Robust Spectrum Sensing Based on Hyperbolic Tangent in Gaussian and Non-Gaussian Noise Environments

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***Abstract*—Simple and reliable spectrum sensing schemes are important for cognitive radio (CR) to avoid interference to the primary users (PUs). At present, most of the existing sensing schemes are proposed in Gaussian noise. Nevertheless, in practice, CR suffers from non-Gaussian noise such as man-made impulsive noise, ultra-wideband interference and co-channel interference. In this article, to handle the detection performance degradation in non-Gaussian impulsive noise environments, a robust spectrum sensing scheme namely hyperbolic tangent based energy detector (HT-ED) is proposed. The proposed HT-ED is a semi-blind method which does not require any a priori knowledge about the primary user's signals. Furthermore, the HT-ED can provide a superior detection performance compared with the conventional energy detector (ED) in a wide range of non-Gaussian noises. The simulation results show that the proposed HT-ED is very robust against impulsive noises which are modeled as the Laplace or α-stable noises. Moreover the detection performance of HT-ED is much better than those of the traditional ED and FLOM-based methods.**

***Index Terms*—cognitive radio, robust spectrum sensing, non-Gaussian noise, hyperbolic tangent.**

I. Introduction

With the rapid development of wireless communication, the shortage of the traditional fixed spectrum allocation policies is more and more serious. These fixed rules lead to a severe problem that some radio bands are terribly busy while other bands are underused. As a result, the utilization of spectrum is low and unbalanced. Cognitive radio (CR) is seen as a promising technology to deal with this contradiction between the growing spetrum congestion and the low utilization of radio bands[1,2]. In CR, secondary users (SUs) have an opportunity to access the spectrum bands licensed to primary users (PUs) when the licensed bands are idle. Therefore spectrum sensing is a crucial technology in CR, which guarantees the PUs are not interfered by the SUs.

There are many researchers who have proposed a lot of spectrum sensing algorithms[3-6] to perform the signal detection, recently. Among them, energy detector (ED) based methods are wildly used, because they are simple and easy to implement. Furthermore, energy detector is a semi-blind process which obtains the sensing threshold only dependent on noise, and it compares the detection statistics with the threshold to determine the sensing result.

Unfortunately, these energy based sensing methods are only valid in Gaussian noise environments[7-9] while in the case of non-Gaussian noise, the performances of these methods degrade drastically due to the impulsive noise[10]. As is known to all, Gaussian noise is an idealized model for thermal noise which has no heavy tails. However in practice, almost all kinds of noises produced in various indoor and outdoor environments are not Gaussian noises but non-Gaussian noises which have heavy tails. In indoor environments, the communication signals are disturbed by the man-made impulsive noises which may be produced by electromechanical switches. On the other hand, in outdoor environments, a lot of phenomena such as power lines, lightning in the sky and buildings in radar clutter, are the sources of impulsive noises[11].

Spectrum sensing for non-Gaussian noise has been proposed by some scholars, recently[7,8,12]. [7] presents an accurate kernelized energy detection in impulsive noise. A suprathreshold stochastic resonance based spectrum sensing in nonGaussian noise is proposed in [8]. A fractional lower order moments (FLOMs) based scheme is put forward in [12]. However, there are still some issues for spectrum sensing in non-Gaussian noise environments. First of all, the detection performance under non-Gaussian noise is not good enough. Next, due to the requirement of realtime detection, the computational complexity has to be low. Last, as some SUs may exist under Gaussian noise and others are under non-Gaussian noise, the new algorithm must be able to handle both Gaussian and non-Gaussian noise simultaneously.

To solve the above-mentioned performance degradation problems in non-Gaussian noise environments, we propose a hyperbolic tangent based energy detector (HT-ED) which is motivated by the simplicity of the conventional ED. Hyperbolic tangent function, whose graph is a S-shaped curve, appears in many neural networks as a transfer function[13-15]. This curve is used widely due to the fact that it is the simplest non-linear curve that can strike a graceful balance between linear and non-linear behavior. In this paper, hyperbolic tangent function is applied to suppress the impulsive noise by the non-linear behavior, while it does not restrain the normal noise because of the linear behavior. As will be interpreted in Section III, the hyperbolic tangent is considered as a wonderful choice for modifying the conventional energy detector due to its sensing accuracy and low computational complexity in the p-resence of non-Gaussian noise environments. Furthermore, the HT-ED is quite robust against impulsive noises, because of the fact that the impulsive part of noises is suppressed. Simulation results show that the HT-ED has a superior sensing capability compared to the conventional ED, and the conventional ED fails in α-stable noise scenario when $\alpha < 2$. Besides, when the noise is Laplace noise, the performance of HT-ED is also better than that of the conventional ED.

