Influence of Laplacian Noise on the Performance of Norm-Based Spectrum Sensors

Luiz G. B. Guedes and Dayan A. Guimarães

***Abstract*— Norm-based spectrum sensors may improve the performance of the energy detector (ED) and absolute value cumulating (AVC) detector in non-Gaussian environments, alleviating performance degradation due to impulsive noise, which is modeled by heavy-tailed probability density functions. This study assesses the performance of Norm-based detectors for cooperative spectrum sensing under Laplacian noise, estimating the probability of detection while holding a fixed probability of false alarm across system parameters variations. Numerical results confirm that robustness against impulsive noise varies with the chosen norm.**

***Keywords*— Cognitive radio, dynamic spectrum access, Laplacian noise, spectrum sensing.**

I. INTRODUCTION

One of the most evident concerns in the development of enabling technologies for future mobile communication networks relates to the scarcity of resources, particularly, regarding to the appropriate use of frequency spectrum [1]. The massive number of connected devices along with the multitude of available services require careful spectrum management to optimize its utilization, promoting stable and reliable connectivity in an increasingly challenging communication scenario [2]. However, with the current fixed-band allocation policy in place, two limitations are experienced [3]: the spectrum scarcity, associated with the absence or shortage of new available bands; and spectrum underutilization, linked to the fact that the user holding the right to use the band does not use it continuously.

An enabling technology that arises as an alternative to this reality is dynamic spectrum access (DSA) [2], which can be implemented through secondary networks of cognitive radios performing spectrum sensing and submitted to a dynamic-band allocation policy. A secondary user (SU), unlike the primary user (PU), is not the holder of the right to use a specific spectrum band, but, by performing spectrum sensing, becomes capable of monitoring the frequency spectrum and observing occasions of shared use, whether overlapped or not with the use of the PU [4]. It is worth noting that such activity aims not to compromise the transmissions made by the PUs.

Spectrum sensing is a binary hypothesis test in which one seeks to identify whether the signal detected by the SU was generated under hypothesis $\mathcal{H}_0$ or under hypothesis $\mathcal{H}_1$ [4]. These hypotheses refer, respectively, to the absence and to the presence of the primary signal in the band of interest. This process can be performed by a single SU or by a group of them, known as cooperative spectrum sensing (CSS). Due to the generation of more reliable decisions regarding the occupancy state of the monitored band [5], CSS is usually preferred over the individual mode.

In this work, centralized CSS with data fusion is adopted, where the received signal samples are collected, processed and sent, by each SU, to a fusion center (FC) responsible for treating them in order to form a test statistic T, which is compared with a decision threshold λ. If $T > \lambda$, $\mathcal{H}_1$ is accepted; otherwise, $\mathcal{H}_0$ is accepted. The performance evaluation is conducted through two main metrics: probability of detection, P_{d}, indicating the probability of detecting the presence of the primary signal in the sensed band when it is actually present; probability of false alarm, P_{fa}, which shows the probability of detecting the presence of the primary signal when, in fact, it is not.

Multipath propagation, various types of interference, and noise can degrade spectrum sensing performance [4]. Regarding noise, not only its omnipresent component in communication systems, the additive white Gaussian noise (AWGN), but also the various manifestations of impulsive noise, can degrade system performance [6], [7].

In the literature of spectrum sensing, there is a concern in studying suitable test statistics for environments contaminated by impulsive noise in order to establish a good balance between complexity and performance. The Norm-based detector, also known as the generalized energy detector (GED) [8], improved ED [9] or p-norm detector [10], [11], arises from the fact that an arbitrary exponent $p \in \mathbb{R}^+$, depending on its value, encompasses all spectrum sensors found in the following literature review. For instance, this detector generalizes the ED, where $p = 2$, and, potentially, enhances its performance in non-Gaussian environments.

A. Related work

An adaptation of the ED test statistic, presented in [4], has demonstrated its optimal performance considering a deterministic PU signal under AWGN. Despite being straightforward to implement, ED is constrained by the requirement to know the noise variance.

The absolute value cumulating (AVC) detector has been proposed in [12], where it is claimed as the most suitable technique for spectrum sensing under impulsive noise. A

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proper justification is demonstrated in [7], considering Laplacian impulsive noise with fixed noise power and absence of fading. In [9], it has been derived an improved ED applying an arbitrary exponent $0 < p < 2$ in the absolute value of each sample retrieved from the received signal. The authors have verified that the optimal p value is associated to the amount of collected samples by each SU, the targeted P_{fa} and the signal-to-noise ratio (SNR). Through variations of these parameters, in Laplacian noise environments, the optimal value for p was found being, indeed, upper bounded by 1, which is the AVC particularization.

