Spectrum Sensing for Cognitive Radio Network with Multiple Receive Antennas Under Impulsive Noise Environments

Seungwon Lee, So Ryoung Park, Yun Hee Kim, and Iickho Song

Abstract: **Spectrum sensing with multiple receive antennas is addressed in the cognitive radio network under impulsive noise environments. Based on order statistics, we propose a non-linear combining scheme to cope with the heavy-tail characteristics of the probability density function of impulsive noise. Through computer simulations, it is shown that the proposed scheme exhibits better detection performance than the conventional schemes in impulsive noise environments with Rayleigh fading.**

Index Terms: **Cognitive radio, impulsive noise, non-linear scheme, order statistics, spectrum sensing.**

I. INTRODUCTION

THE proliferation of wireless communication devices and services is increasing at a high pace. Since the usable spectrum is limited, it becomes rather difficult to accommodate the increasing number of devices requiring higher data rate with a static frequency allocation schemes. To improve the efficiency of spectrum utilization, cognitive radio (CR) has been proposed as a solution [1]–[4]. The idea of the CR is to perform spectrum sensing, identify spectrum holes that are not currently being occupied by primary users (PUs), and then dynamically utilize the spectrum holes without causing harmful interference to PUs.

Apparently, spectrum sensing is one of the most important components in the CR. Spectrum sensing should monitor activation of PUs in order to vacate the spectrums occupied by secondary users when PUs begin a transmission over their spectrums. In general, the signal detection techniques for spectrum sensing can be classified into three categories: 1) Matched filter (coherent detection), 2) cyclostationary feature detection, and 3) energy detection (non-coherent detection) [4]. If the CR has the full information on the specifications (e.g., modulation schemes, preambles, or pilot patterns) of the signal of PU, a matched filter is optimal and would result in the best sensing performance (maximum of the signal-to-noise ratio). By exploiting the periodicity of the signal of PU or its statistics such as the mean and autocorrelation, cyclostationary feature detection differentiates the signal energy of PU from the local noise energy [5]. The energy detection, widely used in spectrum sensing because of low computational and implementation complexities, is optimal when the local noise power is available at the CR [3], [6].

In the meantime, diversity techniques are exploited to mitigate the effects of multipath fading and shadowing in wireless communication. In receiver diversity, some diversity combining techniques such as the equal gain combining and selection combining have been incorporated in energy detection in additive white Gaussian noise (AWGN) environment for spectrum sensing in the CR to improve detection performance [2], [7]–[10].

The distribution of noise is one of the key factors influencing the performance of a spectrum sensing scheme. In most of previous studies, the noise is assumed to be AWGN for spectrum sensing in the CR. Although the Gaussian assumption is reasonable from the central limit theorem and allows a mathematically tractable investigation, noise cannot be modeled by the Gaussian distribution in many practical cases [3], [11]. As a result, it is meaningful to consider non-Gaussian noise environment in the spectrum sensing in the CR. Examples of non-Gaussian impairments include man-made impulsive noise, heavy-tailed noise, and co-channel interference from other CRs [12]–[16]. When the noise distribution is non-Gaussian, it is well-known that detectors designed for AWGN do not perform adequately. Taking these observations into account, spectrum sensing for cognitive radio networks in non-Gaussian noise environment has recently been addressed [17]–[25].

In this paper, we propose a class of spectrum sensing schemes, called the ordering and selecting of observations (OSO), in the CR network with multiple receive antennas. Based on the observation that non-linear schemes can successfully alleviate the effects of impulsive noise components in many signal processing applications [1], [12]–[14], we exploit non-linear schemes with a generalized likelihood ratio test (GLRT) detector. The test statistic of the OSO scheme is the log-likelihood ratios (LLRs) obtained at the GLRT detector. Here, the LLR is produced by using a set of selected observations of small magnitude among all observations from receive

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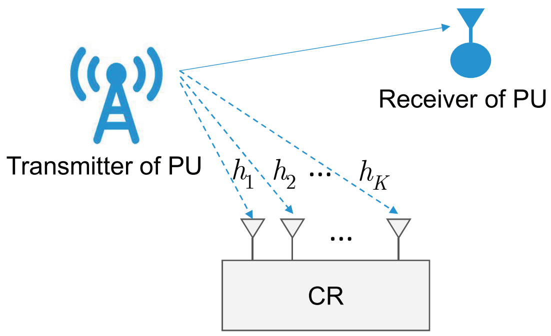

Fig. 1. Structure of a CR network composed of a CR with K receive antennas and a PU with one transmit antenna.

antennas. The OSO scheme provides better detection performance than conventional schemes in impulsive noise environments. The novelty of this paper lies in that (1) a new spectrum sensing scheme is proposed for the CR network with receiver diversity and (2) the performance characteristics of the OSO scheme are compared with the conventional schemes in various noise environments.

This paper is organized as follows. In Section II, the system model is introduced. In Section III, the OSO scheme is described in detail. In Section IV, the performance of the OSO scheme for spectrum sensing is analyzed and compared with that of the conventional schemes in various noise environments with Rayleigh channel fading.

