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Robust spectrum sensing under noise uncertainty for spectrum sharing

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Spectrum sensing plays an important role in spectrum sharing. Energy detection is generally used because it does not require a priori knowledge of primary user (PU) signals; however, it is sensitive to noise uncertainty. An order statistics (OS) detector provides inherent protection against nonhomogeneous background signals. However, no analysis has been conducted yet to apply OS detection to spectrum sensing in a wireless channel to solve noise uncertainty. In this paper, we propose a robust spectrum sensing scheme based on generalized order statistics (GOS) and analyze the exact false alarm and detection probabilities under noise uncertainty. From the equation of the exact false alarm probability, the threshold value is calculated to maintain a constant false alarm rate. The detection probability is obtained from the calculated threshold under noise uncertainty. As a fusion rule for cooperative spectrum sensing, we adopt an OR rule, that is, a 1-out-of-*N* rule, and we call the proposed scheme GOS-OR. The analytical results show that the GOS-OR scheme can achieve optimum performance and maintain the desired false alarm rates if the coefficients of the GOS-OR detector can be correctly selected.

KEYWORDS
energy detection, order statistics, spectrum sensing

1 | INTRODUCTION

With the emergence of new wireless services, there has been an increasing demand for a radio spectrum. Cognitive radio is a type of radio technology that facilitates spectrum sharing because it can detect whether communication channels are in use through spectrum sensing. If a primary user (PU) appears on the operating channel of a cognitive radio device or secondary user (SU), the SU should detect the PU immediately and then switch to the backup channel within the channel move time. This type of spectrum sharing scheme optimizes the use of the available spectrum while minimizing interference to the PU. Thus, spectrum sensing, which is used to measure the channel occupancy, is one of the key technologies for cognitive radio. A number of spectrum sensing algorithms have been studied and can be classified into two categories. The first category requires a priori knowledge about the PU signal, such as a cross-correlation scheme [1] and cyclostationary-based detection [2], whereas the second category does not require any information of the PU, such as the eigenvalue decomposition detector [3] and energy detector (ED) [4–8]. On the other hand, the eigenvalue decomposition detector has significant complexity, and cannot achieve a desired performance in terms of the very small adjacent channel interference (ACI) [9].

An ED is generally used because it does not require a priori knowledge of the PU signals. It provides good detection performance when there is no noise uncertainty. However, an ED is very sensitive to noise uncertainty [4–8]. In practice, the measured data may experience multipath fading and can contain some multipath components, other interferences, and noise itself [4]. On the other hand, spectrum misuse behaviors, such as jamming and spoofing, may impose significant interference on spectrum environments [10,11]. Therefore, an ED cannot guarantee the desired detection performance, and cannot control the constant false alarm rate under noise uncertainty. The order statistics (OS) detector has been known to be robust against nonhomogeneous background signals [12–15]. However, no analysis has been done yet to apply OS detection to spectrum sensing in a wireless channel, to the best of our knowledge. Only a few authors have attempted to apply OS detection to spectrum sensing. Shen et al. [16] proposed a blind spectrum sensing method based on goodness of fit testing of *t*-distribution to solve noise variance uncertainty, and obtained the false alarm and detection performance through simulation. In [17], Rostami et al. have proposed OS based spectrum sensing, but their analysis has only been limited to the AWGN channel, and they obtained detection and false alarm performance through Monte Carlo simulations.

In this paper, we propose a robust spectrum sensing architecture and apply closed form expressions for both the false alarm and detection probabilities for radar detection in nonhomogeneous environments, which were previously derived by the authors [14,15], to spectrum sensing. From the equation of the false alarm probability, the exact threshold value is calculated to maintain a constant false alarm rate. The exact detection and false alarm probabilities are also obtained in nonhomogeneous environments with noise uncertainty.