In [10], it has been proposed, for one SU with multiple antennas or multiple SUs with only one antenna, robust L_p-norm detectors, which do not require any *a priori* information related to the PU signal, performing well in a variety of non-Gaussian noise scenarios in the low SNR regime. In this detector, $p \in \mathbb{R}^+$. Its results overcome ED performances under both short-tailed and heavy-tailed noises. According to the authors, due to the relevance in the context of cognitive radio, the following three non-Gaussian noise models have been chosen: Gaussian mixture noise, generalized Gaussian noise and co-channel interference.

A novel detector based on fractional lower order moment (FLOM) for CSS under αS impulsive noise is addressed in [13], for $0 < p < 1$. The lack of closed-form expressions for the probability density function (PDF) of an αS random variable has prevented the derivation of closed-form expressions. The study exhibited in [14] aimed to accomplish the exact performance analysis of FLOM-based detectors, deriving closed-form expressions for an specific SαS distribution.

The work reported in [15] adapts a class of non-cooperative spectrum sensing with multiple antennas named combining order statistics (COS). This scheme exploits nonlinear combining strategies accompanied by the enhanced ED, which contains the flexibility of using $p \in \mathbb{R}^+$, aiming to mitigate the effects of impulsive noise and various fading types. The SαS distribution has been considered for modeling impulsive noise.

B. *Contributions and paper organization*

There are two main contributions of this work:

- Performance assessment of Norm-based detectors under Laplacian noise for several values of p;
- Analysis of the influence of implementing the COS scheme in combination with the ED, AVC, L_p-Norm and FLOM Norm-based detectors in Laplacian noise environments.

The remainder of this paper is organized as follows: Sections II, III and IV describe, respectively, the Laplacian noise characterization, the signals and system models and the Norm-based test statistics employed in the spectrum sensing performance evaluation addressed in Section V. Section VI concludes the work.

II. Laplacian Noise Model

Noise is considered impulsive when it sporadically exhibits significantly high amplitude levels and short duration in time. Due to its higher probability of occurrence of such levels, unlike AWGN, its samples tend to follow probability distributions that unveil heavy tails.

Several models characterize the statistical behavior of noise with impulsive characteristics [16]. What can differentiate one from another is, for example, the presence or absence of correlation between samples, the frequency with which outliers occur, and complexity. In this work, we employ the Laplacian impulsive noise model [17, p. 16], widely used for manifesting heavy tails and thus modeling scenarios with the presence of AWGN added to the aforementioned peaks. The PDF of Laplacian noise samples is given by

$$f_L(l) = \frac{1}{2b}\exp\left(-\frac{|l|}{b}\right), \tag{1}$$

in which $b > 0$ refers to the scale factor. Since the mean value is fixed, the higher the value of b, the higher the elevation of the tail of the PDF. Figure 1 shows a comparison among Laplace PDFs for different values of b and the Gaussian PDF of reference.

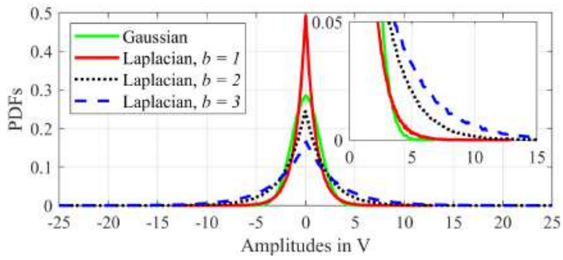

Fig. 1: PDFs of Gaussian and Laplace distributions for zero mean, different values of b and $\sigma^2 = 2$ for all functions.

III. Signals and System Model

The model chosen herein considers centralized CSS with data fusion where m cooperating SUs perform spectrum sensing, each one collecting n samples from the PU signal during a sensing interval. Each SU has these samples available to send directly to the FC via an error-free control channel. The matrix $\mathbf{Y} \in \mathbb{C}^{m\times n}$, formed in the FC, is given by

$$\mathbf{Y} = \mathbf{h}\mathbf{x}^{\text{T}} + (1 - I)\mathbf{V} + I\mathbf{L}, \tag{2}$$