II. SYSTEM MODEL

Consider a simple CR network composed of a CR with K receive antennas and a PU with one transmit antenna as shown in Fig. 1. We assume each antenna on the CR receives N samples, where N is a sample size, i.e., the number of samples in an observation period. A generalization to the case of multiple PUs should be straightforward. The low-pass discrete-time observation

$$x_k(n) = x_{k,I}(n) + jx_{k,Q}(n), \tag{1}$$

on the k-th receive antenna at the n-th time instant with $x_{k,I}(n)$ and $x_{k,Q}(n)$ denoting the in-phase (I) and quadrature (Q) components, respectively, can be expressed as

$$x_k(n) = v_k(n), \tag{2}$$

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

$$x_k(n) = h_k(n)s(n) + v_k(n), \tag{3}$$

when the frequency band is being used by the PU. In (2) and (3), $v_k(n) = v_{k,I}(n) + jv_{k,Q}(n)$ for $k = 1, 2, \cdots, K$ and $n = 1, 2, \cdots, N$ are independent and identically distributed (i.i.d.) complex additive noise components with the common joint probability density function (pdf) f_{V_I,V_Q} of $\{(v_{k,I}(n), v_{k,Q}(n))\}$, $s(n) = s_I(n)+js_Q(n)$ is the transmitted complex signal of the PU, and $h_k(n) = h_{k,I}(n) + jh_{k,Q}(n)$ is the complex channel gain. Note that $h_k(n)s(n)$ is the faded transmitted complex signal. If we assume that the fading is sufficiently slow, the complex channel gains $\{h_k(n)\}_{n=1}^N$ do not change over an observation period. Then the complex channel gains $\{h_k(n)\}_{n=1}^N$ can be simplified as h_k, the complex channel gain on the k-th receive antenna.

When the transmission schemes of the spectrum user are unknown to the CR and the total transmitted signal power is fixed, the transmit diversity technique with multiple transmit antennas does not provide performance improvement [26]. Thus we assume that the PU has one transmit antenna without loss of generality.

The spectrum sensing problem in the CR network can be modeled as a binary hypothesis testing of the null hypothesis

$$\mathcal{H}_0: \quad \text{The frequency band is not being used by PU} \tag{4}$$

against the alternative hypothesis

$$\mathcal{H}_1: \quad \text{The frequency band is being used by PU.} \tag{5}$$

Under this scenario, the decision rule can be expressed as

$$T(\underline{X}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda, \tag{6}$$

where the test statistic $T(\underline{X})$ is a function of the $N \times K$ matrix

$$\underline{X} = [\underline{x}_1, \underline{x}_2, \cdots, \underline{x}_K] \tag{7}$$

and λ denotes the pre-determined threshold satisfying the false alarm probability $\Pr\{T(\underline{X}) > \lambda \,|\, \mathcal{H}_0\}$ with $\underline{x}_k = [x_k(1), x_k(2), \cdots, x_k(N)]^T$ the observation vector of size $N \times 1$ at the k-th receive antenna for $k = 1, 2, \cdots, K$.

III. SPECTRUM SENSING SCHEMES

A. Noise Model

The bivariate isotropic symmetric α-stable (BISαS) model is widely used to characterize non-Gaussian impulsive (or heavy-tailed) noise [27]. The BISαS pdf is expressed as

$$f_{X_1,X_2}(x_1, x_2) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp\left\{-j(x_1t_1 + x_2t_2) - \gamma\left(t_1^2 + t_2^2\right)^{\frac{\alpha}{2}}\right\} dt_1 dt_2, \tag{8}$$

where the parameters $\gamma > 0$ and $0 < \alpha \leq 2$ are the dispersion and characteristic exponent, respectively. The dispersion parameter γ represents the spread of the BISαS pdf: A larger value of γ indicates a wider spread of the BISαS pdf. The characteristic parameter α represents the heaviness of tails of the BISαS pdf: A smaller value of α indicates more severe impulsiveness of the BISαS pdf.

Unless $\alpha = 1$ or 2, no closed-form expression is known for the integral in (8). When $\alpha = 1$, the BISαS pdf (8) is the same as the bivariate Cauchy pdf

$$f_{X_1,X_2}(x_1, x_2) = \frac{\gamma}{2\pi\left(x_1^2 + x_2^2 + \gamma^2\right)^{\frac{3}{2}}}, \tag{9}$$

and the BISαS pdf (8) becomes the bivariate Gaussian pdf

$$f_{X_1,X_2}(x_1,x_2) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x_1^2+x_2^2}{2\sigma^2}\right), \quad (10)$$

with $\sigma^2 = 2\gamma$ the variance when $\alpha = 2$, which corresponds also to the limiting case of no impulsiveness.