On the other hand, collaborative or cooperative spectrum sensing (CSS) is necessary to maintain secure communications among a group of SUs [18–21]. Recently, to defend against spectrum attacks such as the Byzantine failure problem, more general CSS techniques have been studied [22–25]. Among those CSS methods, the OR rule has been known to increase detection probability greatly in a Rayleigh fading channel. Thus, we employ the OR rule and analyze the detection and false alarm probabilities of data fusion based on the decision data from each SU.

2 | MODEL DESCRIPTIONS

Background noise may include an aggregation of various sources, such as thermal noise, multipath components, interference from adjacent systems within the vicinity, and the leakage of signals from other bands. To guarantee the coexistence requirements between the PU and SU under the conditions of a hidden PU and deeply faded channel environments, which are natural in a wireless world, robust detection of the PU is required. Thus, it is necessary to develop a robust scheme of spectrum sensing, which has the characteristics of inherent protection against noise uncertainty.

As the basic architecture of a square-law detector, a collaborative spectrum-sensing scheme, as shown in Figure 1, is proposed. The background noise level is estimated as a function of the received data samples, such as $X_1, X_2, \cdots, X_M$, where M is the number of data samples in the reference window, as shown in Figure 2. The mean level (ML) detector can be obtained by summing all cells, such as $X = \sum_{i=1}^{M} X_i$.

In an order statistic scheme, the data samples in the reference window in Figure 2 are sorted in increasing order. The resulting ordered sequence is $X_{(1)} \le X_{(2)} \le \cdots \le X_{(M)}$, where $X_{(1)}$ is the smallest value and $X_{(M)}$ is the largest. The kth ordered statistics estimator is given by $X = X_{(k)}$. Test cell Y is compared to TX, where T is a scaling factor used to achieve the desired false alarm rate (FAR). Kim et al. have proposed an adaptive detection scheme for DSSS signals based on ordered statistics

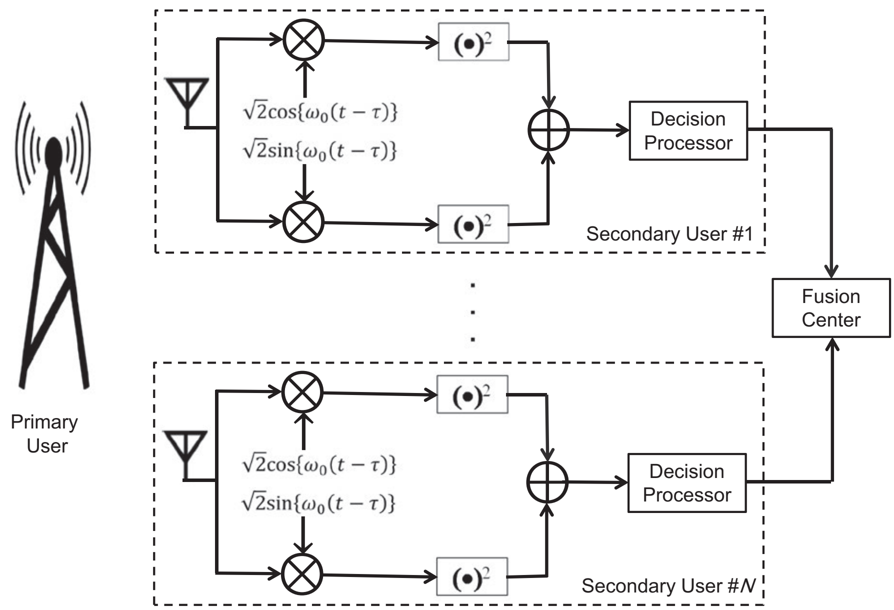

FIGURE 1 Architecture of collaborative spectrum sensing model for spectrum sharing

