\underline{y_m}, N\right) \le \lambda_m | \mathcal{H}_1\right\} \\ &= 1 - \Pr\left\{\mathcal{G}_G\left(\underline{y_m}, N\right) > \lambda_m | \mathcal{H}_1\right\} \\ &= 1 - Q_N\left(\sqrt{\nu_m}, \sqrt{\lambda_m}\right), \end{aligned} \tag{30}$$

where

$$\begin{aligned} Q_b\left(\sqrt{u}, \sqrt{v}\right) = \int_v^{\infty} &\tfrac{1}{2}\left(\tfrac{x}{u}\right)^{\frac{b-1}{2}} \exp\left(-\tfrac{x+u}{2}\right) \\ &\times I_{b-1}\left(\sqrt{xu}\right) dx \end{aligned} \tag{31}$$

is the generalized Marcum's $Q$ function [39], [40] and

$$I_a(x) = \sum_{s=0}^{\infty} \frac{\left(\frac{x}{2}\right)^{a+2s}}{s!\Gamma(a+s+1)} \tag{32}$$

for $x \ge 0$ is the $a$th order modified Bessel function of the first kind.

In fading channels, the false-alarm rate $P_{\text{FA,F}}(\lambda_m)$ will be the same as that in non-fading channels. In other words, we have [21]

$$P_{\text{FA,F}}(\lambda_m) = \frac{\Gamma\left(N, \frac{\lambda_m}{2}\right)}{\Gamma(N)}. \tag{33}$$

The miss rate $P_{\text{M,F}}\left(\lambda_m, f_{\nu_m}\right)$ in fading channels is dependent on the distribution of the non-centrality parameter $\nu_m$. Specifically, by averaging (30) with respect to the non-centrality parameter $\nu_m$, we can obtain the miss rate

$$P_{\text{M,F}}\left(\lambda_m, f_{\nu_m}\right) = 1 - \int_0^{\infty} Q_N\left(\sqrt{x}, \sqrt{\lambda_m}\right) f_{\nu_m}(x) dx \tag{34}$$

in fading channels, where $f_{\nu_m}$ is the pdf of the non-centrality parameter $\nu_m$. For example, in Rayleigh fading channel, we have

$$f_{\nu_m}(x) = \frac{1}{\overline{\nu_m}} \exp\left(-\frac{x}{\overline{\nu_m}}\right) \tag{35}$$

for $x \geq 0$, where $\overline{\nu_m}$ is the expected value of the non-centrality parameter $\nu_m$. Using (35), the miss rate (34) can be expressed as [6]

$$\begin{aligned} P_{\text{M,F}_{\text{Ray}}}(\lambda_m, f_{\nu_m}) &= 1 - \int_0^\infty Q_N\left(\sqrt{x}, \sqrt{\lambda_m}\right) f_{\nu_m}(x)dx \\ &= 1 - \exp\left(-\frac{\lambda_m}{2}\right)\sum_{k=0}^{N-2}\frac{1}{k!}\left(\frac{\lambda_m}{2}\right)^k \\ &+ \left(\frac{1+\overline{\nu_m}}{\overline{\nu_m}}\right)^{N-1}\left[\exp\left\{-\frac{\lambda_m}{2(1+\overline{\nu_m})}\right\}\right. \\ &\left. - \exp\left(-\frac{\lambda_m}{2}\right)\sum_{k=0}^{N-2}\frac{1}{k!}\left(\frac{\lambda_m\overline{\nu_m}}{2(1+\overline{\nu_m})}\right)^k\right] \end{aligned} \tag{36}$$

in Rayleigh fading channel.

### *B. Detection Performance of the CSS Scheme*

Given the false-alarm rates $\{P_{\text{FA},m}\}_{m=1}^M$ and miss rates $\{P_{\text{M},m}\}_{m=1}^M$ of the $M$ CRs, let us express the detection performance of the CSS scheme in which the FC employs a counting rule.