B. Generalized Likelihood Ratio Test

Assuming that the CR has no information of the patterns (e.g., modulation schemes, preambles, or pilot patterns) of the signal of PU, variance of the noise, and channel gain between the PU and CR, the GLRT detector is often used and the unknown parameters are replaced by their maximum likelihood estimates (MLEs). Specifically, assuming the faded transmitted complex signal $h_k(n)s(n)$ is unknown, the MLE of the faded transmitted complex signal $h_k(n)s(n)$ of the k-th receive antenna is used. For the k-th receive antenna with the assumption of i.i.d. noise components, denote the pdf of $x_k(n)$ by $f_{X_k}(x_k(n);\mathcal{H}_z)$ under the hypothesis $\mathcal{H}_z$ for $z = 0$ and 1. Then the common joint pdf of observation vector $\underline{x_k}$ on the k-th receive antenna can be expressed as $f_{\underline{X_k}}\left(\underline{x_k};\mathcal{H}_z\right) = \prod_{n=1}^{N} f_{X_k}(x_k(n);\mathcal{H}_z)$.

The output $T\left(\underline{x_k}\right)$ of the GLRT detector in the k-th receive antenna branch can be expressed as the LLR

$$\begin{aligned} T\left(\underline{x_k}\right) &= \ln\frac{f_{\underline{X_k}}\left(\underline{x_k};\mathcal{H}_1\right)}{f_{\underline{X_k}}\left(\underline{x_k};\mathcal{H}_0\right)} \\ &= \sum_{n=1}^{N}\ln\frac{f_{V_k}\left(x_k(n)-\widehat{h_k(n)s(n)}\right)}{f_{V_k}\left(x_k(n)\right)}, \end{aligned} \quad (11)$$

where $\ln(\cdot)$ is the natural logarithm, $\widehat{h_k(n)s(n)}$ is the MLE of $h_k(n)s(n)$, and $f_{V_k}(x) = f_{V_I,V_Q}(\mathrm{Re}(x),\mathrm{Im}(x))$ is the joint pdf of $v_k(n)$. Under the i.i.d. Cauchy noise environment, the numerator and denominator of the natural logarithm in (11) can be expressed with

$$f_{V_k}(d) = \frac{\gamma_k}{2\pi\left(|d|^2+\gamma_k^2\right)^{\frac{3}{2}}}, \quad (12)$$

using (9), where $\gamma_k = \gamma$ is the dispersion parameter of Cauchy noise distribution for the k-th receive antenna. Similarly, under the i.i.d. Gaussian noise environment, the numerator and denominator of the natural logarithm in (11) can be expressed with

$$f_{V_k}(d) = \frac{1}{2\pi\sigma_k^2}\exp\left(-\frac{|d|^2}{2\sigma_k^2}\right) \quad (13)$$

using (10), where $\sigma_k^2 = 2\gamma_k = \sigma^2$ is the variance of Gaussian noise distribution for the k-th receive antenna. Now, it is easy to obtain the MLE

$$\widehat{h_k(n)s(n)} = x_k(n) \quad (14)$$

of $h_k(n)s(n)$ under the Cauchy and Gaussian noise environments. Then, the output $T(\underline{x_k})$ of the GLRT detector in the k-th receive antenna branch can be expressed as

$$T_C\left(\underline{x_k}\right) = \sum_{n=1}^{N}\ln\left(1+\frac{|x_k(n)|^2}{\gamma_k^2}\right), \quad (15)$$

in Cauchy noise environment and as

$$T_G\left(\underline{x_k}\right) = \frac{1}{2\sigma_k^2}\sum_{n=1}^{N}|x_k(n)|^2, \quad (16)$$

in Gaussian noise environment.

C. Non-linear Schemes

When the noise is impulsive, non-linear schemes are reported to be successful in mitigating the influence of noise components in many signal processing applications. In impulsive noise environment, since observations with larger magnitudes might with high probability have resulted from noise components rather than from signal components, observations with smaller magnitudes by using a non-linear scheme based on order statistics would be best selected to improve the performance.

C.1 The Combining with Order Statistics (COS) Scheme

In [1], the COS scheme exploiting non-linear combining strategies together with the GLRT detector has been proposed. The LLR $T(\underline{x_k})$ obtained at the GLRT detector in the k-th receive antenna branch can be expressed as (15) and (16) in Cauchy and Gaussian noise environments, respectively. With the K LLRs

$$\underline{T} = \left\{T\left(\underline{x_1}\right), T\left(\underline{x_2}\right), \cdots, T\left(\underline{x_K}\right)\right\} \quad (17)$$

obtained at GLRT detectors, an ordering operation will produce the order statistics

$$\left\{T_{[1]}\left(\underline{X}\right), T_{[2]}\left(\underline{X}\right), \cdots, T_{[K]}\left(\underline{X}\right)\right\}, \quad (18)$$

where $T_{[j]}\left(\underline{X}\right)$ is the j-th order statistic in $\underline{T}$. Then, M order statistics $\left\{T_{[i_1]}\left(\underline{X}\right), T_{[i_2]}\left(\underline{X}\right), \cdots, T_{[i_M]}\left(\underline{X}\right)\right\}$ are linearly combined with equal weight to produce the test statistic

$$T_{COS}\left(i_1,i_2,\cdots,i_M;\underline{X}\right) = \sum_{a=1}^{M} T_{[i_a]}(\underline{X}) \quad (19)$$

for spectrum sensing. Here, $M \in \{1,2,\cdots,K\}$ is the number of antenna branches employed in the combining and $1 \leq i_1 < i_2 < \cdots < i_M \leq K$. As in [1], the notation COS$(i_1,i_2,\cdots,i_M)$ is employed in this paper to denote the detector based on the test statistic (19).