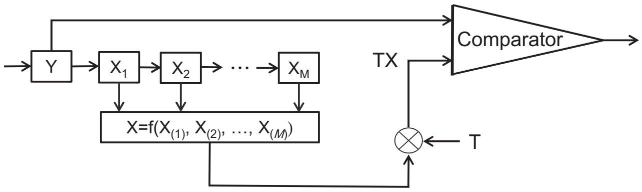

FIGURE 2 Hypothesis testing scheme of local decision processor

and analyzed the detection performance in a homogeneous environment [26,27]. Kim et al. have also derived a generalized order statistics detector for radar target detection in nonhomogeneous environments, which is called a generalized order statistics (GOS) constant false alarm rate (CFAR) detector [14,15], and applied a GOS CFAR detector to the acquisition of PN sequences in multipath fading mobile channels [28]. The power level estimator of a GOS local decision processor in Figure 2 is defined by $X=f\left(X_{(1)},\cdots,X_{(M)}\right)=\sum_{i=1}^{M}\alpha_i X_{(i)}$, where $\alpha_i=1$ or 0. As a fusion rule at a fusion center in Figure 1, we adopt an OR rule, that is, a 1-out-of-N rule, because spectrum sharing is only possible when all SUs are able to use the common channel for communications, where N is the number of SUs. We call the architecture shown in Figure 1 a GOS-OR spectrum-sensing scheme.

3 | ANALYSIS OF GOS-OR SPECTRUM SENSING SCHEME

3.1 | Mathematical derivation of GOS-OR

The PU detection of a local decision processor is declared if Y exceeds the threshold TX, as follows:

$$Y \underset{H_0}{\overset{H_1}{\gtrless}} TX \tag{1}$$

where the alternative hypothesis H_1 corresponds to the presence of a PU signal, while the null hypothesis H_0 corresponds to the absence of a PU signal. It is usually assumed that the square-law reception of Rayleigh faded signals in AWGN have normalized likelihood functions, as follows:

$$p_0(y)=e^{-y}, \tag{2}$$

$$p_1(y)=\frac{e^{-y/(1+S)}}{1+S}, \tag{3}$$

where S is the average signal-to-noise ratio.

The false alarm probability is given by:

$$\begin{aligned} P_{\mathrm{fa}}&=E\left\{P\left[Y>TX|H_0\right]\right\}\\ &=\int_0^\infty f(x)\int_{TX}^\infty p_0(y)dydx\\ &=M_X[T] \end{aligned} \tag{4}$$

where $M_X[T]$ is the MGF of the random variable X.

The detection probability is obtained as

$$\begin{aligned} P_{\mathrm{d}}&=E\left\{P\left[Y>TX|H_1\right]\right\}\\ &=\int_0^\infty f(x)\int_{TX}^\infty p_1(y)dydx\\ &=M_X\left[\frac{T}{1+S}\right]. \end{aligned} \tag{5}$$

On the other hand, if the received data samples include noise uncertainty, such as multipath fading signals, interference signals, and noise itself, the likelihood function of square-law energy detection in this type of nonhomogeneous environment is modeled [14,15,28,29] as

$$p\left(x_i\right)=\frac{e^{-x_i/(1+I_i)}}{1+I_i},\quad 1\le i\le M \tag{6}$$

where I_i is the average interference-to-noise ratio (INR) of each cell in the reference window in Figure 2 and $I_i=0$ in noise-only environments. Thus, the MGF of $X=\sum_{i=1}^{M}\alpha_i X_{(i)}$ for the GOS local decision processor is obtained as

$$\begin{aligned} M_X(s)&=E_X\left[\mathrm{Exp}(-sX)\right]\\ &=E_X\left[\mathrm{Exp}\left(-s\sum_{i=1}^{M}\alpha_i X_{(i)}\right)\right]\\ &=\sum_{\text{All } M! \text{ Inverses}}\int_0^\infty dx_{(1)}\frac{\mathrm{Exp}\left(-\frac{x_{(1)}}{\beta_{(1)}}\right)}{\beta_{(1)}}\times\cdots\\ &\times\int_{x_{(M-1)}}^\infty dx_{(M)}\frac{\mathrm{Exp}\left(-\frac{x_{(M)}}{\beta_{(M)}}\right)}{\beta_{(M)}}\mathrm{Exp}\left(-s\sum_{i=1}^{M}\alpha_i x_{(i)}\right)\\ &=\sum_{\text{All } M! \text{ Inverses}}\prod_{i=1}^{M}\frac{1}{\beta_{(i)}}\left(\sum_{j=i}^{M}\left(\beta_{(j)}^{-1}+s\alpha_j\right)\right)^{-1} \end{aligned} \tag{7}$$