where I specifies the presence of Laplacian noise in (2), if $I = 1$, or its absence, if $I = 0$. The vector $\mathbf{x} \in \mathbb{C}^{n\times 1}$ contains the samples of the PU signal, which are modeled as complex Gaussian random variables with zero mean and variance determined by the average SNR across the SUs. This setting is made to characterize fluctuations in the envelope of modulated and filtered signals. The channel vector $\mathbf{h} \in \mathbb{C}^{m\times 1}$ is constructed by elements h_i characterizing the channel gains between the primary transmitter and the i-th SU, for $i = 1, \ldots, m$. Adjusting the values of these elements over time allows modeling the fading effects imposed by the mobility of the SUs and multipath propagation. It is established that $\mathbf{h} = \mathbf{G}\mathbf{a}$, where $\mathbf{a} \in \mathbb{C}^{m\times 1}$ is a vector composed by complex Gaussian random variables $a_i \sim \mathbb{C}\mathcal{N}[\sqrt{\kappa/(2\kappa+2)}, 1/(\kappa + 1)]$, with $\kappa_{\text{dB}} = 10\log_{10}(\kappa)$, in dB, being the Rice factor of the channels between primary and secondary users. It is modeled as a Gaussian random variable $\kappa_{\text{dB}} \sim \mathcal{N}[\mu_\kappa, \sigma_\kappa]$, dependent on the environment, considering both μ_κ and σ_κ in dB [18].

The present modeling accounts for unequal and time-varying received signal power levels at the SUs, due to distinct distances between the PU transmitter and the SUs, and the movement of the SUs across different sensing events. In this case, the matrix $\mathbf{G} \in \mathbb{R}^{m\times m}$ is given by $\mathbf{G} = \text{diag}(\sqrt{\mathbf{p}/P_{\text{tx}}})$, where $\mathbf{p} = [P_{\text{rx}1}, \dots, P_{\text{rx}m}]^{\text{T}}$ is the vector containing received signal powers across the m SUs, with $[\cdot]^{\text{T}}$ denoting transposition. P_{tx} is the PU's transmission power in watts, and $\text{diag}(\cdot)$ yields a diagonal matrix whose diagonal is built by the elements of the vector in its argument.

The log-distance path loss prediction method [19] is used here to determine the received signal power by the i-th SU, in watts. The area-mean received power, at a given distance d_i from the PU transmitter, is given by

$$P_{\text{rx}i} = P_{\text{tx}} \left(\frac{d_0}{d_i}\right)^{\eta}, \tag{3}$$

where d_0 is a reference distance in the far-field region of the PU transmit antenna and η is the path loss exponent. All distances are given in meters.

To characterize variations in noise powers at the SUs' receivers, the elements of the i-th row of the matrix $\mathbf{V} \in \mathbb{C}^{m\times n}$, from (2), are zero-mean Gaussian random variables with variance

$$\sigma_i^2 = (1 + \rho u_i)\bar{\sigma}^2, \tag{4}$$

where u_i is a realization of a uniform random variable U_i in the interval $[-1, 1]$, $\bar{\sigma}^2$ is the average noise power at the SUs, and $0 \le \rho < 1$ is the fraction of variation of the noise power σ_i^2 around $\bar{\sigma}^2$. With Laplacian noise, the elements of the i-th row of $\mathbf{L} \in \mathbb{C}^{m\times n}$ are independent and identically distributed and the Laplace distribution models the noise samples. They have zero mean and variance as given by (4).

Considering the randomness of σ_i^2 and d_i, the instantaneous SNR at the SUs, γ, is also a random variable. Thus,

$$\gamma = \frac{1}{m}\sum\nolimits_{i=1}^{m} \frac{P_{\text{tx}}\,(d_0/d_i)^{\eta}}{(1+\rho u_i)\bar{\sigma}^2}. \tag{5}$$

The average SNR of the SUs is given by $\text{SNR} = \mathbb{E}[\gamma]$, where $\mathbb{E}[\gamma]$ is the expected value of γ. The final formula for the average SNR across the SUs, established in [20], whose details were omitted here for concision, is given by

$$\text{SNR} = \frac{\ln\left(\frac{1+\rho}{1-\rho}\right)}{2\rho m \bar{\sigma}^2}\sum_{i=1}^{m} P_{\text{rx}i}. \tag{6}$$

Notably, the noise model switches between Gaussian and Laplacian based on I in (2). Thus, the noise statistics in (5) and (6) correspond to either AWGN or Laplacian noise.

IV. Norm-based test statistics

In a centralized CSS with data fusion, a Norm-based spectrum sensor has its test statistic described by

$$T(p) = \sum_{i=1}^{m}\frac{1}{{\sigma_i}^p}\sum_{j=1}^{n}|y_{ij}|^p, \tag{7}$$

where σ_i is the Gaussian or Laplacian noise standard deviation at the i-th SU and y_{ij} denotes the j-th sample collected by the i-th SU, composing the matrix $\mathbf{Y}$ defined in (2). The variable $p > 0$ denotes the norm's order. Table I displays Norm-based spectrum sensors obtained from the literature review, their possible exponent p ranges, with a specific p selected for evaluation in this study.

