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Signal Detection in Generalized Gaussian Distribution Noise With Nakagami Fading Channel

XIAOMEI ZHU[1], TIANJING WANG[1], YAPING BAO[1], FANGQIANG HU[1], AND SEN LI[2]
[1]College of Computer Science and Technology, Nanjing Tech University, Nanjing 211816, China
[2]Department of Information Science and Technology, Dalian Maritime University, Dalian 116000, China

Corresponding author: Xiaomei Zhu (njiczxm@njtech.edu.cn)

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ABSTRACT A fractional order moments-based detector is proposed for the detection of weak signals in additive impulsive noise environment assumed as generalized Gaussian distribution with properly selected parameter values. The asymptotic detection performance is derived and compared with some traditional detectors optimized for operations in Gaussian noise with Nakagami fading communication channels. The analytical and computer simulation results of the fractional order moment-based detector are shown for signal detection with fading channels in the impulsive noise.

INDEX TERMS Signal detection, generalized Gaussian distribution, fractional order moment, Nakagami fading.

I. INTRODUCTION

Signal detection is aimed at testing for the presence or absence of signals in additive noise, which has received widespread attention due to recent demands of modern communication system, such as spectrum sensing in Cognitive radio networks [1], [2] and the dynamic sharing of free frequency spectrum resources in 5G networks [3]–[5], [23]. In the previous signal detection problem, the noise distribution is assumed to be Gaussian, which has been justified in many environment e.g. [7]. But in the actual environment, particularly the spectrum below 100MHz, we need to think about the non-Gaussian noise environments, such as impulsive and heavy-tailed noise [8]. As we known, the probability density function (PDF) of non-Gaussian noise has the heavier tail characteristics than that of Gaussian noise [9], therefore, the performance of detectors that have been designed in Gaussian noise may be significantly reduced in non-Gaussian noise.

There are some effective detectors for signals detection in the non-Gaussian noise environment, for instance, the locally optimum detector(LOD) and the Neyman-Pearson(NP) [9], [10], but they require some known information, for instance, the known form of the signal or the PDF of the receiver noise, which may not be readily available in practice. Generalized likelihood ratio test (GLRT) [11] and Rao test [12], [13] has been studied about detection under the non-Gaussian noise environment, which has the maximum likelihood estimation (MLE) of the unknown parameters, but they need large computational operations.

According to the problems above, we need to design valid detectors which can detect signal availably in additive non-Gaussian noise without any priori knowledge of the signal and the additive noise and can be realized easily in the actual environment.

Recently, the α-stable distribution as an important class of statistical signal processing models has been widespread attention by researchers. But the stable noise does not have finite second- or higher order moments, so the fractional lower order statistics (FLOS) become a new tool to process signal with lower order moments ($0 < p < 2$). By performing fractional exponential operations of the additive noise, the fractional lower order moments (FLOM) can reduce the degree of non-Gaussianity. It has been applied to weak signal detection under α-stable distribution noise in [14], but its application to signal detection under the GGD noise has not yet received much attention.

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In this paper, We consider using fractional lower order moments (FLOM) detector to perceive the presence of the signal under the generalized Gaussian distribution (GGD). The detection performance of the FLOM detector is theoretical analyzed and the closed-form solutions for probabilities of detection and false alarm are derived.Finally, both the numerical and simulation results indicate that the detection performance of the fractional order moment detector is much superior to the traditional energy detector in the GGD noise environments.

The rest of this paper is arranged as follows: We analyze the detection problem and theGGD noise model in Section 2. The performance of the FLOM detector derived in Section 3. We provide numerical and simulation results of the proposed method compared with the traditional detectors in Section 4, and the conclusion is given in Section 5.

II. PROBLEM FORMULATION

A. SYSTEM MODEL

We consider the detection of the presence of the signal $s(n)$ with K multi detectors in the additive background noise $w_k(n)$ through the wireless channel. Signal detection problem is formulated as a binary hypothesis testing problem, they are defined as H_0: *signal absent* and H_1: *signal present*. Under the two hypotheses,the k-th detector receive the observed sample $z_k(n)$, at discrete-time $n \in \{1, 2, \ldots, N\}$, and the observation vectors can be expressed as

$$\begin{cases} H_0: & z_k(n) = w_k(n) \\ H_1: & z_k(n) = h_k s(n) + w_k(n) \end{cases} \tag{1}$$

The $s(n)$ obeys the random distribution of zero-mean and variances $\sigma_s^2 = E[|s(n)|^2]$. h_k is the channel gain between the signal and the k-th detector under fading channel, which are IID and variances $\sigma_h^2 = E[|h_k|^2]$. $w_k(n)$, $s(n)$ and h_k are all IID random variables, independent of each other.