C.2 The Proposed Spectrum Sensing Scheme

Now, we consider the OSO scheme. Fig. 2 shows a block diagram of the OSO scheme. Define the $1\times NK$ vector

$$\underline{y} = \mathrm{vec}^T\left(\underline{X}\right), \quad (20)$$

where vec$\left(\underline{A}\right)$ is the vectorization of a matrix $\underline{A}$: That is, all columns in $\underline{A}$ are listed one by one vertically to form vec$\left(\underline{A}\right)$.

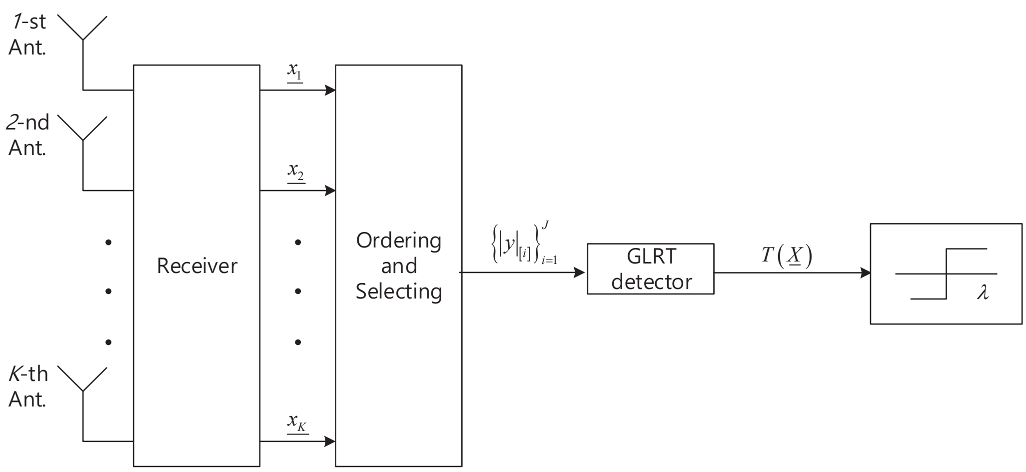

Fig. 2. A block diagram of the OSO scheme.

Now, magnitude ordering operation on the $\underline{y}$ gives the magnitude order statistic vector

$$\underline{|y|_{[\cdot]}} = \left\{ |y|_{[1]}, |y|_{[2]}, \cdots, |y|_{[NK]} \right\} \tag{21}$$

where $|y|_{[j]}$ is called the j-th magnitude order statistic and is the j-th smallest observation among the NK absolute values in $\underline{y}$; that is,

$$0 \leq |y|_{[1]} \leq |y|_{[2]} \leq \cdots \leq |y|_{[NK]}. \tag{22}$$

Then, a set $\left\{ |y|_{[1]}, |y|_{[2]}, \cdots, |y|_{[J]} \right\}$ of J smallest order statistics for $1 \leq J \leq NK$ is selected to produce the test statistics

$$T_{C,OSO}(\underline{X}) = \sum_{i=1}^{J} \ln \left(1 + \frac{|y|_{[i]}^2}{\gamma_i^2} \right) \tag{23}$$

in Cauchy noise environment ($\alpha = 1$) and

$$T_{G,OSO}(\underline{X}) = \sum_{i=1}^{J} \frac{|y|_{[i]}^2}{2\sigma_i^2} \tag{24}$$

in Gaussian noise environment ($\alpha = 2$), where $\gamma_i = \gamma$ is the dispersion parameter of Cauchy noise distribution for the receive antenna associated with $|y|_{[i]}$ and $\sigma_i^2 = 2\gamma_i = \sigma^2$ is the variance of Gaussian noise distribution for the receive antenna associated with $|y|_{[i]}$. Note that (24) is also well-known as the energy detector.

The proposed test statistics in (23) and (24) are produced by the J smallest observations to reduce the effect of impulsive noise. First, the value of the proposed test statistics, like other appropriately chosen statistics, under the alternative hypothesis with positive signal components will tend to be larger than that under the null hypothesis. Second, as it is clearly observed, the proposed test statistics are based on the J smallest observations, which makes the proposed test statistics less sensitive to the more frequent occurrences of noise components of high magnitudes in impulsive environment (than in non-impulsive noise environment). In essence, the proposed test statistics are stochastically smaller than a threshold under the null hypothesis while they are stochastically greater than the threshold under the alternative hypothesis: In the detection procedure, in addition, order statistics are exploited to reduce the influence of the impulsive noise components.