where $\beta_{(i)}=1+I_{(i)}$ and $I_{(i)}$ is INR of the ith smallest value after ordering the data samples in the power level estimator in Figure 2. Furthermore, All $M!$ Inverses indicates the possible transformations between $\{X_1, X_2, \cdots, X_M\}$ and $\{X_{(1)}, X_{(2)}, \cdots, X_{(M)}\}$.

Therefore, the false alarm probability for the GOS detector is obtained from (4) and (7), as follows:

$$P_{\mathrm{fa}}=\sum_{\text{All } M! \text{ inverses}}\prod_{i=1}^{M}\beta_{(i)}^{-1}\left[\sum_{j=i}^{M}\left(\beta_{(j)}^{-1}+T\alpha_j\right)\right]^{-1}. \tag{8}$$

If there exists only Gaussian noise in the reference cells, $I_{(i)}=0$. Then, becomes

$$\begin{aligned} P_{\mathrm{fa}}&=M!\frac{1}{\sum_{j=1}^{M}(1+T\alpha_j)}\frac{1}{\sum_{j=2}^{M}(1+T\alpha_j)}\times\cdots\times\frac{1}{\sum_{j=M}^{M}(1+T\alpha_j)}\\ &=\frac{M}{M+T\sum_{j=1}^{M}\alpha_j}\times\frac{M-1}{(M-1)+T\sum_{j=2}^{M}\alpha_j}\times\cdots\times\frac{1}{1+T\sum_{j=M}^{M}\alpha_j}\\ &=\prod_{i=1}^{M}\frac{M-i+1}{(M-i+1)+T\sum_{j=i}^{M}\alpha_j}. \end{aligned} \tag{9}$$

TABLE 1 Threshold coefficient T of GOS-OR ($M = 8$)

Type of decision processor	$P_{fa} = 10^{-2}$	$P_{fa} = 10^{-3}$	$P_{fa} = 10^{-4}$
GOS(1, 2, …, 8)	0.7783	1.3714	2.1623
GOS(1, 2, …, 7)	1.2419	2.2504	3.6540
GOS(1, 2, …, 6)	1.9763	3.7212	6.2908
GOS(6)	5.8696	11.0859	18.7751
GOS(1, 2, 3, 4, 5)	3.3094	6.5748	11.7693
GOS(1, 2, 3, 4)	6.1326	13.2224	25.8646

As a special case of the GOS detector, the OS detector is implemented with

$$\alpha_j = \begin{cases} 1 & \text{if } j=k, \\ 0 & \text{if } j \neq k, 1 \leq j \leq M. \end{cases} \tag{10}$$

Then, (9) reduces to

$$\begin{aligned} P_{fa} &= \prod_{i=1}^{M} \frac{M-i+1}{M-i+1+T\sum_{j=i}^{M}\alpha_j} \\ &= \frac{M}{M+T} \times \frac{M-1}{(M-1)+T} \times \cdots \times \frac{M-k+1}{(M-k+1)+T} \\ &\quad \times \frac{M-k}{M-k} \times \cdots \times \frac{1}{1} \\ &= k \binom{M}{k} \frac{(k-1)!(M+T-k)!}{(M+T)!}. \end{aligned} \tag{11}$$

Equation (11) corresponds to the well-known equation of false alarm probability for the OS CFAR detector derived by Rohling [12]. If we set all the coefficients of $\{\alpha_i, 1 \leq i \leq M\}$ to one, then (9) becomes

$$P_{fa} = \frac{1}{(1+T)^M}, \tag{12}$$

which corresponds to the false alarm probability of the ML detector. On the other hand, the detection probability is obtained from (5) and (7) as

$$P_d = \sum_{\text{All } M! \text{ inverses}} \prod_{i=1}^{M} \beta_{(i)}^{-1} \left[\sum_{j=i}^{M} \left(\beta_{(j)}^{-1} + \frac{T\alpha_j}{1+S} \right) \right]^{-1}. \tag{13}$$