B. NOISE MODEL

We imagine that the background noise $w_k(n)$ under both hypotheses in (1) is part of the GGD family and is a GGD with zero-mean and variance σ_w^2. When the variance $\sigma_w^2 > 0$ and the shape factor $\beta > 0$, the GGD's PDF is [16]

$$p\left(w_k(n); \beta\right) = \frac{\beta\Gamma\left(4/\beta\right)}{2\pi\sigma_w^2(\Gamma\left(2/\beta\right))^2} \exp\left(-\frac{1}{B}\left(\frac{|w_k(n)|}{\sigma_w}\right)^\beta\right) \tag{2}$$

$$B = \left(\frac{\Gamma\left(2/\beta\right)}{\Gamma\left(4/\beta\right)}\right)^{\beta/2} \tag{3}$$

where $\Gamma(\alpha) = \int_0^\infty x^{\alpha-1}e^{-x}dx$. The GGD has some special cases, for example, the Laplacian distribution with $\beta = 1$ and the Gaussian distribution when $\beta = 2$, the impulse probability function as $\beta \to 0$, in addition the uniform distribution when $\beta \to \infty$.

Since (2) are zero whit the odd origin moments, the absolute value of order moments are researched in this paper. The finite order moments of GGD is shown by,

$$E\left(|w_k(n)|^p\right) = \left(\frac{\Gamma\left(2/\beta\right)}{\Gamma\left(4/\beta\right)}\right)^{p/2} \frac{\Gamma\left((p+2)/\beta\right)}{\Gamma\left(2/\beta\right)}\sigma_w^p \tag{4}$$

Here, the orders is not just integer, it can be any value with $p > 0$.

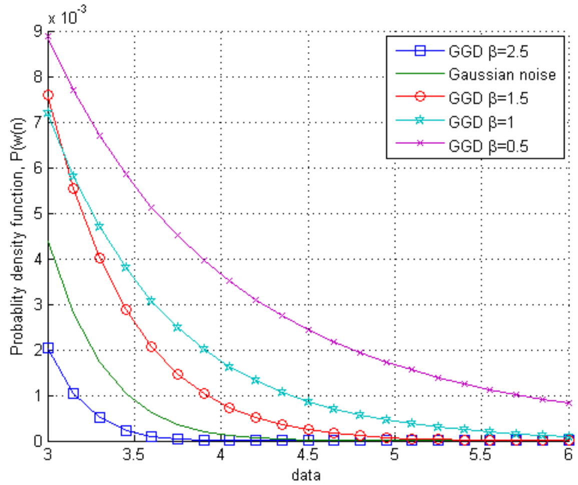

FIGURE 1. PDF of Gaussian and GGD with different shape factor β.

Fig. 1 shows the PDF of the GGD noise with different values of the shape factor β. The different rate of decay for the tail with different β are obtained. When $\beta > 2$, the tail decays faster than that of the normal distribution, but when $0 < \beta < 2$, the tail decays more slowly than that of the normal distribution. According to the above result, the GGD can be used to fit the non-Gaussian noises with different shape factor β in signal detection practical systems, and moreover a higher degree of non-Gaussianity can be modeled with a smaller value of β. In practical system, the shape factor β can be obtained by the signal estimation methods of the additive noise such as the moments estimation. The "heavier" tail of the GGD noise means larger noise samples, then the signal detection problem under non-Gaussian noise environment must consider a large noise samples, which will lead to the high probability of false alarm.

C. CHANNEL MODEL

Nakagami distribution is normally used to express the signals which has been transmitted through multipath fading channels. The PDF of the channel gains can be express by [20]

$$p\left(h_k\right) = \frac{2}{\Gamma\left(m\right)}\left(\frac{m}{\Omega}\right)^m (h)^{2m-1}e^{-m(h_k)^2/\Omega}, \quad h_k > 0 \tag{5}$$

where $\Omega = E\left[H^2\right]$, m is the Nakagami fading parameter of the communication channel. When $m = 0.5$, the Nakagami is a one-side Gaussian fading , when $m = 1$, it is a Rayleigh fading, and when $m \to \infty$, it expresses non-fading.