D. Complexity Analysis

In this section, the complexity of the OSO and COS schemes are compared. The computational complexity of the OSO scheme depends on two major operations; 1) ordering operation and 2) computation of the test statistic $T_{C,OSO}(\underline{X})$ in (23) in Cauchy noise environment and $T_{G,OSO}(\underline{X})$ in (24) in Gaussian noise environment. For convenience, we assume that the dispersion parameters $\{\gamma_k\}_{k=1}^{K}$ are the same in Cauchy noise environment. Similarly, we assume that variances of Gaussian noise distribution $\{\sigma_k^2\}_{k=1}^{K}$ are the same in Gaussian noise environment. First, for the ordering of the NK values in $\underline{X}$, we need $2NK$ multiplications and NK additions to obtain the magnitude order statistic vector $\underline{|X|_{[\cdot]}}$, and then, $\lceil NK \log NK \rceil$ comparisons (additions). Second, for the computation of the test statistic $T(\underline{X})$, we need $2J - 1$ additions and J divisions in Cauchy noise environment and 1 division and $J - 1$ additions in Gaussian noise environment.

On the other hand, the COS scheme requires $\lceil K \log K \rceil$ comparisons (additions) for ordering operation. Secondly, for computation of K LLRs, $(3N - 1)K$ additions, $2NK$ multiplications, and NK divisions in Cauchy noise environment and $2NK$ multiplications, $(2N - 1)K$ additions, and K divisions in Gaussian noise environment are required in addition. Since the test statistic of the COS scheme is the sum of one or more order statistics of the LLRs, $M - 1$ additions are required where

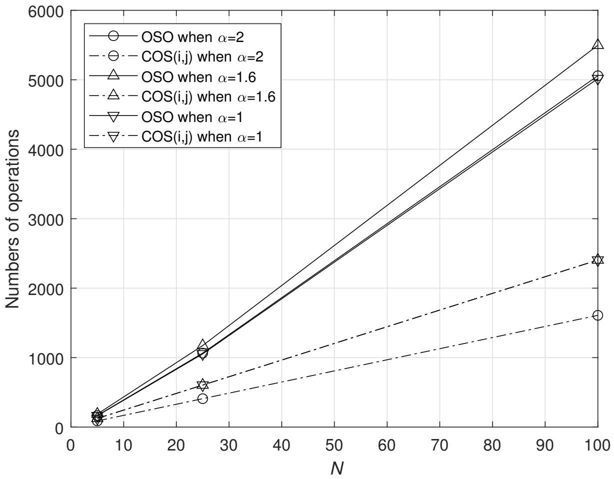

Fig. 3. The numbers of operations of OSO and COS for the scenarios in Section IV.

M is the number of antenna branches employed in the combining. The computational complexities are summarized in Tables 1 and 2 for BISαS noise environments with $\alpha = 1$, 1.6, and $\alpha = 2$.

Table 1. Computational complexity of the OSO and COS schemes in BISαS noise environments with $\alpha = 1$ and 1.6.

	Number of multiplications	Number of additions
COS	$3NK$	$\lceil K\log K\rceil + (3N-1)K + M - 1$
OSO	$2NK + J$	$\lceil NK\log NK\rceil + NK + 2J - 1$

Table 2. Computational complexity of the OSO and COS schemes in BISαS noise environment with $\alpha = 2$.

	Number of multiplications	Number of additions
COS	$(2N+1)K$	$\lceil K\log K\rceil + (2N-1)K + M - 1$
OSO	$2NK + 1$	$\lceil NK\log NK\rceil + NK + J - 1$

Fig. 3 shows the complexity in terms of the number of operations (addition + multiplication) of the OSO and COS for the scenarios considered in Section IV. Although it is not straightfoward to simply compare the computational complexity between addition and multiplication, the multiplication can be slower than addition when the algorithms are implemented in hardware [28], [29]. As an attempt to provide the numbers of the two operations more specifically, we have included Tables 3 and 4, which show that the OSO requires less and more multiplications and additions, respectively, than the COS.

IV. PERFORMANCE COMPARISONS

Let us now compare the performance of several schemes in various noise environments, assuming that CR is exposed to BISαS noise with $\alpha = 2$, 1.6, or 1 and $\gamma = 1$. We consider slowly varying Rayleigh fading channel where the complex channel gains $\{h_k\}$ on the k-th receive antenna with

Table 3. The numbers of additions of OSO and COS for the scenarios in Section IV.

BISαS	$\alpha = 1$			$\alpha = 1.6$			$\alpha = 2$		
N	5	25	100	5	25	100	5	25	100
COS	65	305	1205	65	305	1205	45	205	805
OSO	118	824	4097	134	904	4417	126	864	4257

Table 4. The numbers of multiplications of OSO and COS for the scenarios in Section IV.

BISαS	$\alpha = 1$			$\alpha = 1.6$			$\alpha = 2$		
N	5	25	100	5	25	100	5	25	100
COS	60	300	1200	60	300	1200	44	204	804
OSO	46	230	920	54	270	1080	41	201	801

$\mathbf{E}\left(|h_k|^2\right) = 1$ may change at the beginning of each observation period. Here, $\mathbf{E}(\cdot)$ is the expectation operator. For simplicity, we assume that all the transmitted signals are set to constant values with $s_I(n) = s_Q(n)$ and normalized to make the total transmit signal power $P = \sum_{n=1}^{N} |s(n)|^2$. The number K of receive antennas on the CR is chosen to be 4 based in the performance-complexity tradeoff since no significant gain is achieved for $K > 4$ [30] while hardware cost and complexity increases.