The paper is organized as follows. Signal model and traditional energy detection are briefly depicted in Section II. The elaborate description of the proposed HT-ED is displayed in Section III. In Section IV, the performances of the proposed scheme are evaluated numerically. Conclusions are provided in Section V.

II. Signal model and traditional energy detector

A. Signal model

This paper considers a single cognitive user spectrum sensing scenario. The cognitive user detects the transmitting state of PU by the received signals $X = [x(1), x(2), \cdots, x(N)]$, where N is the number of samples and $x(n)$ is the sample signal at discrete time n. Then the signal received by the cognitive user is described as

$$\begin{cases} H_0 : x(n) = v(n) \\ H_1 : x(n) = s(n) + v(n), (n = 1, 2, \cdots, N) \end{cases} \tag{1}$$

where $n = 1, 2, \cdots, N$ is the sample index. $s(n)$ represents the signal transmitted by PU, and it can be assumed as a Gaussian signal with mean 0 and variance σ_s^2. $v(n)$ is the additive noise with mean 0 and variance σ_v^2. Without loss of generality, we assume that the noise $v(n)$ and the PU's signal $s(n)$ are independent. More over, the received signal samples $s(n)$ are assumed to be independent and identically distributed (i.i.d.). In this paper, the additive noise is modeled as Gaussian or non-Gaussian distributions. Particularly, Laplace and α-stable noise are applied to model the practical man-made impulsive noise. H_0 and H_1 denote the absence and presence of the PU, respectively.

B. Traditional energy detector

The purpose of the energy detector is to test whether the PU signal is present (Hypothesis H_1) or not (Hypothesis H_0). If the decision is H_0, the SU can obtain the opportunity to use the spectrum for transmitting information. The energy detector statistic is calculated as

$$T_{ed}(X) = \sum_{m=1}^{M} x(m)^2 \tag{2}$$

where $X = [x(1), x(2), ..., x(M)]^T$ is the sampled signal data set. A threshold γ is needed to make the decision between present and absent. Then we have the detection scheme

$$\begin{cases} H_0 : T_{ed}(X) < \gamma \\ H_1 : T_{ed}(X) > \gamma \end{cases} \tag{3}$$

If the statistic is smaller than the threshold γ, the decision is H_0. If not, the present of PU (H_1) is considered. When the noise $v(n)$ is Gaussian noise, the statistic distribution of the received signal $x(n)$ is a norm distribution in both hypotheses

$$\begin{cases} H_0 : X \sim \mathcal{N}\left(0, \sigma_v^2\right) \\ H_1 : X \sim \mathcal{N}\left(0, \sigma_v^2 + \sigma_s^2\right) \end{cases} \tag{4}$$

So the decision statistic $T_{ed}(X)$ in the case of H_0, will follow a central chi-square distribution with a degree of freedom M. However, in the case of H_1, $T_{ed}(X)$ obeys a non-central chi-square distribution with the same degree of freedom and a non centrality parameter 2ζ, ($\zeta = \sigma_s^2/\sigma_v^2$).

According to the central limit theorem[16], in order to make a reliable test result, the sample number should be large enough, and then $T_{ed}(X)$ approximately follows Gaussian distribution

$$\begin{cases} H_0 : T_{ed}(X) \sim \mathcal{N}\left(M\sigma_v^2, 2M\sigma_v^4\right) \\ H_1 : T_{ed}(X) \sim \mathcal{N}\left(M\left(\sigma_s^2 + \sigma_v^2\right), 2M\left(\sigma_s^2 + \sigma_v^2\right)^2\right) \end{cases} \tag{5}$$