III. FRACTIONAL LOWER ORDER MOMENT BASED DETECTOR FOR SIGNAL DETECTION

The FLOM detector can optimize the detection performance by a tunable parameter P, $P = p_1, p_2, \ldots, p_K$. The detection statistic of the FLOM detector is follow

$$y_{FLOM} = \frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}|z_k(n)|^{p_k} \quad (6)$$

where p_k is a variable value under $0 < p_k < 2$. When $p_k = 2$, the FLOM detection is simplified to energy detection. With a given p_k, y_{FLOM} can be compared to a pre-scribed threshold λ. If $y_{FLOM} > \lambda$, the detector determines that signal exists, otherwise the signal does not exist.

The equation (6) shows that the structure of the FLOM scheme is simple and low implementation complexity. It need not *any a priori knowledge* of noise, signal and channel, however the detection performance of the FLOM detector is better than that of second- (the energy detector) or higher-order moments based detectors for non-Gaussian noise environment. This will be given in Section 4.

Using (4), the mean u_0 and σ_0^2 under H_0 can be calculated,

$$\begin{aligned} u_0 &= E[y_{FLOM}|H_0] \\ &= \frac{1}{KN}E\left[\sum_{k=1}^{K}\sum_{n=1}^{N}|w_k(n)|^{p_k}\right] \\ &= \frac{1}{K}\sum_{k=1}^{K}\left(\frac{\Gamma(2/\beta_k)}{\Gamma(4/\beta_k)}\right)^{p_k/2}\frac{\Gamma((p_k+2)/\beta_k)}{\Gamma(2/\beta_k)}\sigma_w^{p_k} \end{aligned} \quad (7)$$

where β_k is the shape factor of the GGD noise received by k-th antenna, $0 < p_k < 2$. The variance σ_0^2 under H_0 can be expressed as

$$\begin{aligned} \sigma_0^2 &= E[(y_{FLOM} - E[y_{FLOM}])^2|H_0] \\ &= E[{y_{FLOM}}^2 - E^2[y_{FLOM}]|H_0] \end{aligned} \quad (8)$$

Substituting (6) into (8), noting that $z_k(n) = w_k(n)$ and using (4), we obtain

$$\begin{aligned} \sigma_0^2 &= E[(\frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}[|w_k(n)|^{p_k}])^2] \\ &\quad -\{\frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}E[|w_k(n)|^{p_k}]\}^2 \\ &= \frac{1}{(KN)^2}\{NE[\sum_{k=1}^{K}|w_k(n)|^{2p_k}] \\ &\quad + \sum_{\substack{k,i=1 \\ k\neq i \text{ or } n\neq j}}^{K}\sum_{n,j=1}^{N}E[|w_k(n)|^{p_k}|w_i(j)|^{p_i}] \\ &\quad - N\sum_{k=1}^{K}E^2[|w_k(n)|^{p_k}] \\ &\quad - \sum_{\substack{k,i=1 \\ k\neq i \text{ or } n\neq j}}^{K}\sum_{n,j=1}^{N}E[|w_k(n)|^{p_k}|w_i(j)|^{p_i}]\} \\ &= \frac{1}{K^2N}\{\sum_{k=1}^{K}E[|w_k(n)|^{2p_k}] - \sum_{k=1}^{K}E^2[|w_k(n)|^{p_k}]\} \\ &= \frac{1}{KN}\sum_{k=1}^{K}\left(\frac{\Gamma(2/\beta_k)}{\Gamma(4/\beta_k)}\right)^{p_k}\sigma_w^{2p_k}[\frac{\Gamma((2p_k+2)/\beta_k)}{\Gamma(2/\beta_k)} \\ &\quad -(\frac{\Gamma((p_k+2)/\beta_k)}{\Gamma(2/\beta_k)})^2] \end{aligned} \quad (9)$$

The mean u_1 of y_{FLOM} under H_1 is given as

$$\begin{aligned} u_1 &= E[y_{FLOM}|H_1] \\ &= \frac{1}{KN}E\left[\sum_{k=1}^{K}\sum_{n=1}^{N}|h_k s(n) + w_k(n)|^{p_k}\right] \end{aligned} \quad (10)$$

We combine the binomial theorem to compute $|h_k s(n) + w_k(n)|^{p_k}$, leading to

$$\begin{aligned} u_1 &= \frac{1}{K}\sum_{k=1}^{K}E[|w_k(n)|^{p_k} + p_k|h_k s(n)||w_k(n)|^{p_k-1} \\ &\quad + \frac{p_k(p_k-1)}{2!}|h_k s(n)|^2|w_k(n)|^{p_k-2} + \ldots] \end{aligned} \quad (11)$$