When the OR rule is employed in the FC, the false-alarm and miss rates of the CSS scheme can be expressed as

$$P_{\text{FA,OR}} = 1 - \prod_{m=1}^{M}(1 - P_{\text{FA},m}) \tag{37}$$

and

$$P_{\text{M,OR}} = \prod_{m=1}^{M} P_{\text{M},m}, \tag{38}$$

respectively. Similarly, when the AND rule is employed, we have the false-alarm rate

$$P_{\text{FA,AND}} = \prod_{m=1}^{M} P_{\text{FA},m} \tag{39}$$

and the miss rate

$$P_{\text{M,AND}} = 1 - \prod_{m=1}^{M}(1 - P_{\text{M},m}). \tag{40}$$

Finally, when the MJ rule is employed, the false-alarm rate $P_{\text{FA,MJ}}$ and miss rate $P_{\text{M,MJ}}$ are expressed as

$$\begin{aligned} P_{\text{FA,MJ}} &= \sum_{i=\lceil \frac{M}{2}\rceil}^{M} \Pr\left\{\sum_{m=1}^{M} x_m = i \,\middle|\, \mathcal{H}_0\right\} \\ &= \sum_{i=\lceil \frac{M}{2}\rceil}^{M}\sum_{j=1}^{|\mathcal{Z}(\underline{x},i)|} \Pr\left\{\underline{x} = \underline{x}_{i,j} \,\middle|\, \mathcal{H}_0\right\} \\ &= \sum_{i=\lceil \frac{M}{2}\rceil}^{M}\sum_{j=1}^{|\mathcal{Z}(\underline{x},i)|}\prod_{m=1}^{M} P_{\text{FA},m}^{x_{i,j,m}}(1 - P_{\text{FA},m})^{1-x_{i,j,m}} \end{aligned} \tag{41}$$

and

$$\begin{aligned} P_{\text{M,MJ}} &= 1 - \sum_{i=\lceil \frac{M}{2}\rceil}^{M} \Pr\left\{\sum_{m=1}^{M} x_m = i \,\middle|\, \mathcal{H}_1\right\} \\ &= 1 - \sum_{i=\lceil \frac{M}{2}\rceil}^{M}\sum_{j=1}^{|\mathcal{Z}(\underline{x},i)|}\prod_{m=1}^{M}(1 - P_{\text{M},m})^{x_{i,j,m}} P_{\text{M},m}^{1-x_{i,j,m}}, \end{aligned} \tag{42}$$

where $|\cdot|$ denotes the cardinality of a set, $\mathcal{Z}(\underline{x}, i)$ is the set of all $\underline{x}$ such that

$$\sum_{m=1}^{M} x_m = i, \tag{43}$$

and $\underline{x}_{i,j} = [x_{i,j,1},\ x_{i,j,2}, \cdots, x_{i,j,M}]$ denotes the $j$th element in the set $\mathcal{Z}(\underline{x}, i)$. In passing, let us note that

$$|\mathcal{Z}(\underline{x}, i)| = \frac{M!}{i!(M-i)!}. \tag{44}$$

## V. PERFORMANCE EVALUATION IN IMPULSIVE NOISE

In this section, in terms of receiver operation characteristic (ROC), we investigate the performance characteristics of the CSS scheme incorporating GSO detectors under various noise circumstances. Note that the SNR is usually not considered when the noise is drawn from a distribution with infinite variance since the characterization of the SNR is not possible. In the characterization of performance in this paper, we have thus specified the corresponding 'SNR' (that is, the relative strength of the signal and noise) by specifying the parameters $\alpha$ and $\gamma$ of the BIS$\alpha$S distribution and the signal power $P_s = \sum_{n=1}^{N} |s(n)|^2$: Specifically, we assume that the CRs can be exposed to BIS$\alpha$S noise with $\gamma = 1$ and $\alpha = 2$, 1.5, and 1. The channel we consider is a slowly-varying Rayleigh fading channel, where the complex channel gains $\{h_m\}_{m=1}^M$ may change at each symbol time with

$$\mathbb{E}\left\{|h_m|^2\right\} = 1. \tag{45}$$

We also assume the signal power

$$P_s = \sum_{n=1}^{N} |s(n)|^2 \tag{46}$$

is 10 with

$$s(1) = s(2) = \cdots = s(N) \tag{47}$$

and $s_I(n) = s_Q(n)$ for simplicity. In the numerical simulations herein, the ROCs are obtained from Monte Carlo simulation of $10^6$ runs at each value of false-alarm probability.