Therefore, the detection and false alarm probabilities can be expressed as

$$P_d = Q\left(\frac{\gamma - M\left(\sigma_s^2 + \sigma_v^2\right)}{\sqrt{2M}\left(\sigma_s^2 + \sigma_v^2\right)}\right) \tag{6}$$

and

$$P_f = Q\left(\frac{\gamma - M\sigma_v^2}{\sqrt{2M}\sigma_v^2}\right) \tag{7}$$

respectively, where $Q(x) = \frac{1}{2\pi}\int_x^{+\infty} e^{\frac{-t^2}{2}} dt$ is the Q-function which is the tail probability of the standard normal distribution. The threshold γ can be calculated by a predefined false alarm probability

$$\gamma = Q^{-1}(P_f)\sqrt{2M}\sigma_v^2 + M\sigma_v^2 \tag{8}$$

Then the detection probability can be expressed as

$$P_d = Q\left(\frac{Q^{-1}(P_f)\sqrt{2M}\sigma_v^2 - M\sigma_s^2}{\sqrt{2M}\left(\sigma_s^2 + \sigma_v^2\right)}\right) \tag{9}$$

III. Hyperbolic tangent based energy detector

In this section, we, firstly, describe three noise models: Gaussian noise, Laplace noise and α-stable noise. Gaussian noise is the idealized noise model for most of the signal processing, regardless of actual situations. However, Laplace noise and α-stable noise are non-Gaussian modeled for real situations. Next, we derive the hyperbolic tangent based energy detector elaborately.

A. Noise model

1) Gaussian noise: Gaussian distribution can be expressed as

$$f_g(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-u_g)^2}{2\sigma^2}} \tag{10}$$

where u_g is the mean value and σ is the standard deviation. The normal distribution is the bell-shaped curve with no heavy tails and widely applied in signal processing to model the ideal noise.

2) Laplace noise: Laplace distribution is a typical model used for the non-Gaussian noise in wireless communications, because of its heavy-tail behavior, and the probability density function can be shown by the following

$$f_l(x) = \frac{1}{2\lambda} e^{-\frac{|x-u_l|}{\lambda}} \tag{11}$$

where u_l is the location parameter, $\lambda > 0$ is the scale parameter, the higher the value λ is, the heavier the tail is when the location parameter u_l is fixed. Therefore, Laplace is appropriate for modeling the non-Gaussian noise in practical wireless communications.

3) α-stable noise: As the α-stable distribution has no closed form expression for the probability density function, its characteristic function is used to describe α-stable distribution:

$$\varphi(x) = \exp\left\{ j\mu x - r|x|^{\alpha} \left[1 + j\beta sign(x)\, w(x,\alpha) \right] \right\} \tag{12}$$

where

$$w(x,\alpha) = \begin{cases} \tan\left(\frac{\pi\alpha}{2}\right), \alpha \neq 1 \\ \frac{2}{\pi}\log|x|, \alpha = 1 \end{cases} \tag{13}$$

where $-\infty < \mu < +\infty$ is the location parameter; $r > 0$ is the dispersion parameter, which relates to the distributions spread around the center; $-1 < \beta < 1$ is the symmetry parameter, when $\beta = 0$, the distribution is symmetric about μ, and it is called a symmetry α-stable distribution ($S\alpha S$); $0 < \alpha \leq 2$ is the characteristic exponent parameter, which determines the heaviness of the tail, it has more impulsive noise under a smaller α. In this paper, we assume $\beta = 0$ and $\mu = 0$, then the characteristic function is

$$\varphi(x) = e^{-r|x|^{\alpha}} \tag{14}$$

B. Hyperbolic tangent based energy detector

In this subsection, we first take a brief look at the fundamental concepts of hyperbolic tangent and then propose a new robust spectrum sensing scheme, called hyperbolic tangent based energy detector (HT-ED).

1) Hyperbolic tangent: Hyperbolic tangent has been applied considerable popularity in neural network as a nonlinear transfer function for neurons in the last decades because of its robustness and simplicity. The hyperbolic tangent is expressed as

$$y(n) = \tanh(ax(n)) = 1 - \frac{2}{e^{2ax(n)} + 1} \tag{15}$$

where a is the shape parameter which is related to the slope of the function, and $a > 0$. Fig. 1 is the hyperbolic tangent curves with different shape parameters. From Fig. 1, we find that the larger the shape parameter, the steeper slope at the origin of coordinates $(0,0)$. We can also see that the range of the hyperbolic tangent is $(-1,1)$, that is $\underset{x\to+\infty}{y} = \tanh(ax(n)) = 1$, and $\underset{x\to-\infty}{y} = \tanh(ax(n)) = -1$.