Because low SNR assumption, $h_k s(n) \ll w_k(n)$, and $s(n)$ has zero mean, thus high order terms and the first order term of $|h_k s(n)|$ are ignored, and using (4), we can obtain

$$\begin{aligned} u_1 &\approx \frac{1}{K}\sum_{k=1}^{K}E[|w_k(n)|^{p_k} \\ &\quad + \frac{p_k(p_k-1)}{2!}|h_k s(n)|^2|w_k(n)|^{p_k-2}] \\ &= u_0 + \frac{1}{2K}\sum_{k=1}^{K}p_k(p_k-1)E[|h_k s(n)|^2|w_k(n)|^{p_k-2}] \\ &= u_0 + \frac{\sigma_s^2}{2K}\sum_{k=1}^{K}|h_k|^2 p_k(p_k-1)\left(\frac{\Gamma(2/\beta_k)}{\Gamma(4/\beta_k)}\right)^{(p_k-2)/2} \\ &\quad \frac{\Gamma((p_k)/\beta_k)}{\Gamma(2/\beta_k)}\sigma_w^{p_k-2} \end{aligned} \quad (12)$$

With the approximate method to calculate u_1, the variance σ_1^2 is derived as

$$\begin{aligned} \sigma_1^2 &= E[(y_{FLOM} - E[y_{FLOM}])^2|H_1] \\ &= E[{y_{FLOM}}^2 - E^2[y_{FLOM}]|H_1] \\ &= E\{[\frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}|h_k s(n) + w_k(n)|^{p_k}]^2\} \\ &\quad -\{\frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}E[|h_k s(n) + w_k(n)|^{p_k}]\}^2 \\ &= \frac{1}{K^2N}\{\sum_{k=1}^{K}E[|h_k s(n) + w_k(n)|^{2p_k}] \\ &\quad - \sum_{k=1}^{K}E^2[|h_k s(n) + w_k(n)|^{p_k}]\} \end{aligned} \quad (13)$$

The binomial theorem is used to calculate approximately $|h_k s(n)+w_k(n)|^{2p_k}$ and $|h_k s(n)+w_k(n)|^{p_k}$, leading to

$$\begin{aligned}\sigma_1^2 &= \frac{1}{K^2N}\{\sum_{k=1}^{K} E[|w_k(n)|^{2p_k} + 2p_k|h_k s(n)||w_k(n)|^{2p_k-1} \\ &+\frac{2p_k(2p_k-1)}{2!}|h_k s(n)|^2|w_k(n)|^{2p_k-2}+\ldots] \\ &-E^2[|w_k(n)|^{p_k}+p_k|h_k s(n)||w_k(n)|^{p_k-1} \\ &+\frac{p_k(p_k-1)}{2!}|h_k s(n)|^2|w_k(n)|^{p_k-2}+\ldots]\} \end{aligned} \tag{14}$$

According to the assumption of low SNR, the $|h_k s(n)| << |w_k(n)|$ is given. We can ignore the higher-order terms, at the same time, the h_k is constant and $s(n)$ is zero mean under the detecting process, so we can get

$$\begin{aligned}\sigma_1^2 &\approx \frac{1}{K^2N}\{\sum_{k=1}^{K} E[|w_k(n)|^{2p_k} \\ &+\frac{2p_k(2p_k-1)}{2!}|h_k s(n)|^2|w_k(n)|^{2p_k-2}] \\ &-E^2[|w_k(n)|^{p_k}+\frac{p_k(p_k-1)}{2!}|h_k s(n)|^2|w_k(n)|^{p_k-2}]\} \\ &= \frac{1}{K^2N}\sum_{k=1}^{K}\{E[|w_k(n)|^{2p_k}]-E^2[|w_k(n)|^{p_k}] \\ &+\sigma_s^2|h_k|^2 p_k(2p_k-1)E[|w_k(n)|^{2p_k-2}] \\ &-\sigma_s^2|h_k|^2 p_k(p_k-1)E[|w_k(n)|^{p_k-2}]\} \\ &\approx \sigma_0^2+\frac{\sigma_s^2}{K^2N}\sum_{k=1}^{K}|h_k|^2\left(\frac{\Gamma(2/\beta_k)}{\Gamma(4/\beta_k)}\right)^{p_k-1} p_k\sigma_w^{2p_k-2} \\ &\{(2p_k-1)\frac{\Gamma(2p_k/\beta_k)}{\Gamma(2/\beta_k)} \\ &-(p_k-1)\frac{\Gamma((p_k+2)/\beta_k)\,\Gamma(p_k/\beta_k)}{2\Gamma^2(2/\beta_k)}\}. \end{aligned} \tag{15}$$