The detection threshold λ is often pre-determined to satisfy the false alarm probability. In Gaussian noise environments, methods and procedures on how to obtain the detection threshold λ has been explained in many research papers such as [31] and [32]. For the BISαS pdf (8), however, no closed-form expression is known to exist. Therefore, the detection threshold has been obtained in experimentally, not theoretically, in this paper.

The performance of spectrum sensing schemes are here measured in terms of receiver operation characteristic (ROC). In the simulation, the ROC of each scheme under various BISαS noise environments is obtained by Monte-Carlo simulation of 10^6 independent realizations for each point.

The notation $\mathrm{OSO_C}(J)$ and $\mathrm{OSO_G}(J)$ will be used to denote the OSO scheme with the test statistic obtained using (23) and (24), respectively. Since the lack of a closed-form expression for the BISαS pdf (except for $\alpha = 1$ and 2) prohibits the exact evaluation of the test statistics, we have obtained the test statistics from (23) when $\alpha = 2$, 1.6, and 1 and using (24) when $\alpha = 2$. Note that Cauchy detectors have frequently been used as a useful alternative under the general impulsive noise circumstances because of their acceptable performance in various impulsive environments, although they are only suboptimal when the noise is not Cauchy. In addition, we would also like to note that, because the energy detector is known to result in a severe performance degradation in impulsive noise environments, $\mathrm{OSO_G}(J)$ is considered only in BISαS noise environment with $\alpha = 2$. Since the $\mathrm{OSO_C}(J)$ and $\mathrm{OSO_G}(J)$ have almost the same tendency of performance as shown in Fig. 4, we will consider only the ROCs of $\mathrm{OSO_C}(J)$ in various noise environments with Rayleigh fading.

We have first tried to find appropriate value of J in order to improve the detection performance of the CR exploit-

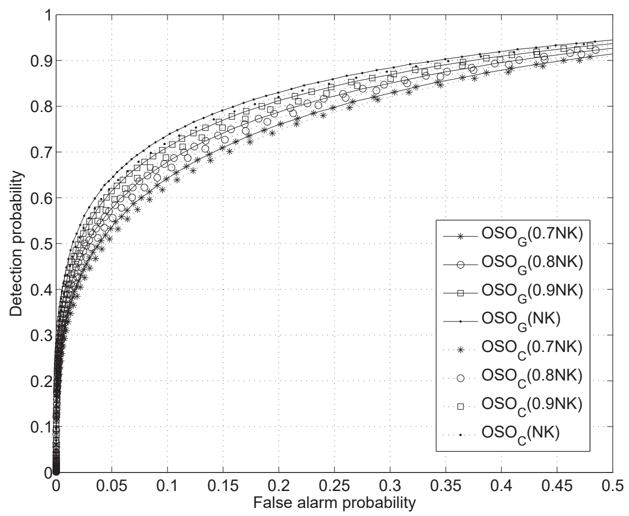

Fig. 4. The ROCs of $\mathrm{OSO_C}(J)$ and $\mathrm{OSO_G}(J)$ in BISαS noise environment with $\alpha = 2$.

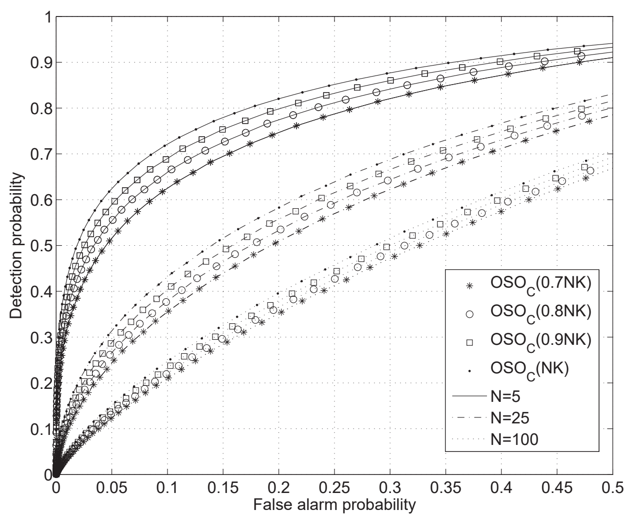

Fig. 5. The ROCs of $\mathrm{OSO_C}(J)$ for various values of J and N in BISαS noise environment with $\alpha = 2$.

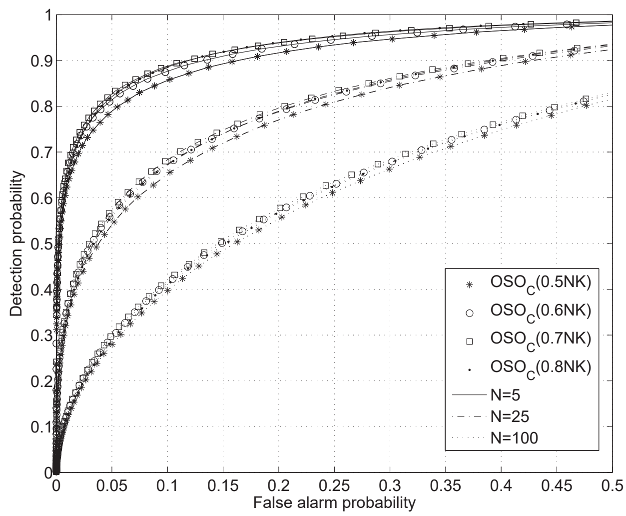

Fig. 6. The ROCs of $\mathrm{OSO_C}(J)$ for various values of J and N in BISαS noise environment with $\alpha = 1.6$.