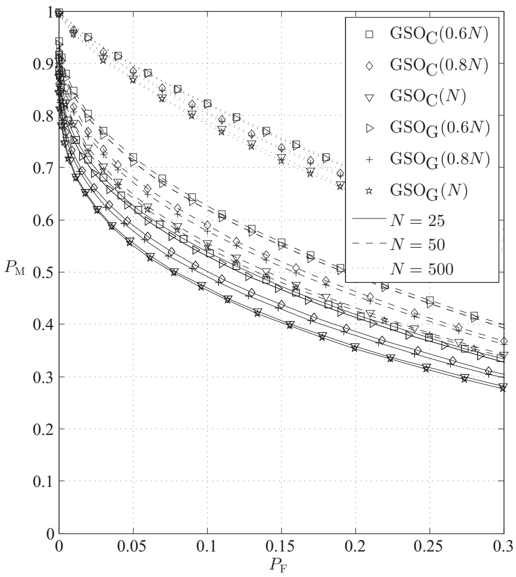


Fig. 4. The ROCs of GSO detectors for various values of $J$ and $N$ in BIS$\alpha$S noise with $\alpha = 2$ (Gaussian noise) under fixed total signal power.

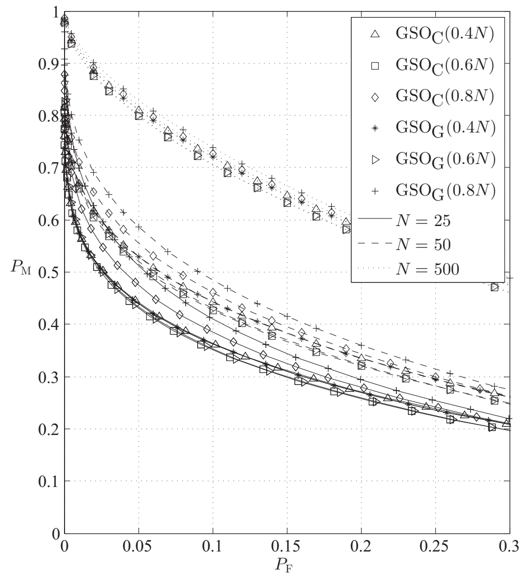


Fig. 5. The ROCs of GSO detectors for various values of $J$ and $N$ in BIS$\alpha$S noise with $\alpha = 1.5$.

### A. *Influence of the Number $J_m$ on the Performance*

Before analyzing the performance characteristics of several CSS schemes in detail, let us first investigate how the number $J_m$ of selected observations in the GSO detector can be set in order for the CSS scheme to produce improved detection performance. Here, assuming $M = 1$ and $J_m = J$, the notations $\mathrm{GSO_C}(J)$ and $\mathrm{GSO_G}(J)$ will be used to denote the GSO detectors employing $\mathcal{G}_C\left(\underline{y_m}, J\right)$ and $\mathcal{G}_G\left(\underline{y_m}, J\right)$, respectively. In addition, although there exist infinitely many possible choices of the number $J$ in theory, we consider only five cases $\{0.2N, 0.4N, \cdots, N\}$ from a practical reason.

Figs. 4–6 show the performance characteristics of GSO detectors for some values of $J$ and $N$, where $P_\mathrm{F}$ and $P_\mathrm{M}$ denote the false-alarm and miss rates, respectively, of a GSO detector. It is clearly observed that the GSO detectors perform better when $N$ is smaller because the signal power $P_s/N$ per observation is higher when $N$ is smaller. In addition, near $P_\mathrm{F} = 0$, the rate of change of $P_\mathrm{M}$ is larger when $N$ is smaller. We can also observe that the performance of $\mathrm{GSO_C}(J)$ is quite close to that of $\mathrm{GSO_G}(J)$.