We guess that N in any given detection interval is sufficiently large, in view of the central limit theorem, even $w_k(n)$ is non-Gaussian noise distribution, the distribution of the FLOM detector statistics is similar to a Gaussian distribution. So for H_0, the FLOM detector statistics is expressed as Gaussian with mean u_0 and variance σ_0^2 and, for H_1, with mean u_1 and variance σ_1^2, respectively. Therefore Pfa and Pd of the FLOM detector is computed as

$$P_{fa} = \{y_{FLOM} > \lambda|H_0\} = Q(\frac{\lambda-u_0}{\sqrt{\sigma_0^2}}) \tag{16}$$

$$P_d = \{y_{FLOM} > \lambda|H_1\} = Q(\frac{\lambda-u_1}{\sqrt{\sigma_1^2}}) \tag{17}$$

where λ is the detection threshold, $Q(a)=\int_a^\infty \frac{1}{\sqrt{2\pi}}e^{-\frac{y^2}{2}}dy$ is the Gaussian Q-function.

For the fading communication channels, the P_{fa} and P_d depend on the channel gain h_k. In order to make the problem tractable, we consider the low SNR case, $\sigma_s^2 \to 0$, $\sigma_1^2 \approx \sigma_0^2$. λ is determined by a fixed P_{fa} according to (16), substituting λ into (17), we obtain the detection probability P_d

$$\begin{aligned}P_d &= E_h\left\{Q\left(\frac{\lambda-u_1}{\sqrt{\sigma_1^2}}\right)\right\} \\ &\approx E_h\left\{Q\left(\frac{\sqrt{\sigma_0^2}Q^{-1}(P_{fa})+u_0-u_1}{\sqrt{\sigma_0^2}}\right)\right\} \\ &= E_h\left\{Q\left(Q^{-1}(P_{fa})-\frac{\sigma_s^2}{2K\sigma_0}\sum_{k=1}^{K}|h_k|^2p_k(p_k-1)t\right)\right\} \\ &= E_\xi\left\{Q\left(Q^{-1}(P_{fa})-\xi\right)\right\} \end{aligned} \tag{18}$$

where

$$t = \left(\frac{\Gamma(2/\beta_k)}{\Gamma(4/\beta_k)}\right)^{(p_k-2)/2}\frac{\Gamma((p_k)/\beta_k)}{\Gamma(2/\beta_k)}\sigma_w^{p_k-2} \tag{19}$$

$$\xi = \frac{\sigma_s^2}{2K\sigma_0}\sum_{k=1}^{K}|h_k|^2p_k(p_k-1)t \tag{20}$$

where $Q^{-1}(\cdot)$ is the inverse of the Gaussian Q-function. For calculation of (18), the PDF of ξ, $p_\xi(\xi)$ is needed. As has been pointed out in [22] and [23], a K-detector system transmitted in a Nakagami independent fading channel equals to an $L = Km$ channel diversity for a Rayleigh fading channel, this lead to

$$p_\xi(\xi) = \frac{\xi^{L-1}}{(L-1)!\bar{\xi}^L}\exp(-\xi/\bar{\xi}) \tag{21}$$

The noise signal and fading gains are IID progress, for simplicity, $p_k = p$, $\beta_k = \beta$. $\bar{\xi}$ is the average value of ξ, is defined as

$$\bar{\xi} = \frac{\sigma_s^2\sigma_h^2}{2\sigma_0}p(p-1)\left(\frac{\Gamma(2/\beta)}{\Gamma(4/\beta)}\right)^{(p-2)/2}\frac{\Gamma((p)/\beta)}{\Gamma(2/\beta)}\sigma_w^{p-2} \tag{22}$$

Then (18) is written as

$$\begin{aligned}P_d &= E_\xi\left\{Q\left(Q^{-1}(P_{fa})-\xi\right)\right\} \\ &= \int_0^\infty Q\left(Q^{-1}(P_{fa})-\xi\right)p_\xi(\xi)d\xi \end{aligned} \tag{23}$$

where $P_{fa} \le 1/2$, we have $Q^{-1}(P_{fa}) \ge 0$. The expression of the Gaussian Q-function $Q(a)=\int_a^\infty \frac{1}{\sqrt{2\pi}}e^{-\frac{y^2}{2}}dy$. By putting (21) into (23), P_{fa} of the FLOM detector under Nakagami fading channel is expressed as

$$P_d = \frac{1}{\sqrt{2\pi}}\int_0^\infty\int_{Q^{-1}(P_{fa})-\xi}^\infty e^{-y^2/2}dy\frac{\xi^{L-1}}{(L-1)!\bar{\xi}^L}e^{(-\xi/\bar{\xi})}d\xi \tag{24}$$

P_d can be easily evaluated by MATLAB through the expression of (24).