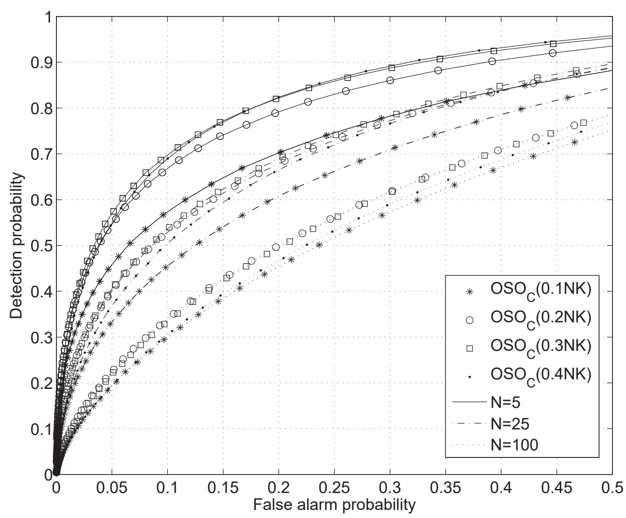

Fig. 7. The ROCs of $\mathrm{OSO_C}(J)$ for various values of J and N in BISαS noise environment with $\alpha = 1$.

ing the $\mathrm{OSO_C}(J)$ scheme by assuming that the number N of observations and the number J of selected observations are among $\{5, 25, 100\}$ and $\{0.1NK, 0.2NK, \cdots, NK\}$, respectively. Figs. 5–7 show the detection performance of the $\mathrm{OSO_C}(J)$ for various values of J and N in BISαS noise environments with $\alpha = 2$, 1.6, and 1. It is noteworthy that the signal power P/N per observation is higher when N is smaller since we fixed the total transmit signal power P: As a consequence, the performance of the proposed detector is better when N is smaller than when N is larger, which is clearly observed in all the figures.

In Fig. 5, $\mathrm{OSO_C}(J)$ with larger value of J shows a better detection performance in BISαS noise environments with $\alpha = 2$. In Figs. 6 and 7, $\mathrm{OSO_C}(J)$ with $J = 0.7NK$ and $J = 0.3NK$ shows better detection performance than $\mathrm{OSO_C}(J)$ with other values of J in BISαS noise environments with $\alpha = 1.6$ and 1, respectively. The simulation results of Figs. 5–7 clearly show that detection performance of $\mathrm{OSO_C}(J)$ with a smaller value of J is better than that with a larger value of J, especially as the impulsiveness of noise gets more severe.

Hereafter we consider detectors with $J = NK, 0.7NK$, and $0.3NK$ for BISαS noise environments with $\alpha = 2$, 1.6, and 1, respectively. For the sake of simplicity, we let $\mathrm{OSO_C}$ stand for $\mathrm{OSO_C}(NK)$, $\mathrm{OSO_C}(0.7NK)$, and $\mathrm{OSO_C}(0.3NK)$ in BISαS noise environments with $\alpha = 2$, 1.6, and 1, respectively. First, since the COS scheme exhibits the best detection performance among the conventional schemes in impulsive noise environments [1], we compare the detection performances of the $\mathrm{OSO_C}$,

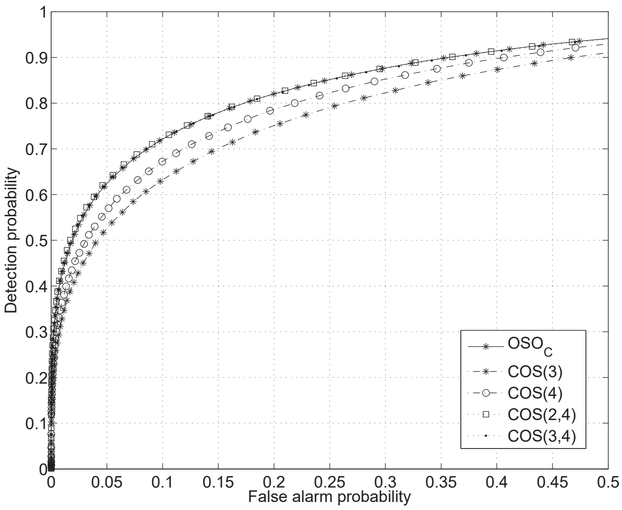

Fig. 8. The ROCs of OSO_C, COS (i_1), and COS (i_1, i_2) in BISαS noise environment with $\alpha = 2$.

