ROBUST SPECTRUM SENSING FOR COGNITIVE RADIO

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ABSTRACT

This paper studies spectrum sensing in the context of cognitive radio. The proposed detector is robust with respect to disturbing impulses, that are in practice present in many cases in addition to the Gaussian noise. The presence of impulsive noise deteriorates the performance of the detectors derived using Gaussian assumption. In the paper we model the noise explicitly consisting of two components and derive the proper detector. Asymptotic analysis of the detector is then presented and formulae for probabilities of correct detection and fault alarm are derived. The theoretical findings are verified in our simulation study.

1. INTRODUCTION

Traditionally the spectral bands required for work by any radio equipment are licensed to the users and cannot be utilized by anybody else even if the licensed users do not use the spectrum at the given location and time by themselves. This leaves a large amount of radio spectrum unused in practice. Recently the cognitive radio paradigm has emerged that can overcome this problem by allowing unlicensed users opportunistically access the spectrum, given that they do not interfere with the primary users. In order to do so the secondary users need first to detect if the primary users are using the spectrum or not. Because of radio effects like shadowing and fading the signal of the primary user may be rather weak at the position of the secondary user. This leaves the secondary user with the requirement of detecting a potentially weak primary user signal in unknown noise. For instance IEEE 802.22 suggests that the cognitive radio needs to detect the primary signals that have power level as low as -22 dB below the noise level [1].

In the literature there are several detectors proposed for this purpose [2, 3], most popular of them probably being the energy detector. The popularity is partly because of simplicity of the energy detector but also because it does not need any assumptions on the waveforms emitted by primary users.

The noise is usually assumed to be white and Gaussian but in real life situations this does not need to be the case. In particular one has to consider the presence of impulsive noise, both man-made and natural. Non-Gaussian ambient noise is a major impairment to signal processing techniques that are based on a Gaussian assumption [4]. The examples of the impulsive noise include man–made noise like car ignition, emissions from the microwave ovens or natural impulsive noise due to e.g. lightning. For measurement results concentrating on impulsive noise see e.g. [5, 6] and references therein.

In this paper we will develop an energy–like detector that is not sensitive to impulsive noise. The derivation is based on modelling the impulsive component of the noise explicitly by a uniform distribution. We allow the impulses to occur only with certain probability and preserve the usual Gaussian noise component for most of the time. This results in an intuitively rather satisfying noise model.

In the analysis part of the paper we derive the formulae for probabilities of detection, P_D, and fault alarm, P_F, of the proposed detector but also for the time required to reach a given P_D and P_F level with certain signal and noise powers. Finally we present some simulation results. The simulation results are consistent with our theoretical findings.

2. ROBUST DETECTOR

We consider the problem of detecting the presence of primary users in a given frequency band without any prior knowledge of primary transmissions. The detection problem we need to solve is [3, 7]

$$\begin{aligned} H_0 &: x(t) = v(t) \\ H_1 &: x(t) = \alpha(t)s(t) + v(t), \end{aligned} \tag{1}$$

i.e. the received waveform $x(t)$ may be noise $v(t)$ only or it may consist of a sum of signal of interest $s(t)$ and noise $v(t)$ and the variable t denotes discrete time. The signal of interest, $s(t)$, is assumed to be passed through a slow Rayleigh fading channel with attenuation $\alpha(t)$. The detector has to decide which of the hypotheses is more likely given the received waveform $x(t)$. We assume that the noise $v(t)$ comprises a sum of zero mean additive white Gaussian noise $v_g(t)$ process and an additional impulsive noise component $v_i(t)$. The impulsive noise component is assumed not to be present most of the time but appear with certain probability c so that the impulsive component obeys the probability density function (PDF)

$$f_i(x) = \frac{c}{b-a} + (1-c)\delta(x), \tag{2}$$

with $0 < c < 1$ and a and b being the lower and upper limits on the values that the noise can take. In practice a and b may for instance represent the smallest and largest numbers that can be represented at the output of analogue to digital (A/D) converter that is included at the input of the processing system. Note that we have limited also the Gaussian noise component to lay between a and b resulting in a minor deviation from Gaussianity. The deviation is, however, small because we assume that $b-a$ is much larger than the standard deviation of the Gaussian noise. The uniform distribution is selected because of its maximum entropy property i.e. there is nothing assumed to be known about the origin of the impulses. This noise model takes into account that most of the time the noise is Gaussian and that the impulses that disturb the detection based on Gaussian assumption occur only with certain probability c. As such, the noise model is more intuitively satisfying than other popular models for impulsive noise like Laplacian.