IV. NUMERICAL AND SIMULATION RESULTS

In this section, we use the FLOM detector to detect the primary user signal in Cognitive Radio Network (CRN) and give the simulation and numerical results. Here the $s(n)$ is assumed to be a Gaussian random variable with zero-mean and the GGD noise with $0 < \beta < 2$ is generated by the three-step method [21]. Here,$P_f a = 0.1, N = 1000$, if there is no special explanation.

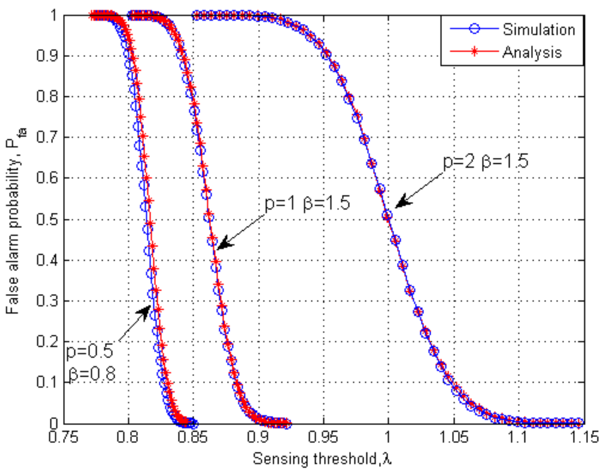

FIGURE 2. Effect of the detection threshold on Pfa with N=1000, $K = 1$, $SNR = -15$dB.

Fig. 2 shows the effect of the the detection threshold on Pfa for different β and p. It can be seen that the P_{fa} decreases with increasing the detection threshold. From Fig. 2, it is clear that the theoretical results agree well with the simulation results.

In Fig. 3, we display P_d of the FLOM detector varies according to p. Here in order to compare the different performance of the detectors based on the lower order moments, the second order moments and the higher order moments, we assume $0 < p < 10$ with the shape factor $\beta = 0.8$ and 1.5 in the simulation. It is seen that the P_d decreases with p increasing. The results verify that the performance of FLOM detector ($p < 2$) is better than the traditional detectors, such as the second moment ($p = 2$) based detectors and the higher moments ($p > 2$) based detectors. The numerical results agree well with their simulations.

In Fig. 4, we compare the receiver operating characteristic (ROC) curves of different p and β. Note that with $\beta = 0.8$ (or $\beta = 1.5$), the smaller the value of p is, the higher the performance of the FLOM detector will achieve. Similarly, when $p = 1$, the smaller β has the better performance. Specially, in the case of $\beta = 1.5$, when $p = 2$ (the energy detector), its performance is worse as compared to $p = 1$. Thus, traditional energy detector has poorer performance than our FLOM detector in non-Gaussian noise. Among 4 groups of data, the ROC curves for $p = 0.5$, $\beta = 0.8$ achieve the best detection performance.

Fig. 5 shows the probability of detection with different SNR. The Pd increase as SNR increasing. The numerical results are in close agreement with the simulation results.

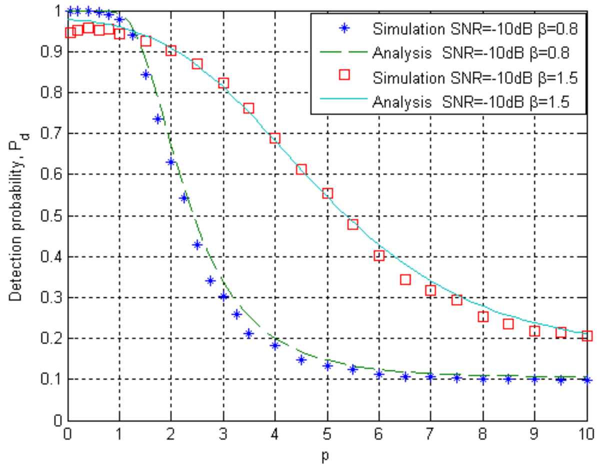

FIGURE 3. Pd versus p with $K = 1$ and $\beta_1 = 0.8$, $\beta_2 = 1.5$.