As it is easily anticipated, GSO detectors with larger values of $J$ perform better than those with smaller values of $J$ in Gaussian noise circumstance in Fig. 4; in Fig. 5 (Fig. 6), it is observed that the GSO detectors with $J = 0.6N$ ($J = 0.2N$) outperform those with other values of $J$ in BIS$\alpha$S noise with $\alpha = 1.5$ ($\alpha = 1$). An important implication in this observation is that a GSO detector with a smaller value of $J$ would perform better than that with a larger value of $J$ when the impulsiveness of noise is higher.

Based on the observations from Figs. 4–6, from now on we will concentrate on the GSO detectors with $J = N$, $0.6N$, and $0.2N$ when the noise circumstance is BIS$\alpha$S with $\alpha = 2$, 1.5, and 1, respectively: For convenience, let $\mathrm{G_C}$ stand for the detectors $\mathrm{GSO_C}(N)$, $\mathrm{GSO_C}(0.6N)$, and $\mathrm{GSO_C}(0.2N)$ when the noise circumstance is BIS$\alpha$S with $\alpha = 2$, 1.5, and 1, respectively. Similarly, let $\mathrm{G_G}$ represent the detectors $\mathrm{GSO_G}(N)$, $\mathrm{GSO_G}(0.6N)$, and $\mathrm{GSO_G}(0.2N)$ when the noise circumstance is BIS$\alpha$S with $\alpha = 2$, 1.5, and 1, respectively.

Table 1. The specifications (values of $\alpha$) of noise environment.

| Noise environment | | 1st CR | 2nd CR | 3rd CR | 4th CR |
|---|---|---|---|---|---|
| (less | NE 1 | 2 | 2 | 2 | 2 |
| impulsive) ↑ | NE 2 | 2 | 2 | 1 | 1 |
| | NE 3 | 2 | 1 | 1 | 1 |
| (more | NE 4 | 1.5 | 1.5 | 1.5 | 1 |
| impulsive) ↓ | NE 5 | 1 | 1 | 1 | 1 |

Fig. 7 shows the performance characteristics of the four detectors $\mathrm{G_C}$, $\mathrm{G_G}$, $\mathrm{GSO_C}(N)$, and $\mathrm{GSO_G}(N)$. It is again clear that the detectors $\mathrm{G_C}$ and $\mathrm{G_G}$ outperform the GLRT detectors $\mathrm{GSO_C}(N)$ and $\mathrm{GSO_G}(N)$ (which are the GLRT detectors) when the noise circumstance is BIS$\alpha$S with $\alpha = 1.5$ and 1. When the noise circumstance is Gaussian (BIS$\alpha$S with $\alpha = 2$), the detectors $\mathrm{G_C}$ and $\mathrm{G_G}$ are the same as, and consequently exhibit the same performance as, the detectors $\mathrm{GSO_C}(N)$ and $\mathrm{GSO_G}(N)$, respectively. In the meantime, it is noteworthy that $\mathrm{GSO_C}(N)$ performs better than $\mathrm{GSO_G}(N)$ when the noise circumstance is BIS$\alpha$S with $\alpha = 1.5$ and 1 as confirmed in [21] also.

### B. *Performances Comparison of CSS Schemes*

Assume that the number $N$ of observations is 50, the number $M$ of CRs is 4, and the thresholds $\{\lambda_m\}_{m=1}^{4}$ are chosen to produce identical false-alarm rate for the 4 CRs. For the comparisons of the performance characteristics of several CSS schemes, we consider five cases of noise environment (NE) varying from non-impulsive (purely Gaussian) to highly-impulsive (purely Cauchy) environments: The specifications, the values of $\alpha$ of the BIS$\alpha$S noise to which the CRs are exposed, of the five cases of NE are shown in Table 1. Note that NE $i+1$ imposes a higher degree of noise impulsiveness on the CCRN than NE $i$.