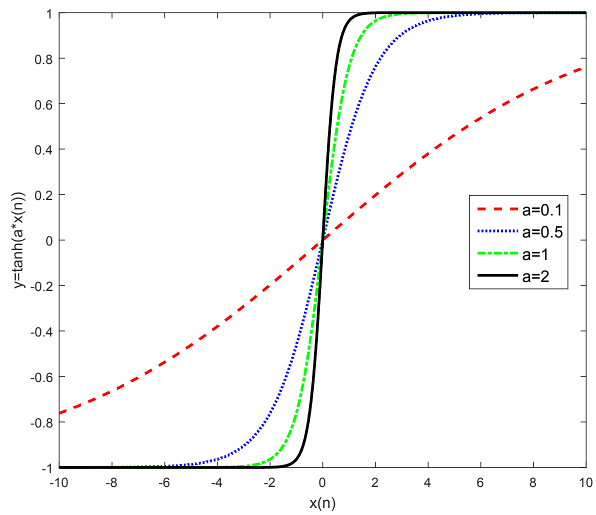

Fig. 1. Hyperbolic tangent curves with different shape parameters

2) Hyperbolic tangent based energy detector (HT-ED): Conventional energy detector is a simple algorithm for spectrum sensing, and it is easy to implement in CR systems. But it has no ability to copy with the impulsive noise, as a consequence, the performance of ED degrade drastically in non-Gaussian noise. According to the previous description, hyperbolic tangent can deal with the impulsive noise by its non-linear behavior. Motivated by the simplicity of the conventional energy detector and the non-linear property of the hyperbolic tangent, the hyperbolic tangent based energy detector (HT-ED) is proposed which is simple and easy to implement. The test statistic of ED is defined as $T_{ed} = \frac{1}{M}\sum\limits_{m=1}^{M} x(m)^2$, where $x(m)$ is the received signal sample. Thus, we can make a hyperbolic tangent map of the samples and then the test statistic of the HT-ED is showed as follows:

$$T_{ht-ed} = \frac{1}{M}\sum_{m=1}^{M} \tanh^2(ax(m)) \tag{16}$$

As the Taylor expansion of $\tanh(x)$ is expressed as

$$\begin{aligned} \tanh(x) &= x - \frac{x^3}{3} + \frac{2x^5}{15} - \frac{17x^7}{315} + \cdots\cdots \\ &= \sum_{n=1}^{\infty} \frac{B_{2n}4^n(4^n-1)}{(2n)!} x^{2n-1} \end{aligned} \tag{17}$$

So, $\tanh^2(ax)$ can be expressed as

$$\tanh^2(ax) = \left(ax - \frac{(ax)^3}{3} + \frac{2(ax)^5}{15} - \frac{17(ax)^7}{315} + \cdots\cdots\right)^2 \tag{18}$$

We can see the higher order moments as well as the second moment are employed in HT-ED. The HT-ED which can be seen as an improved non-linear version of the ED takes use of the second moment and the higher order moments of the signal. Higher order moment has a great potential to copy with non-Gaussian noises[17].

According to the central limit theorem[16], if the sample number M is large enough, T_{ht-ed} approximately follows Gaussian distribution

$$\begin{cases} H_0 : T_{ht-ed} \sim N(m_0, v_0) \\ H_1 : T_{ht-ed} \sim N(m_1, v_1) \end{cases} \tag{19}$$

where m_k and v_k, $k = 0, 1$, are the mean and the variance of T_{ht-ed} under H_0 and H_1, respectively. And they are defined as follows:

$$m_k = E\left\{\tanh^2(ax(m))\right\}, k = 0, 1 \tag{20}$$

and

$$\begin{aligned} v_k^2 &= \tfrac{1}{M}\left(E\left\{\tanh^4(ax(m))\right\} - \left(E\left\{\tanh^2(ax(m))\right\}\right)^2\right) \\ &= \tfrac{1}{M}\left(E\left\{\tanh^4(ax(m))\right\} - m_k^2\right) \end{aligned} \tag{21}$$

respectively, where $E\{\cdot\}$ represents the expectation of a variable. It should be pointed out that the theoretical mean value m_k and the theoretical variance v_k^2 for the Gaussian noise and non-Gaussian noise scenarios are not provided here due to the space considerations. In this article, we replace the theoretical mean value m_k and the theoretical variance v_k^2 with the statistical mean value $\tilde{m}_k$ and the statistical variance $\tilde{v}_k^2$, respectively, as follows:

$$\tilde{m}_k = \frac{1}{M}\sum_{m=1}^{M}\tanh^2(ax(m)), k = 0, 1 \tag{22}$$

$$\tilde{v}_k^2 = \frac{1}{M}\left(\frac{1}{M}\sum_{m=1}^{M}\tanh^4(ax(m)) - \tilde{m}_k^2\right), k = 0, 1 \tag{23}$$