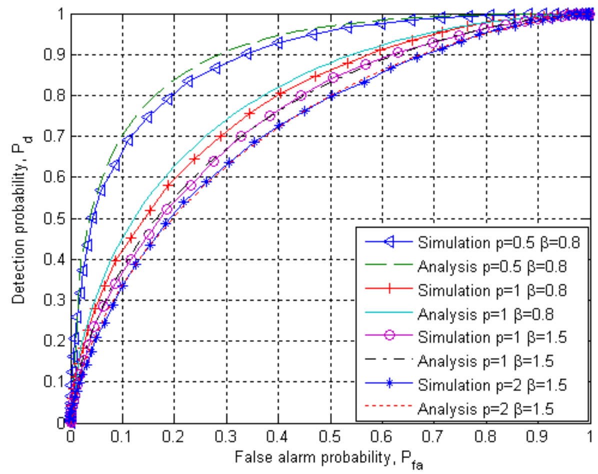

FIGURE 4. Effect of p and β on the ROC of the proposed detector for $SNR = -15$dB, $K = 1$, $N = 1000$.

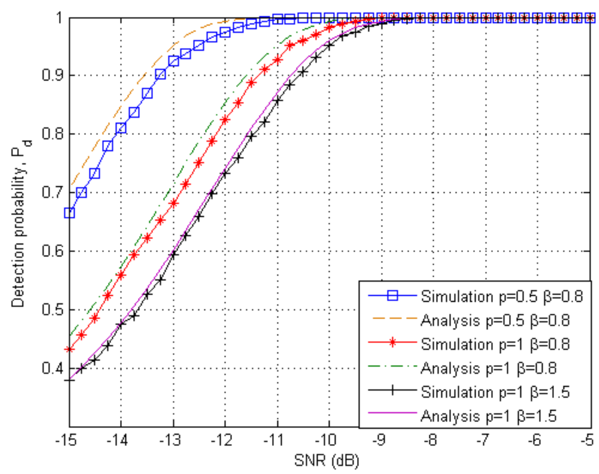

FIGURE 5. Pd versus SNR for different p and β with $K = 1$.

Fig. 6 shows the relation between the pd and β. From Fig. 6, it shows that as β decreases, the Pd of the FLOM method is increased significantly,however that of the

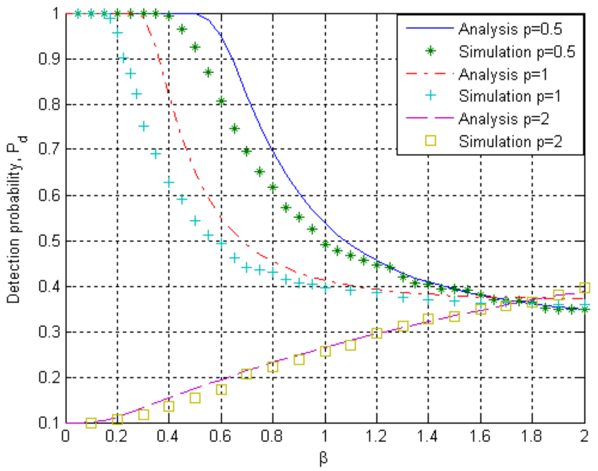

FIGURE 6. Probability of detection of the proposed detector and energy detector (p = 2) versus β.

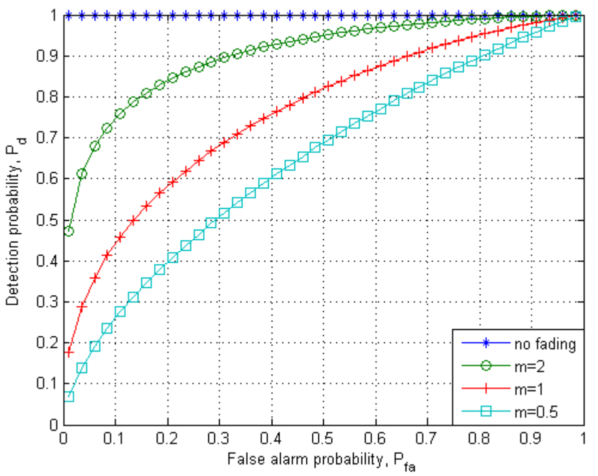

FIGURE 7. ROC for Nakagami channels with different *m*.