The noise $v(t)$ is modelled as consisting of two components with the largest component determining the outcome entirely at each time instant [10]

$$v(t) = v_g(t) + v_i(t) \approx \max[v_g(t), v_i(t)]. \quad (3)$$

Let us denote the variances of primary user signal and noise as σ_s^2 and σ_n^2. Let us also denote a common variance as

$$\sigma_l^2 = \begin{cases} \sigma_n^2 & l = 0 \\ \sigma_n^2 + \sigma_s^2 & l = 1 \end{cases}.$$

With this notation we can express the conditional PDF-s corresponding to our two hypotheses for $l = 0, 1$ as

$$p(x|H_l) = \begin{cases} \beta_l \max\left(\frac{1-c}{\sqrt{2\pi}\sigma_l} e^{-\frac{|x|^2}{2\sigma_l^2}}, \frac{c}{b-a}\right) & a < x < b \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The normalization factors β_l can be found by solving $\int_a^b p(x|H_l)dx = 1$ for β_l. This results in

$$\beta_l = \left[(1-c)\operatorname{erf}\left(\sqrt{\frac{\eta_l}{2\sigma_l^2}}\right) + c\left(1 - \frac{2\sqrt{\eta_l}}{b-a}\right)\right]^{-1} \quad (5)$$

where $\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x \exp(-t^2)dt$ and

$$\eta_l = -2\sigma_l^2 \ln\left(\frac{c}{1-c} \frac{\sqrt{2\pi\sigma_l^2}}{b-a}\right) \quad (6)$$

is the intersection point of the Gaussian and uniform distributions.

We can give to PDF-s of x in the interval $a \le x \le b$ a more convenient form for future derivation

$$\begin{aligned} p(x|H_l) &= \beta_l \max\left(\frac{1-c}{\sqrt{2\pi\sigma_l^2}} e^{-\frac{|x|^2}{2\sigma_l^2}}, \frac{c}{b-a}\right) \\ &= \frac{\beta_l(1-c)}{\sqrt{2\pi\sigma_l^2}} e^{-\frac{1}{2\sigma_l^2}\min\left(|x|^2, \eta_l\right)}. \end{aligned}$$

PDFs of $y = x^2$ are then $p(y) = \frac{p(x)}{\frac{dy}{dx}}$ and hence

$$p(y|H_l) = \frac{\beta_l(1-c)}{\sqrt{2\pi y \sigma_l^2}} e^{-\frac{1}{2\sigma_l^2}\min(y, \eta_l)}. \quad (7)$$

Suppose that we have made N observations of the variable y and we have collected these observations into a vector $\mathbf{y}$. Also assume that the observations at different time instances are statistically independent of each other. Then the joint probability density function is a product of the individual probability densities

$$p(\mathbf{y} \mid H_l) = \prod_{n=1}^N p(y_n \mid H_l), \quad l = 0, 1. \quad (8)$$

The likelihood ratio for the above hypothesis reads

$$L(y) = \prod_{n=1}^N \frac{\beta_1}{\beta_0} \sqrt{\frac{\sigma_0^2}{\sigma_1^2}} \frac{e^{-\frac{1}{2\sigma_1^2}\min(y_n, \eta_1)}}{e^{-\frac{1}{2\sigma_0^2}\min(y_n, \eta_0)}} \quad (9)$$

Taking the logarithm of both sides of (9) and simplifying we readily obtain the log-likelihood ratio

$$\begin{aligned} \ln L &= \frac{N}{2} \ln\left(\frac{\beta_1^2 \sigma_0^2}{\beta_0^2 \sigma_1^2}\right) \quad (10) \\ &\quad - \frac{1}{2\sigma_1^2} \sum_{n=1}^N \min(y_n, \eta_1) + \frac{1}{2\sigma_0^2} \sum_{n=1}^N \min(y_n, \eta_0) \end{aligned}$$

Our detector thus needs to decide in favour of H_1 if the log–likelihood ratio is larger than a threshold. Otherwise the hypothesis H_0 is selected.