The probabilities of a collaborative false alarm and detection for a GOS-OR model may be written as follows [18,19]

$$P_{cfa} = 1 - \left(1 - P_{fa}\right)^N, \tag{14}$$

$$P_{cd} = 1 - \left(1 - P_d\right)^N, \tag{15}$$

where P_{fa} and P_d are the false alarm and detection probabilities of a local decision processor, as given by (8) and (13) , respectively.

To demonstrate the performance of the GOS-OR spectrum-sensing algorithm from Figure 1, we assume that the number of SUs (N) is 5 and the number of data samples (M) is equal to 8. Here, T is calculated for the desired FAR according to various forms of the GOS algorithm from (9) , as shown in Table 1. GOS(6) indicates that the sixth smallest sample is selected as the background power level and GOS(1, 2, …, 8) is defined as the summation of the background power level for all samples in the window in Figure 2.

3.2 | Performance analysis of GOS-OR

Figure 3 shows the detection probabilities of various types of GOS detectors in homogeneous environments. As expected, the GOS(1, 2, …, 8) detector achieves the best performance among the four types of GOS detectors, whereas the GOS(6) detector shows the least performance because the detection performance in homogeneous situations improves as the number of noise samples increases. To keep the performance comparison consistent, the desired FAR of $P_{fa} = 10^{-3}$ is used for all graphs.

Figure 4 shows the collaborative detection probability of the GOS-OR detector in homogeneous environments with no noise uncertainty. The detection performance improves significantly with the number of SUs, and the number of SUs in Figure 4 is 5. On the other hand, the collaborative false alarm increases linearly with the number of SUs because the GOS-OR employs the OR rule of each SU. Thus, $P_{cfa} = 1 - (1 - 0.001)^5 \approx 0.005$.

Let us consider that the reference window in Figure 2 contains two interfering signals whose distribution is different from that of noise. To demonstrate the operation of GOS-OR in the low SINR environment, let us assume that the power level of the interference signal is equivalent to that of the PU signal. In this case, the power level estimate of the GOS(1, 2, …, 8) detector includes two interfering signals, and that of the GOS(1, 2, …, 7) detector may contain one interfering signal. From Figure 5, we can see that the detection performance of both the GOS(1, 2, …, 8) and GOS(1, 2, …, 7) detectors degrades severely in this type of nonhomogeneous environment with noise uncertainty. In particular, the GOS(1, 2, …, 8) detector has the worst detection performance among the four detectors. On the other hand, both the GOS(1, 2, …, 6) and GOS(6) detectors maintain their detection performance well because they exclude interfering signals in the estimation of the background power level.

From Figure 6, we can also see that both the GOS(1, 2, …, 6), and GOS(6) detectors maintain the desired FAR relatively well, whereas the false alarms of both the GOS(1, 2, …, 8) and GOS(1, 2, …, 7) detectors become significantly smaller with the increase of INR, which means that the detection performances of both the GOS(1, 2, …, 8) and GOS(1, 2, …, 7) worsen, as shown in Figure 5. This means that both the GOS(1, 2, …, 8) and GOS(1, 2, …, 7) detectors might miss the PU detection with high probability under this type of noise uncertainty, as shown in Figure 5.