According to the approximate distribution of the HT-ED test statistic, the false alarm probability and the detection probability of the HT-ED spectrum sensing scheme are expressed as

$$P_f = Q\left(\frac{\gamma - \tilde{m}_0}{\tilde{v}_0}\right) \tag{24}$$

and

$$P_d = Q\left(\frac{\gamma - \tilde{m}_1}{\tilde{v}_1}\right) \tag{25}$$

Algorithm 1 HT-ED Based Robust Spectrum Sensing

Fine Sensing Stage (Offline)

Calculate the statistical mean value $\tilde{m}_0$ and the statistical variance $\tilde{v}_0^2$ of the HT-ED test statistic under H_0:

$\tilde{m}_0 = \frac{1}{M}\sum\limits_{m=1}^{M}\tanh^2(ax(m))$

$\tilde{v}_0^2 = \frac{1}{M}\left(\frac{1}{M}\sum\limits_{m=1}^{M}\tanh^4(ax(m)) - \tilde{m}_0^2\right)$

Compute the sensing threshold:

$\gamma = Q^{-1}(P_f)\,\tilde{v}_0 + \tilde{m}_0$

Fast Sensing Stage (Online)

Measure the HT-ED test statistic of the new samples:

$T_{ht-ed} = \frac{1}{M}\sum\limits_{m=1}^{M}\tanh^2(ax(m))$

Detect the state of spectrum:

$H_0 : T_{ht-ed}(X) < \gamma$ or $H_1 : T_{ht-ed}(X) > \gamma$

respectively. In order to find the sensing threshold γ, we assume P_f is preset in the range of $[0.01, 0.1]$. So, the sensing threshold is expressed as

$$\gamma = Q^{-1}(P_f)\,\tilde{v}_0 + \tilde{m}_0 \tag{26}$$

Next, we introduce the proposed HT-ED based spectrum sensing algorithm from the practical perspective. The two stage sensing supported by the IEEE 802.22[18] is applied in the practical procedure in which fine sensing stage is designed for extracting pure noise samples, and these samples are used in the following fast sensing stage. More detailed descriptions of the stages are that the statistical mean $\tilde{m}_0$ and the statistical variance $\tilde{v}_0^2$ of the noise are calculated for obtaining the sensing threshold γ in the fine sensing stage, then in the fast sensing stage, the sensing threshold is used to detect the hypotheses. During the fine sensing stage, longer time spans are considered for accurate detection, while the fast sensing stage is much faster to meet the practical requirements in cognitive radio system. So the robust sensing algorithm based on HT-ED is summarized in Algorithm 1.

IV. Simulation results

In this section, the performance of the proposed HT-ED algorithm is simulated in practical impulsive man-made noises to confirm its accuracy and robustness. To verify the performance, the simulation considers a one-primary and one-secondary users scenario where SU performs the spectrum sensing test by HT-ED algorithm. The cardinality of the samples set in sensing task is chosen as $M = 200$. The shape parameter of the hyperbolic tangent is assumed to be fixed, $a = 0.5$. In addition, the preset noise distributions for generating noise samples are Gaussian, Laplace or α-stable. Moreover, the monte carlo method is applied in the simulations, and the number of iteration in each simulation is 1000. The conventional ED which has been widely discussed in previous literatures[4,5] is compared with the proposed HT-ED scheme. The receiver operating characteristic (ROC) curves and the detection probability in different signal-to-noise ratios (SNRs) are used to depict the detection performance of both algorithms in various noise scenarios.