If there is no impulsive noise i.e. $c \to 0$ we have

$$\begin{aligned} \lim_{c \to 0} \eta_l &= -2\sigma_l^2 \ln(0) = \infty \\ \lim_{c \to 0} \beta_l &= 1 \\ \lim_{c \to 0} \frac{N}{2} \ln\left(\frac{\beta_1^2 \sigma_0^2}{\beta_0^2 \sigma_1^2}\right) &= \frac{N}{2} \ln\left(\frac{\sigma_0^2}{\sigma_1^2}\right) \end{aligned}$$

and the test reduces to an ordinary energy detector

$$\frac{1}{N} \sum_{n=1}^N y_n > \frac{\sigma_0^2 \sigma_1^2}{\sigma_1^2 - \sigma_0^2} \ln\left(\frac{\sigma_0^2}{\sigma_1^2}\right). \quad (11)$$

3. ESTIMATION OF UNKNOWN PARAMETERS

Parameters η_0 and η_1 are dependent on the Gaussian noise variance σ_n, signal variance σ_s and the impulse probability c. Those parameters may not be known in advance and if they are not, they must be estimated from the input signal. In some applications it is known for certain that during some times the primary user is silent and during some other times it is working. The question is about all the other times. For those applications we derive the maximum likelihood estimators for σ_n, σ_s and c below. For other applications we can use the techniques outlined in e.g. [8]. In [9] it is shown that if we can observe a length N noise only realization then the maximum likelihood estimator of noise variance is

$$\hat{\sigma}_n = \frac{1}{N_1} \sum_{i \in M_1} x^2(i). \quad (12)$$

Here M_1 is a set that contains all signal samples that satisfy $x^2 < -2\sigma_n^2 \left(\ln \sigma_n + \ln \frac{c\sqrt{2\pi}}{(1-c)(b-a)}\right)$ and N_1 is the number of elements in set M_1. Let M_2 and N_2 denote the complementary set. If signal of interest $s(t)$ is also present then the log–likelihood function can be written as

$$\begin{aligned} \ln L &= \sum_{n=0}^{N-1} \left[\ln \frac{\beta_1(1-c)}{\sqrt{2\pi}} \right. \quad (13) \\ &\quad \left. - \ln \sqrt{\sigma_n^2 + \sigma_s^2} - \frac{1}{(\sigma_n^2 + \sigma_s^2)} \min(x^2, \eta_1)\right] \end{aligned}$$

Derivative of the log-likelihood function respect to σ_s equals

$$\frac{\partial}{\partial \sigma_s} \ln L = -\frac{N\sigma_s}{\sigma_n^2+\sigma_s^2} - \\ -\frac{\sigma_s}{(\sigma_n^2+\sigma_s^2)^2}\sum_{M_1} x^2 + \sum_{M_2} \frac{\sigma_s}{\sigma_n^2+\sigma_s^2}. \tag{14}$$

Equating (14) to zero results in

$$\sigma_s^2 = \frac{1}{N_1}\sum_{i\in M_1} x^2(i) - \hat{\sigma}_n^2. \tag{15}$$

In order to obtain estimate for c let us compute the derivative of log-likelihood with respect to c

$$\frac{\partial}{\partial c} \ln L = \frac{cN-N_2}{c(c-1)}. \tag{16}$$

Setting above to zero we get an estimate

$$\hat{c} = \frac{N_2}{N}. \tag{17}$$

4. PERFORMANCE ANALYSIS

In this Section we perform the asymptotic analysis of the detector in case of large N. We first note that the detector computes if

$$\frac{1}{2\sigma_0^2}\frac{1}{N}\sum_{n=1}^{N}\min(y_n,\eta_0) - \frac{1}{2\sigma_1^2}\frac{1}{N}\sum_{n=1}^{N}\min(y_n,\eta_1) > \gamma \tag{18}$$

where

$$\gamma = \frac{\ln L}{N} - \frac{1}{2}\ln\left(\frac{\beta_1^2\sigma_0^2}{\beta_0^2\sigma_1^2}\right)$$

We thus need to find a difference between weighted arithmetical means of saturated variables and compare the result to a threshold in order to perform the detection.