Figs. 8–12 show the performance characteristics of the CSS schemes based on the detectors $\mathrm{G_C}$, $\mathrm{G_G}$, $\mathrm{GSO_C}(N)$, and

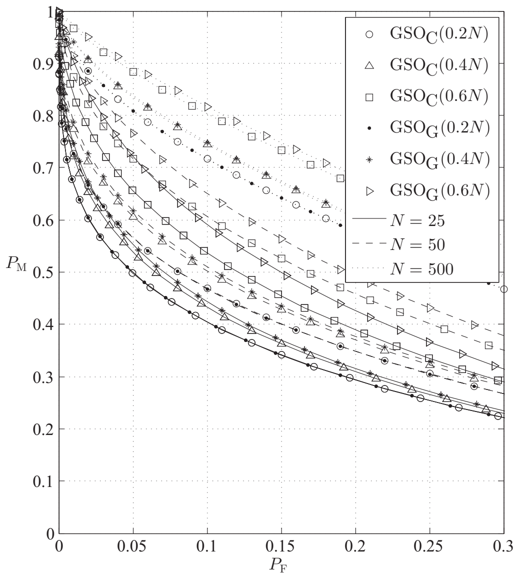


Fig. 6. The ROCs of GSO detectors for various values of $J$ and $N$ in BIS$\alpha$S noise with $\alpha = 1$ (Cauchy noise).

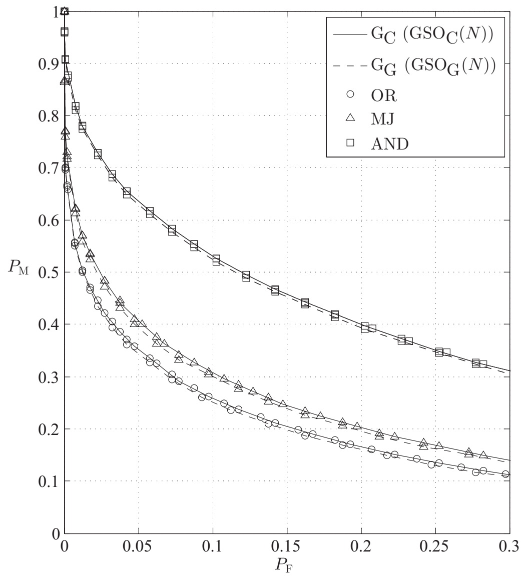


Fig. 8. The ROCs of the CSS schemes based on $\mathrm{G_C}$, $\mathrm{G_G}$, $\mathrm{GSO_C}(N)$, and $\mathrm{GSO_G}(N)$ with three counting rules in NE 1 (purely Gaussian).

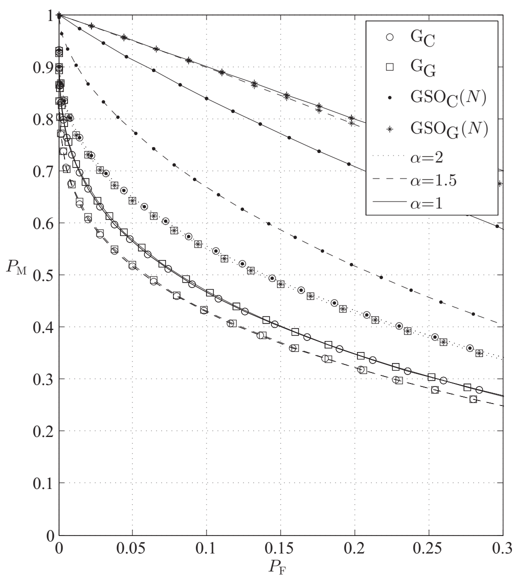


Fig. 7. The ROCs of the detectors $\mathrm{G_C}$, $\mathrm{G_G}$, $\mathrm{GSO_C}(N)$, and $\mathrm{GSO_G}(N)$ in BIS$\alpha$S noise circumstances when $N = 50$ and $(\alpha, J) = (1, 0.2N)$, $(1.5, 0.6N)$, and $(2, N)$.