Firstly, we investigate the performance of the proposed HT-ED and the conventional ED in Laplace noise (LN) and Gaussian noise (GN) scenarios. Fig.2 shows the ROC curves of both schemes with SNR=-10dB. As represented in Fig.2, the performances of both schemes are almost the same in GN as expected. However, in the case of LN, the proposed HT-ED has a better performance than the conventional ED. This is because of the fact that the HT-ED has the ability to restrain the impulse noise and scale the normal signal linearly as well. Fig.3 shows the detection probability of both schemes against different SNRs with the false alarm probability $P_f = 0.01$. As depicted in Fig.3, compared with the conventional ED, the new HT-ED has a better detection performance in LN.

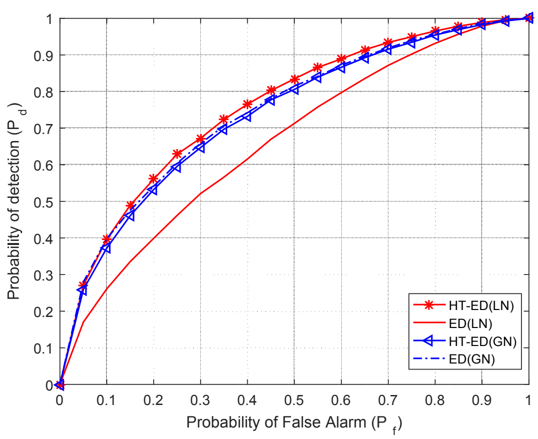

Fig. 2. ROC curves for GN and LN scenario ($u = 0$,$\lambda = 1$), where $M = 200$, $a = 0.5$ and $SNR = -10dB$.

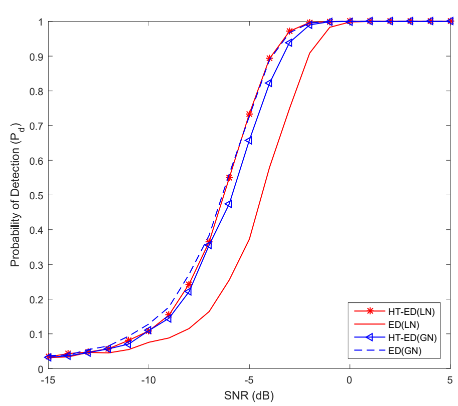

Fig. 3. Detection probability vs. SNR for GN and LN scenario ($u = 0$,$\lambda = 1$), where $M = 200$, $a = 0.5$ and $P_f = 0.01$

Next, we simulate the performance of the HT-ED and the comparison among the new method and the ED scheme in various α-stable impulsive noises. As the SNR in α-stable noise cannot be expressed, the generalized signal-to-noise ratio (GSNR) defined as $GSNR = \sigma_s^2/r$ is used to replace SNR, where σ_s^2 is the power of signal, and r is the dispersion parameter of α-stable noise. Fig.4 shows the ROC curves for the proposed and the ED schemes with different α-stable noises $\alpha = 0.5, 1, 1.5, 2$, $\beta = 0$ and $GSNR = -10dB$. It is worthwhile to note that if $\alpha = 1$ and $\beta = 0$, the α-stable distribution is Cauchy distribution, while if $\alpha = 2$, the distribution is Gaussian distribution. Fig.5 demonstrates the detection probability for both algorithms with different GSNRs in α-stable distribution. Fig.4 and Fig.5 show that the HT-ED performs much better than the ED when $\alpha < 2$. Moreover, it also can be found in the simulation results the proposed algorithm is very robust against various impulsive noises. On the contrast, the conventional ED dose not have the ability to sense the spectrum in these impulsive noises. These are due to the fact that the hyperbolic tangent $f(x) = \tanh(ax)$, is bounded among -1 and 1 regardless of the noise density.

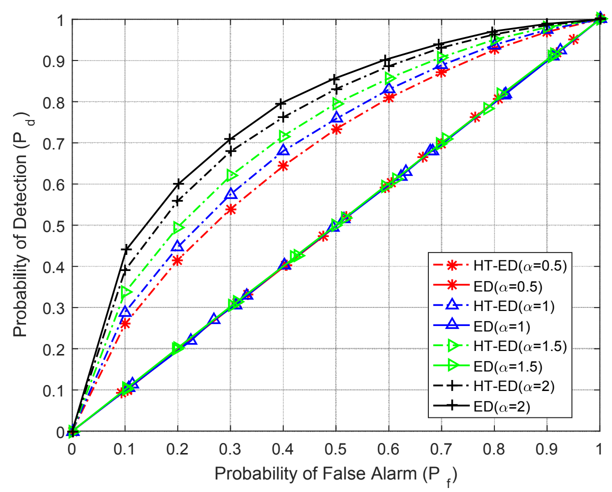

Fig. 4. ROC curves for α-table noise scenario with various α, where $M = 200$, $a = 0.5$ and $GSNR = -10dB$.