Let us concentrate on the variables under the summations in (18) and define a new variable z_k as

$$z_k = h(y) = \min(y,\eta_k),\ k=0,1. \tag{19}$$

The function $h(y)$ is a saturation nonlinearity. The probability density function of the output of $z_k = h(y)$ is given by [10].

$$p_z(z_k) = \left.\frac{p_y(y)}{\frac{dz_k}{dy}}\right|_{y=h_i^{-1}(z_k)}. \tag{20}$$

For sake of simplicity let us assume that $b=-a$. We need to investigate PDF-s in four different cases, two sums in (18), $k=0,1$ and two hypothesis $l=0,1$. Substituting (7) into above in those four cases we get the following four PDF-s:

$$p(z_0|H_0) = \frac{\beta_0(1-c)}{\sqrt{2\pi z_0\sigma_0^2}}e^{-\frac{z_0}{2\sigma_0^2}}\Pi(0,\eta_0) \\ +c\beta_0\left(1-\frac{\sqrt{\eta_0}}{b}\right)\delta(z_0-\eta_0) \tag{21}$$

if $l=0$ and $k=0$,

$$p(z_1|H_0) = \frac{\beta_0(1-c)}{\sqrt{2\pi z_1\sigma_0^2}}e^{-\frac{z_1}{2\sigma_0^2}}\Pi(0,\eta_0) \\ +\frac{c\beta_0}{2b\sqrt{z_1}}\Pi(\eta_0,\eta_1)+c\beta_0(1-\frac{\sqrt{\eta_1}}{b})\delta(z_1-\eta_1) \tag{22}$$

if $l=0$ and $k=1$,

$$p(z_0|H_1) = \frac{\beta_1(1-c)}{\sqrt{2\pi z_0\sigma_1^2}}e^{-\frac{z_0}{2\sigma_1^2}}\Pi(0,\eta_0) \\ +\left[\beta_1(1-c)\left(\mathrm{erf}\sqrt{\frac{\eta_1}{2\sigma_1^2}}-\mathrm{erf}\sqrt{\frac{\eta_0}{2\sigma_1^2}}\right)\right. \\ \left.+\beta_1 c\left(1-\frac{\sqrt{\eta_1}}{b}\right)\right]\delta(z_0-\eta_0) \tag{23}$$

if $l=1$ and $k=0$ and

$$p(z_1|H_1) = \frac{\beta_1(1-c)}{\sqrt{2\pi z_1\sigma_1^2}}e^{-\frac{z_1}{2\sigma_1^2}}\Pi(0,\eta_1) \\ +\frac{\beta_1 c(b-\sqrt{\eta_1})}{b}\delta(z_1-\eta_1) \tag{24}$$

if $l=1$ and $k=1$. The function $\Pi(c,d)$ equals one between c and d and is zero otherwise. The cases are illustrated in Figure 1.

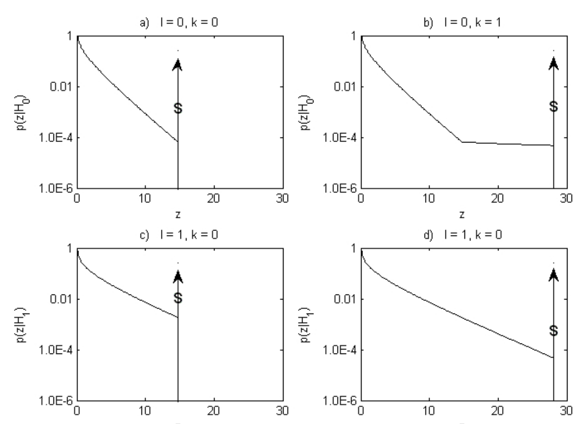

Figure 1: Probability density functions of the four cases.