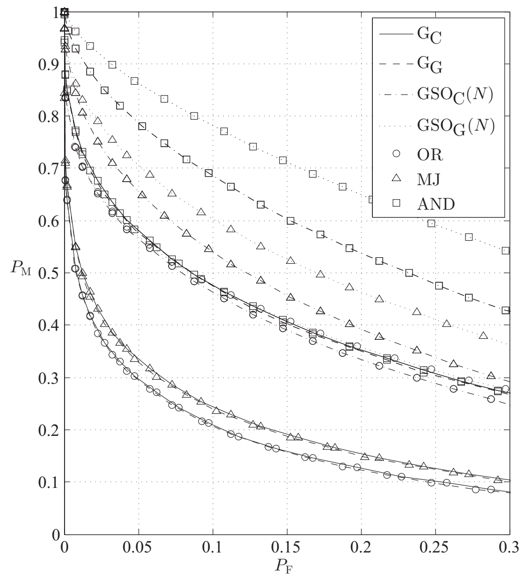


Fig. 9. The ROCs of the CSS schemes based on $\mathrm{G_C}$, $\mathrm{G_G}$, $\mathrm{GSO_C}(N)$, and $\mathrm{GSO_G}(N)$ with three counting rules in NE 2.

$\mathrm{GSO_G}(N)$, where $P_\mathrm{F}$ and $P_\mathrm{M}$ now denote the false-alarm and miss rates, respectively, of a CSS scheme. We would like to mention that the $M$ CRs in the CSS scheme based on $\mathrm{G_C}$, as well as those in the CSS scheme based on $\mathrm{G_G}$, will in general employ different detectors. For example, in the CSS scheme based on $\mathrm{G_C}$, the first CR employs $\mathrm{GSO_C}(N)$ and the second–fourth CRs employ $\mathrm{GSO_C}(0.2N)$ in NE 3; in the CSS scheme based on $\mathrm{G_G}$, the first–third CRs would employ $\mathrm{GSO_G}(0.6N)$ and the fourth CR would employ $\mathrm{GSO_G}(0.2N)$ in NE 4.

First, let us focus our attention on the detection performance in terms of detectors; we compare the performance characteristics among the CSS schemes employing the same counting rule but different detectors. It is clearly observed that, in impulsive noise environments (NE 2–5), the CSS schemes with $\mathrm{G_C}$ and $\mathrm{G_G}$ significantly outperform those with $\mathrm{GSO_C}(N)$ and $\mathrm{GSO_G}(N)$: This observation confirms that the detectors $\mathrm{G_C}$ and $\mathrm{G_G}$ can successfully mitigate the degradation in detection performance caused by impulsive noise.

Let us next make comparisons among the counting rules under the same detectors. It is observed that, when the detector $\mathrm{G_C}$ or $\mathrm{G_G}$ is employed in a CSS scheme, the OR and AND rules generally result in the best and worst performance, respectively, in the non-Gaussian cases NE 2–5. If the number of CRs exposed to impulsive noise is small or the impulsiveness of noise is relatively low as in NE 2, the OR and AND rules again result in the best and worst performance, respectively, when the CSS scheme employs $\mathrm{GSO_C}(N)$ or $\mathrm{GSO_G}(N)$. On the other hand, if the number of CRs exposed to impulsive noise is large or if the impulsiveness of noise is high as in NE 4, the MJ and

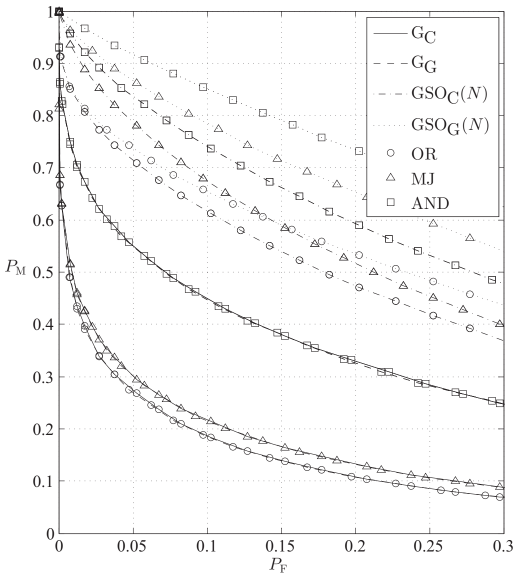


Fig. 10. The ROCs of the CSS schemes based on $G_C$, $G_G$, $GSO_C(N)$, and $GSO_G(N)$ with three counting rules in NE 3.