Figure 7 shows the collaborative detection probability of the GOS-OR detector in nonhomogeneous environments

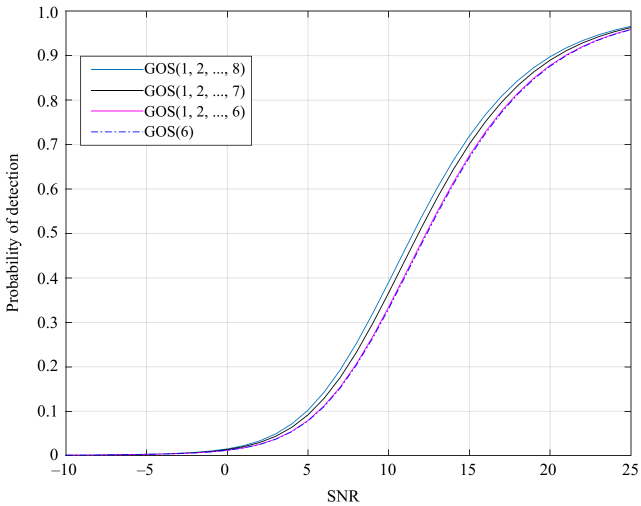

FIGURE 3 Detection probabilities of various types of GOS detectors in homogeneous environments ($M = 8$)

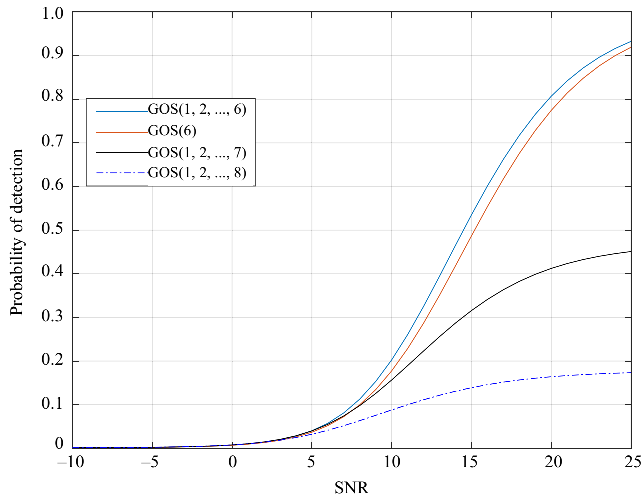

FIGURE 5 Detection probabilities of various types of GOS detectors in nonhomogeneous environments with noise uncertainty ($M = 8$, no. of interferers = 2, SIR = 1)

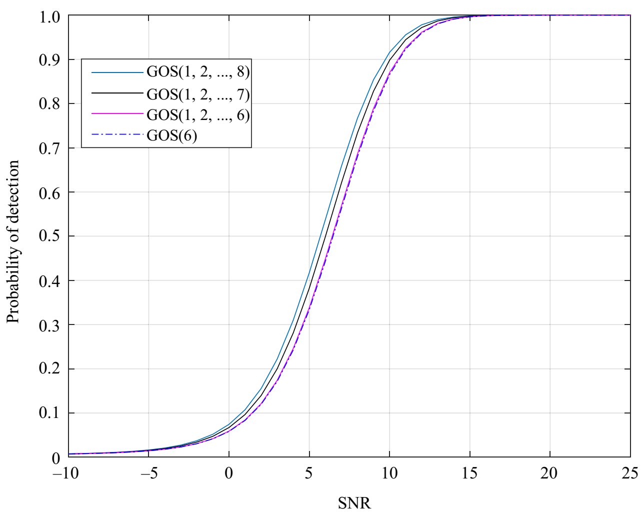

FIGURE 4 Collaborative detection probabilities of various types of GOS-OR detectors in homogeneous environments ($M = 8$, $N = 5$)

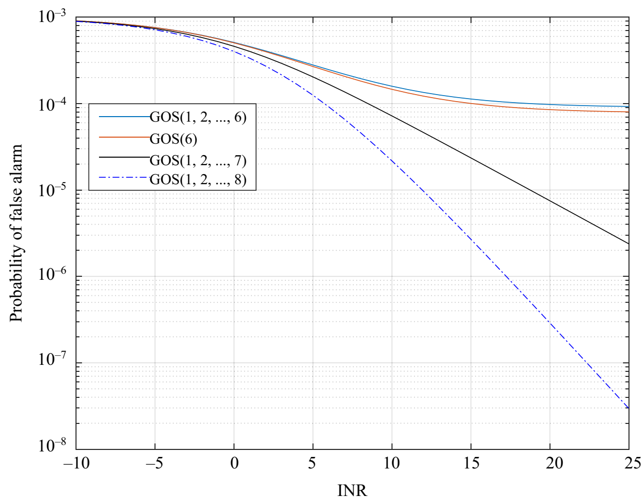

FIGURE 6 False alarm probabilities of various types of GOS detectors in nonhomogeneous environments with noise uncertainty ($M = 8$, no. of interferers = 2)