Combining the results we can reach a common expression covering all the cases as

$$p(z_k|H_l) = \frac{\beta_l(1-c)}{\sqrt{2\pi\sigma_l^2 z_k}}e^{-\frac{z_k}{2\sigma_l^2}}\Pi(0,\eta_{m_1}) \\ +m_2\frac{\beta_0 c}{2b\sqrt{z_k}}\Pi(\eta_0,\eta_1)+\delta(z_k-\eta_k)\theta_{k,l}, \tag{25}$$

where $\theta_{k,l} = \beta_l(1-c)m_3\left[\mathrm{erf}\left(\sqrt{\frac{\eta_1}{2\sigma_1^2}}\right)-\mathrm{erf}\left(\sqrt{\frac{\eta_0}{2\sigma_1^2}}\right)\right]$ $+\beta_l c\left(1-\frac{\sqrt{\eta_{m_4}}}{b}\right)$, $m_1=1$, if $l=1$ and $k=1$ and is zero otherwise, $m_2 = 1$, if $l = 0$ and $k = 1$ and is zero otherwise and $m_3 = 1$, if $l = 1$ and $k = 0$ and is zero otherwise, $m_4 = 0$, if $l = 0$ and $k = 0$ and is one otherwise.

This distribution has mean

$$
\begin{aligned}
E[z_k|H_l] &= \beta_l(1-c)\left[\sigma_l^2 \operatorname{erf}\left(\sqrt{\frac{\eta_{m_1}}{2\sigma_l^2}}\right)\right. \\
&\quad \left. -\sqrt{\frac{2\sigma_l^2\eta_{m_1}}{\pi}} e^{-\frac{\eta_{m_1}}{2\sigma_l^2}}\right] \\
&\quad +\frac{\beta_0 c}{3b}(\eta_1^{\frac{3}{2}} - \eta_0^{\frac{3}{2}})m_2 + \eta_k\theta_{k,l}
\end{aligned} \tag{26}
$$

and second moment

$$
\begin{aligned}
E[z_k^2|H_l] &= \beta_l(1-c)\left[3\sigma_l^4 \operatorname{erf}\left(\sqrt{\frac{\eta_{m_1}}{2\sigma_l^2}}\right)\right. \\
&\quad \left. -\sqrt{\frac{2\sigma_l^2\eta_{m_1}}{\pi}} e^{-\frac{\eta_{m_1}}{2\sigma_l^2}}(\eta_{m_1}+3\sigma_l^2)\right] \\
&\quad +\frac{\beta_0 c}{5b}(\eta_1^{\frac{5}{2}} - \eta_0^{\frac{5}{2}})m_2 + \eta_k^2\theta_{k,l}.
\end{aligned} \tag{27}
$$

The crosscorrelation between z_0 and z_1 is perfect if $z_1 < \eta_0$ and in this case $E[z_0 z_1|H_l] = E[z_0^2|H_l]$. This happens with probability

$$
P(z_1 < \eta_0) = \int_0^{\eta_0} p_z(z_1|H_l)dz_1 = \beta_l(1-c)\operatorname{erf}\left(\sqrt{\frac{\eta_0}{2\sigma_l^2}}\right). \tag{28}
$$

If $z_1 > \eta_0$, $z_0 = \eta_0$ and hence $E[z_0 z_1] = \eta_0 E_{z_1>\eta_0}[z_1]$, where $E_{z_1>\eta_0}[z_1]$ is the mean of z_1 above η_0. This happens with probability $1-P(z_1 < \eta_0)$ and the cross-correlation is therefore

$$
\begin{aligned}
E[z_0 z_1|H_l] &= P(z_1 < \eta_0)E[z_0^2|H_l] \\
&\quad +[1-P(z_1 < \eta_0)]\eta_0 E_{z_1>\eta_0}[z_1|H_l].
\end{aligned} \tag{29}
$$