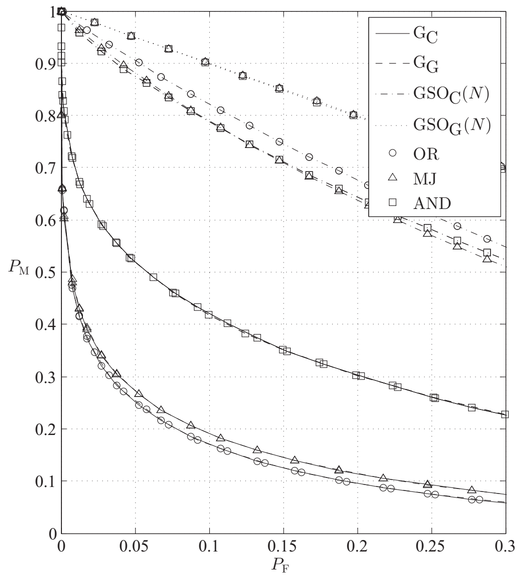


Fig. 12. The ROCs of the CSS schemes based on $G_C$, $G_G$, $GSO_C(N)$, and $GSO_G(N)$ with three counting rules in NE 5 (purely Cauchy).

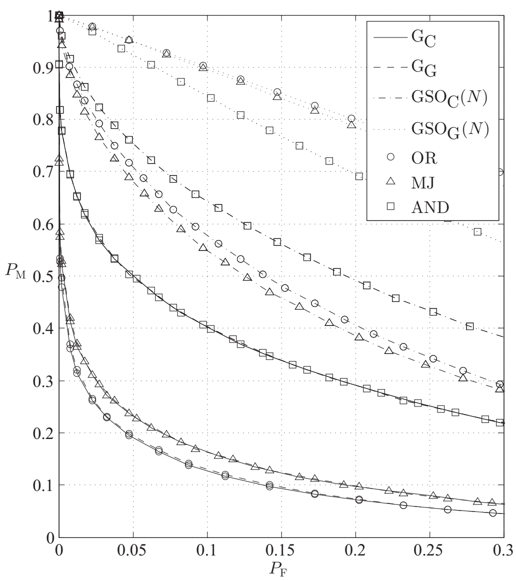


Fig. 11. The ROCs of the CSS schemes based on $G_C$, $G_G$, $GSO_C(N)$, and $GSO_G(N)$ with three counting rules in NE 4.

AND rules provide the best performance when the CSS scheme employs $GSO_C(N)$ and $GSO_G(N)$, respectively.

Another interesting observation is that, as the number of CRs exposed to impulsive noise gets larger or the impulsiveness of noise gets more severe, the difference in the detection performances originated from selecting different detectors becomes larger than that caused by choosing different counting rules. In other words, as more CRs are exposed to impulsive noise or as the impulsiveness of noise gets more severe, the detector has more influence on the detection performance of a CSS scheme than the counting rule.

## VI. CONCLUDING REMARK

We have addressed spectrum sensing in cooperative cognitive radio networks under impulsive noise circumstances. The nonlinear scheme of cooperative spectrum sensing proposed in this paper adopts a selection of the order statistics of observations. Based on the order statistics of observations and a modification of the generalized likelihood ratio test, the detector in the proposed scheme provides significant performance improvements over the conventional schemes when the number of observations with small magnitudes is chosen appropriately according to the noise circumstance. From the results of numerical simulations, it is confirmed that the proposed scheme for cooperative spectrum sensing outperforms the conventional schemes in impulsive noise environment with Rayleigh fading. It is also observed that, as the impulsiveness of noise gets more severe and as the number of CRs exposed to impulsive noise gets larger, the proposed scheme exhibits a better detection performance when a smaller number of observations is incorporated by the detector.


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