with noise uncertainty, wherein the reference window in Figure 2 includes two interfering signals. As expected, the collaborative detection performance improves dramatically over that of a local decision processor. The collaborative detection performances of both the G(1, 2, …, 6)-OR and GOS(6)-OR detectors improve with the number of SUs, as expected, whereas those of both the GOS(1, 2, …, 8)-OR and GOS(1, 2, …, 7)-OR detectors are still degraded owing to the interfering signals in the reference window.

It is also shown in Figure 8 that the GOS(1, 2, …, 6)-OR and GOS(6)-OR detectors maintain the desired FAR well, even though the collaborative FARs increase compared to those of local detectors, whereas the false alarms of both the GOS(1, 2, …, 8)-OR and GOS(1, 2, …, 7)-OR detectors become even smaller with an increase of INR, which means that the detection performance of the both the GOS(1, 2, …, 8)-OR and GOS(1, 2, …, 7)-OR detectors worsens, as shown in Figure 7. Thus, both the GOS(1, 2, …, 8)-OR and GOS(1, 2, …, 7)-OR detectors may miss a PU detection with high probability, even when the collaborative spectrum-sensing scheme is employed.

3.3 | Adaptive estimation of the number of nonhomogeneous signals

As discussed in Section 3.2, it is very important to eliminate nonhomogeneous samples or outliers in the reference window to minimize the missed detection of a PU under noise

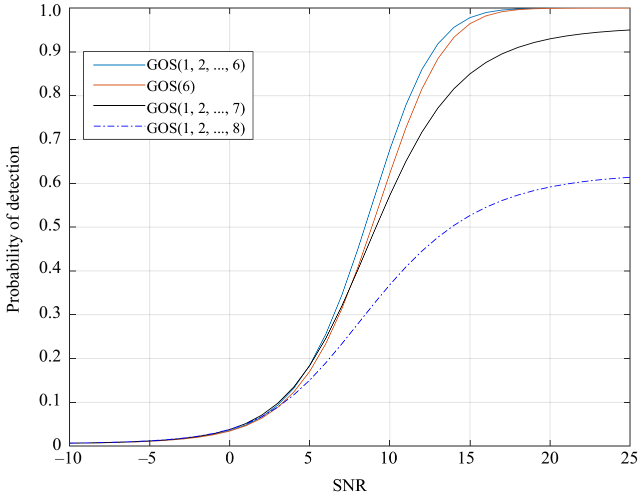

FIGURE 7 Collaborative detection probability of various types of GOS-OR detectors in nonhomogeneous environments with noise uncertainty ($M = 8$, $N = 5$, no. of interferers = 2, SIR = 1)

uncertainty. As shown in Section 3.2, the GOS-OR detector has inherent protection against these outliers if the threshold coefficients α are correctly determined. Thus, we need to determine the value of the threshold coefficients correctly. In real situations, there might be several types of signals, including interfering signals and SU signals, as well as thermal noise. First, we should discriminate the noise samples from SU signals, and SU signals should not enter into the reference window. All SUs should have this capability. We then need to know the number of interference samples in the reference window. With these aspects in mind, we propose the following algorithm. The power level estimate X is obtained by GOS(1, 2, …, M/2). Every sample is tested with this threshold value TX of the GOS(1, 2, …, M/2) detector, and if any sample exceeds this threshold, the number of interferer in the window, denoted by $N(I)$, is increased by 1. This process is continued until every sample in the reference window is tested. Finally, we set the threshold coefficient as follows:

$$\alpha_i = \begin{cases} 1 & \text{if } 1 \le i \le M - N(I), \\ 0 & \text{if } M - N(I) + 1 \le i \le M. \end{cases} \tag{16}$$