Examining (18) we see that to proceed we need the moments of the variable

$$
w = \frac{1}{2\sigma_0^2}z_0 - \frac{1}{2\sigma_1^2}z_1. \tag{30}
$$

The mean of w is

$$
E[w|H_l] = \frac{E[z_0|H_l]}{2\sigma_0^2} - \frac{E[z_1|H_l]}{2\sigma_1^2} \tag{31}
$$

and its second moment equals

$$
E[w^2|H_l] = \frac{E[z_0^2|H_l]}{4\sigma_0^4} - \frac{2E[z_0 z_1|H_l]}{4\sigma_0^2\sigma_1^2} + \frac{E[z_1^2|H_l]}{4\sigma_1^4}. \tag{32}
$$

The variance is equal to

$$
\sigma_{H_l}^2 = E[w^2|H_l] - E^2[w|H_l]. \tag{33}
$$

Let us now note that according to (18), the detector computes a sample average of N i.i.d. random variables w. According to the central limit theorem [10] the distribution of such a sum approaches Gaussian with mean $E[w|H_l]$ and variance $\frac{\sigma_{H_l}^2}{N}$, $l = 0,1$ when N increases, independent of the shape of the original distribution of the variables w. We can therefore for large N evaluate the probability of correct detection as

$$
\begin{aligned}
P_D &= \int_\gamma^\infty p_w(w \mid H_1)dw \\
&= \frac{1}{2}\operatorname{erfc}\left(\frac{(\gamma - E[w \mid H_1])\sqrt{N}}{\sqrt{2}\sigma_{H_1}}\right),
\end{aligned} \tag{34}
$$

The probability of fault alarm is correspondingly

$$
\begin{aligned}
P_F &= \int_\gamma^\infty p_w(w \mid H_0)dw \\
&= \frac{1}{2}\operatorname{erfc}\left(\frac{(\gamma - E[w \mid H_0])\sqrt{N}}{\sqrt{2}\sigma_{H_0}}\right).
\end{aligned} \tag{35}
$$

The threshold γ and the number of samples N that are required to reach given P_F and P_D can be found by solving system of equations formed by (34) and (35)

$$
\begin{cases}
\sqrt{2}\sigma_{H_0}\operatorname{erfc}^{-1}(2P_F) = [\gamma - E(w|H_0)]\sqrt{N} \\
\sqrt{2}\sigma_{H_1}\operatorname{erfc}^{-1}(2P_D) = [\gamma - E(w|H_1)]\sqrt{N}
\end{cases}. \tag{36}
$$

Solving the system for N and γ we obtain that in order to reach the operating point (P_F, P_D) we need

$$
\begin{cases}
N = 2\left[\frac{\sigma_{H_1}\operatorname{erfc}^{-1}(2P_D) - \sigma_{H_0}\operatorname{erfc}^{-1}(2P_F)}{E(w|H_0)-E(w|H_1)}\right]^2 \\
\gamma = \frac{\sigma_{H_1}\operatorname{erfc}^{-1}(2P_D)E(w|H_0) - \sigma_{H_0}\operatorname{erfc}^{-1}(2P_F)E(w|H_1)}{\sigma_{H_1}\operatorname{erfc}^{-1}(2P_D) - \sigma_{H_0}\operatorname{erfc}^{-1}(2P_F)}
\end{cases}. \tag{37}
$$

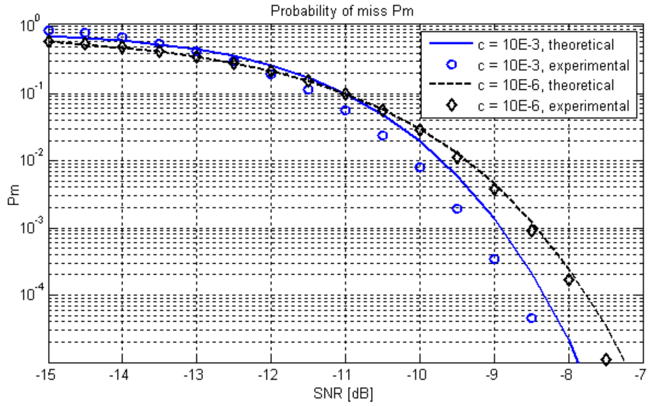

Figure 2: Probability of missed detection as function of SNR.