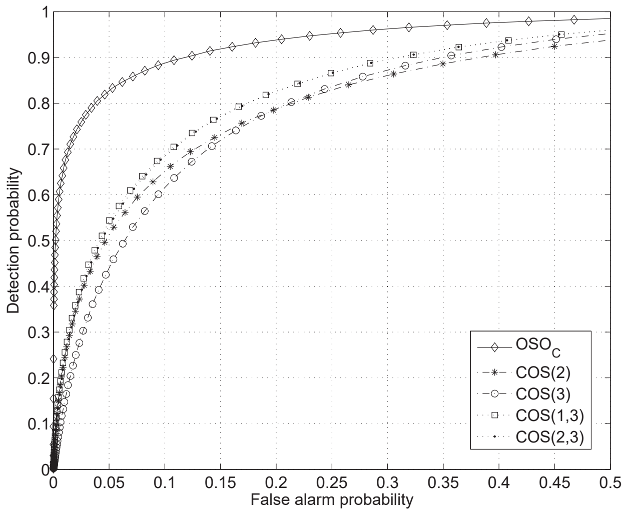

Fig. 9. The ROCs of OSO_C, COS (i_1), and COS (i_1, i_2) in BISαS noise environment with $\alpha = 1.6$.

COS (i_1), and COS (i_1, i_2). Figs. 8–10 show that detection performances of OSO_C, COS (i_1), and COS (i_1, i_2) in the BISαS noise with $\alpha = 2$, 1.6, and 1. It is observed that OSO_C outperforms COS (i_1) and COS (i_1, i_2) in the BISαS noise with $\alpha = 1.6$ and 1 and has the same performance as COS (i_1, i_2) in the BISαS noise with $\alpha = 2$.

It is clearly observed that the OSO outperforms the COS, especially when the impulsiveness of the noise is high. Although the OSO requires slightly higher computational complexity than the COS, the performance improvement of the OSO is significant enough to justify such an increase of complexity.

The performances of COS and OSO are also explainable from the viewpoint of signal detection theory. It is well known that an observation with a very large magnitude should be considered not as a signal plus noise but just as a noise in impulsive noise environments. Thus, when the noise is impulsive and the impulsiveness of noise gets higher, selecting smaller observations generally leads to a better performance than selecting larger observations. The main difference between COS and OSO lies in how to obtain the test statistic with the observations. In COS, the LLR of each antenna is firstly obtained using N observations, and then, the linear combination of the M smallest LLRs selected among a total of K LLRs becomes the test statistic. In OSO, on the other hand, the J smallest observations are firstly selected among a total of NK observations of K antennas, and then, the LLR of these J smallest observations becomes the test statistic. Thus, the values of observations employed to produce the test statistic of OSO are smaller than those used to produce the test statistic of COS, and consequently, the detection performance of OSO would be better than that of COS when the impulsiveness of noise is more severe.

V. CONCLUDING REMARK

In this paper, we have proposed a class of spectrum sensing schemes called the OSO, which provides reasonable performance for spectrum sensing in impulsive noise environments with Rayleigh fading. The OSO scheme employs the GLRT and non-linear diversity combining strategy. The test statistic of the OSO is obtained by using a number of selected observations with small magnitudes. The number of selected observations in this paper is determined by simulation.

The performance of the OSO and COS has been compared in various noise environments via Monte-Carlo simulations. From simulation results, OSO scheme is observed to provide better detection performance than COS in impulsive noise environments. In addition, as the impulsiveness of noise gets higher, the gap between the detection performances of OSO and COS becomes wider.

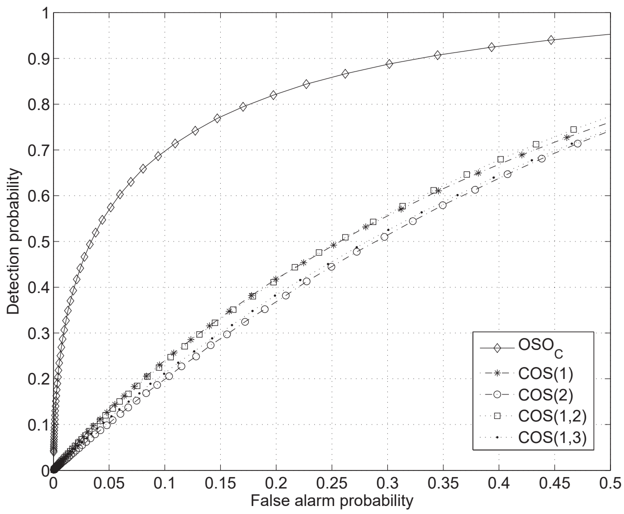

Fig. 10. The ROCs of OSO_C, COS (i_1), and COS (i_1, i_2) in BISαS noise environment with $\alpha = 1$.

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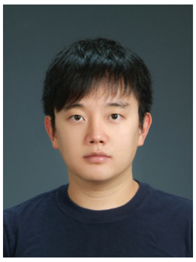

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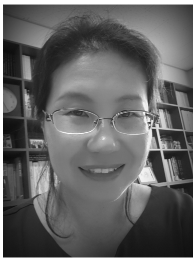

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