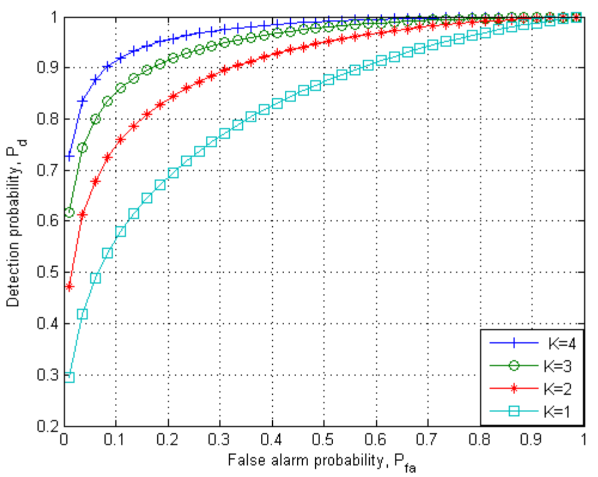

FIGURE 8. ROC of the detector over Nakagami channels with different *K*.

ED decreases. That is to say, under the non-Gaussian noise environment, ED scheme is failed and the performance of the FLOM detector is perfect. At the same time, the result shows that the performance of the FLOM detector is increasing with p decreasing, which agrees with the results of Fig. 3.

Fig. 7 compares the ROC curves for Nakagami fading channels with $m = 2, 1, 0.5$, $p = 0.5$, $SNR = -15$dB, $K = 4$. From Fig. 7, we can see that when the value of m increases, the detection performance is increasing. Figs. 8 shows the effect of the number of detectors K on the ROC for m = 2. Obviously, the bigger the number of detectors is, the higher the performance will achieve. Thus, it is useful for multi-detector cooperative detection to gain a better performance of detecting the received signal.

V. CONCLUSIONS

The fractional order moments of the received signal has been proposed to detect the presence or absence of signal. The performance of the detector has been verified by theoretical analysis and Monte Carlo simulation. The detector, as a blind detector, can be used for detection applications under generalized gaussian distribution noise environment without any priori-knowledge of noise, channel and signal.

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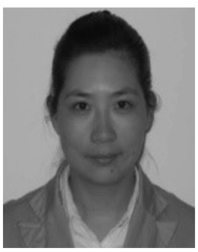
XIAOMEI ZHU received the M.Sc. degree in computer science from the China University of Mining and Technology, in 2004, and the Ph.D. degree in signal processing from the University of Nanjing University of Posts and Telecommunications, in 2014. In 2004, she joined the College of Computer Science and Technology, Nanjing Tech University, where she was a Teacher and is currently an Associate Professor. Her research interests include the investigation of signal detection and estimation, spectrum sensing, and deep learning for modern communications systems. Her research has been funded by the NSFC (No. 61501223).



TIANJING WANG received the Ph.D. degree in signal processing from the University of Nanjing University of Posts and Telecommunications, in 2009. In 2000, she joined the College of Computer Science and Technology, Nanjing Tech University, where she served as an Associate Professor. Her research interests include the investigation of spectrum sensing, cognitive radio systems, and compressed sensing. Her research has been funded by the NSFC (No. 61501224).

YAPING BAO received the M.Sc. degree in control system from Southeast University, in 2001. In 2003, she joined the College of Computer Science and Technology, Nanjing Tech University, where she served as a Teacher and is currently a Professor. Her research interests include the investigation of signal detection and estimation and FPGA-based system design.

FANGQIANG HU received the B.S. and M.S. degrees in electrical engineering from Southeast University, Nanjing, China, in 1999 and 2004, respectively, where he is currently pursuing the Ph.D. degree in electrical engineering. He also serves with Nanjing Tech University as a Lecturer. His current research interests include the investigation of signal detection and estimation and the field of GPS multipath and position.

SEN LI received the B.S. degree in microelectronics from Liaoning University, Shenyang, China, in 1996, the M.S. degree in information and communication engineering from Dalian Maritime University, Dalian, China, in 1999, and the Ph.D. degree in information and signal processing from the Dalian University of Technology, Dalian, in 2011. In 2013, she held a Postdoctoral Position with the Department of Electrical and Computer Engineering, Concordia University, Montreal, QC, Canada. She is currently an Associate Professor with the Department of Information Science and Technology, Dalian Maritime University.