The performance of the new HT-ED scheme is compared to that of the FLOM-based algorithm[12]. The test statistic of FLOM-based algorithm which is similar to energy detector is expressed as $T_{FLOM} = \sum_{i=0}^{M} |x_i|^p$, where the power p ranges in interval from 0 to 2, i.e., $(0, 2]$. As the performance of the FLOM-based scheme for impulsive noise is acceptable, we adopt FLOMs to show the superiority of the HT-ED scheme. Fig. 6 is the ROC curves comparison of HT-ED for different shape parameters $a = 0.25, 0.5, 1.0$ and FLOM-based scheme with different powers $p = 0.5, 1.0, 1.5$ for the α-stable noise distributions with $\alpha = 1$. In addition, the GSNR and the cardinality of the received samples set are set as $GSNR = -5dB$ and $M = 400$, respectively. As illustrated in Fig. 6, performance of HT-ED is more outstanding than that of FLOM-based scheme. As seen in the picture, when the shape parameter a ranges from 0.25 to 1, as greater the a in HT-ED, the performance of the HT-ED becomes better. It

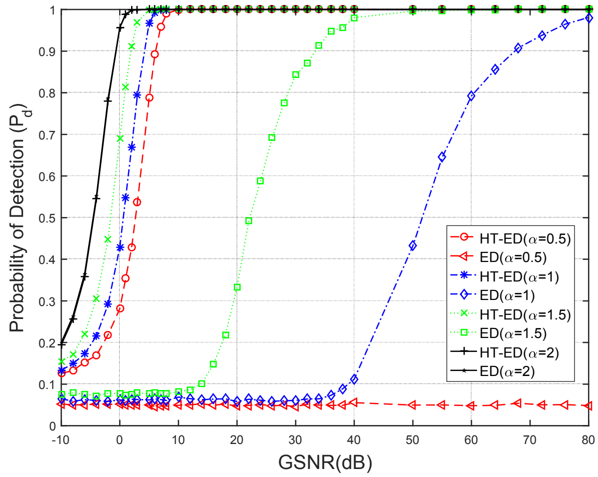

Fig. 5. Detection probability vs. GSNR for α-table noise scenario with various α, where $M = 200$, $a = 0.5$ and $P_f = 0.01$.

is worth mentioning that a most appropriate shape parameter corresponds to the best performance. This is because that the most appropriate shape parameter means the impulsive noise is just suppressed to 1 or -1, and the normal signal is mapped linearly.

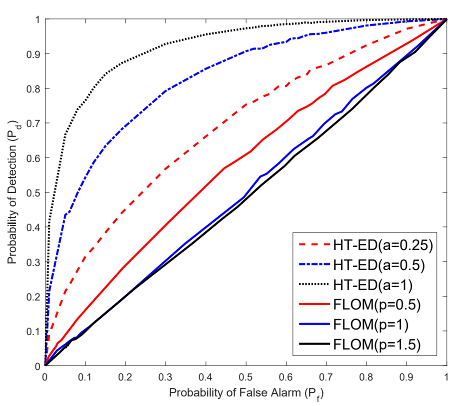

Fig. 6. ROC curves comparison of proposed HT-ED with $a = 0.25, 0.5, 1$ and FLOM-based scheme with $p = 0.5, 1.0, 1.5$ for the α-stable noise distributions with different $\alpha = 1$, where $M = 400$, $GSNR = -5dB$.

V. Conclusion

In this work, a robust spectrum sensing algorithm, called the hyperbolic tangent based energy detector, is proposed for non-Gaussian impulsive man-made noise. The hyperbolic tangent has the ability to suppress the impulsive noise, on the other hand it does not suppress the normal signal. Consequently the proposed HT-ED has the ability to ignore the influence of impulsive noise and then obtains a robust performance. So it performs pretty well for the case of α-stable noise when $\alpha < 2$, while the conventional ED can not deal with the impulsive noise and it leads to a poor performance.

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