5. SIMULATION RESULTS

In Figure 2 we present the probability of missed detection $P_m = 1 - P_D$ as the function of SNR. The blue and black lines are the theoretical results with $c = 10^{-3}$ and $c = 10^{-6}$ respectively and the circles and diamonds represent the corresponding simulation results. One can observe a fast decrease of the curves as SNR increases. One can also observe that the intensity of impulsive noise c does not influence the result much.

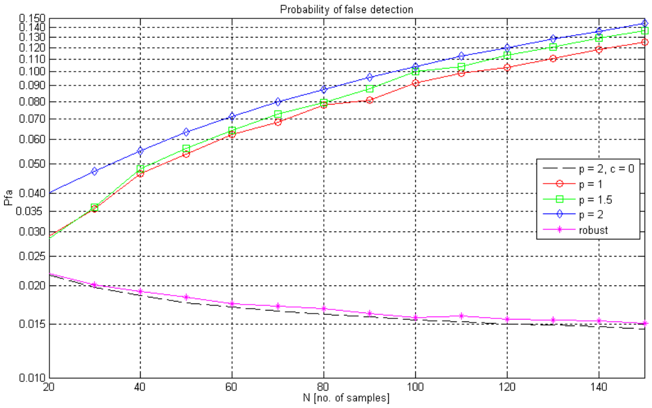

Figure 3: Probability of fault alarm as function of N.

Figure 3 depicts the dependence of the probability of fault alarm from the number of samples N for ordinary energy detector if there is no impulsive noise (black dashed line). It also shows the curves corresponding to the ordinary energy detector (blue line) and the proposed robust detector (magenta line) in the presence of impulsive noise with intensity $c = 0.001$. For comparison we show the results of the robust L_p norm detector with $p = 1$ (red line) and $p = 1.5$ (green line) of [11] in the same noise. The proposed detector operates in these conditions almost as well as the ordinary energy detector in Gaussian noise and outperforms all the others.

Finally we investigate how many samples should the detector involve for our analysis to apply. In the simulation example we have used the following parameters to compute the probability of miss $P_m(\gamma) = 1 - P_D(\gamma) : \sigma_n = 1, \sigma_s = 2, c = 0.01$ and $b = -a = 100$. In Figure 4 one can see that with $N = 5$, the simulation and theory vaguely remember each other. The situation improves if we increase the number of samples to 15 and already with $N = 30$ the theoretical curve and simulation dots are rather close to each other. We note that $N = 30$ is much smaller than N found from (37) for cognitive radio applications. A similar result can be obtained for the probability of fault alarm P_F.

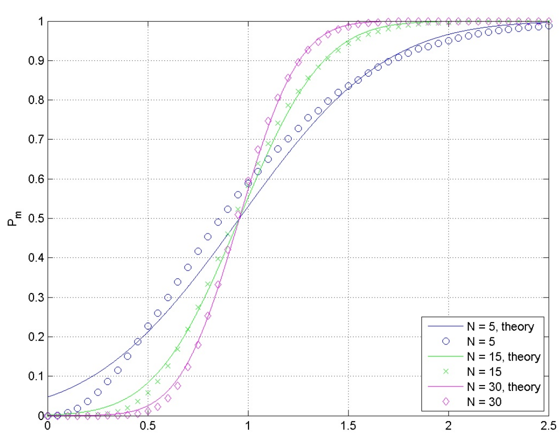

Figure 4: Probability of miss.

6. CONCLUSIONS

In this paper we proposed a robust energy detector for spectrum sensing in cognitive radio applications. The derivation of our detector is based on a noise model that explicitly includes two components – clipped Gaussian distribution and impulses with uniform distribution. Error analysis of the algorithm was carried out. It was shown that the proposed algorithm outperforms the existing similar algorithms in the presence of impulsive noise.

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