Figure 9 shows simulations of thresholds for three types of GOS detectors. From the figure, we can see that the threshold of the GOS(1, 2, …, 8) detector is too high to detect the PU signal under noise uncertainty and that of the GOS(1, 2, …, 6) detector works well when the number of interfering signals is less than or equal to two. On the other hand, the adaptive GOS detector works well as long as the number of interfering signals is less than M/2 because it adaptively estimates the number of interfering signals and eliminates those components.

4 | CONCLUSIONS

Noise uncertainty is a serious problem in an ED. Even though OS detectors provide inherent protection against nonhomogeneous background signals, no work has been done yet to apply OS detection to spectrum sensing, to the best of our knowledge. Only a few authors have attempted to apply order statistics to spectrum sensing, but their analyses have only been limited to Monte Carlo simulations. In this paper, we have proposed a new spectrum sensing-scheme based on the generalized order statistics and data fusion algorithm of an OR rule, and analyzed their detection and false alarm probabilities precisely.

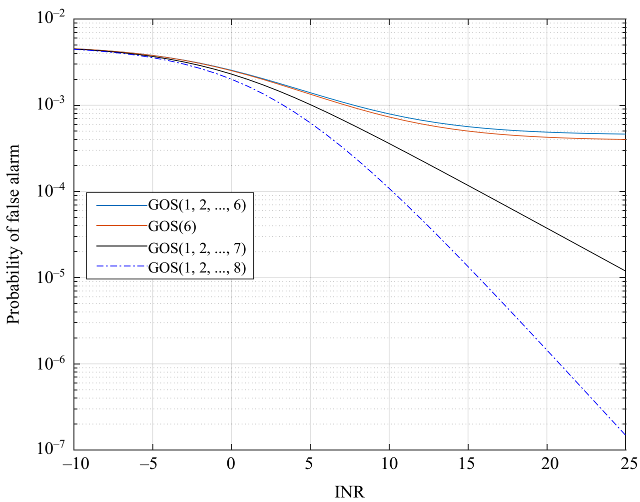

FIGURE 8 Collaborative false alarm probability of various types of GOS-OR detectors in nonhomogeneous environments with noise uncertainty ($M = 8$, $N = 5$, no. of interferers = 2)

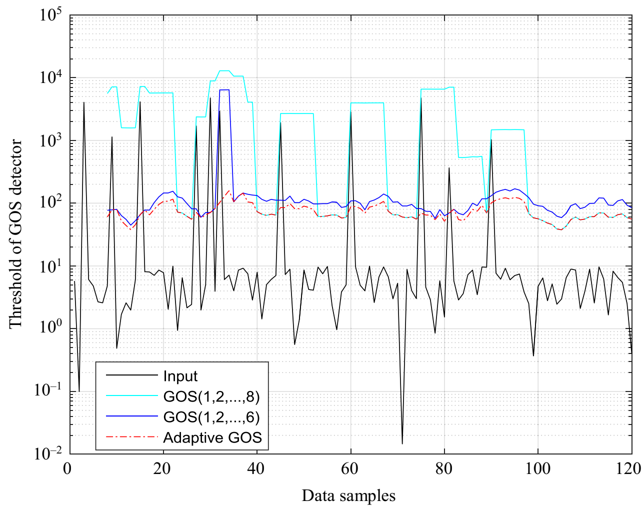

FIGURE 9 Thresholds of various types of GOS detectors with noise uncertainty ($M = 8$, $P_{fa} = 0.001$)

Analytical results show that the GOS-OR architecture can achieve optimum performance and maintain the desired false alarm rate if the exact coefficients of the GOS-OR detector can be selected. Here, one important aspect is to eliminate the interfering signals in the estimation of the power level. The adaptive estimation of the number of nonhomogeneous data samples in the reference window is addressed in Section 3.3.

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