TABLE I: Correspondence between the value of exponent p and the Norm-based spectrum sensors.

Range of p	Norm-Based Spectrum Sensor	p selected
1	AVC	1
2	ED	2
$\mathbb{R}^+$	L_p-Norm	4
<1	FLOM	0.5

It should be noted that works dealing with L_p-Norm [10] and FLOM [13] detectors, while employing the concept of norm on received signal samples, do not precisely specify the exponents of σ_i in (7). Here, we extend the configuration followed by [4] for the ED and [7] for the AVC, maintaining the same value of p for both $|y_{ij}|$ and σ_i.

The computational burden of Norm-based detectors, setting p as an integer value, primarily stems from nm multiplications, resulting in a complexity of $\mathcal{O}(nm)$. Due to the fact that (7) can be rewritten as $T(p) = \sum_{i=1}^{m}\frac{1}{{\sigma_i}^p}\sum_{j=1}^{n}|y_{ij}|^p = \sum_{i=1}^{m}\frac{1}{{\sigma_i}^p}\sum_{j=1}^{n}\exp(p\text{log}(|y_{ij}|))$, when p is not an integer number, the complexity of the test statistic involves evaluating logarithms at a specific precision level q, and $M(q)$ represents the complexity of multiplying numbers with q digits [9], resulting in $\mathcal{O}(nmM(k)\text{log}(|y_{ij}|))$. Additionally, the method used to estimate the noise variance augments the computational complexity. These detectors are semi-blind, as they do not require information about the PU signal but utilize noise level information.

The test statistic of the COS Norm-based scheme [15] requires each SU to initially compute a local test statistic using a Norm-based detection process as follows

$$t_i = \frac{1}{\sigma_i^p}\sum_{j=1}^{n}|y_{ij}|^p, \tag{8}$$

where t_i is the output of the local test statistic reached by the i-th SU. Having the vector $\mathbf{t} = [t_1\ t_2\ \dots\ t_m]$ available, it is sufficient to reorder it in ascending order, that is, $t_{(1)} < t_{(2)} < \cdots < t_{(m)}$, in which $t_{(k)}$ is the k-th order statistic in $\mathbf{t}$. The final expression for the COS Norm-based test statistic is

$$T_{\text{COS}} = \sum_{k=1}^{K} t_{(k)}, \tag{9}$$

where $K = 1, 2,\ \dots, m$. The notation COS Norm-based $(1, 2, \dots, K)$ will be used to denote COS scheme with the Norm-based detection and the test statistic in (9). For example, if we consider $m = 4$, COS Norm-based (1,4) corresponds to the selection and summation of $t_{(1)}$ and $t_{(4)}$ to form the test statistic in (9), which will be compared to the decision threshold. In other words, the smallest and largest values are selected for combination. As used in the following performance assessment, COS Norm-based (4) builds the test statistic only by the presence of $t_{(4)}$, which associates to the selection of the largest value. Figure 2 depicts the block diagram of the COS Norm-based detector.

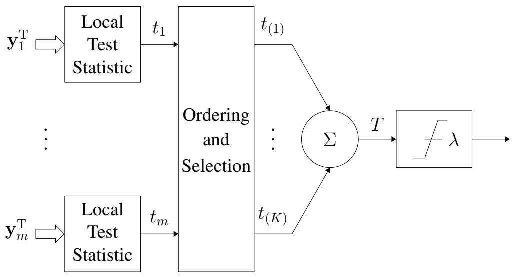

Fig. 2: Block diagram of the COS Norm-based scheme.

V. Numerical results

In this section, we present computer simulation results of the centralized CSS with data fusion both in the absence and presence of impulsive noise in terms of $P_{\rm d}$ values achieved in accordance with the variation of some system parameters, assuming $P_{\rm fa} = 0.1$ [21], for ED, AVC, FLOM and L_p-Norm detectors, inserted or not in a COS scheme. Each point on a curve has been generated from 10000 Monte Carlo events using the Matlab R2019a. The MATLAB code used to obtain the results is available at [22].

Using the pure AWGN scenario as reference, the value of the average SNR has been adapted, in part of the cases, so that the respective best detector yields $P_{\rm d} \approx 0.9$ at the mid-value of the system parameter being analyzed. Thus, variations in $P_{\rm d}$ can be clearly perceived. When fixed, for a better adequacy of situations more likely to occur in practice, the system configuration parameters are: $m = 4$ SUs, which corresponds to a small number of cooperative cognitive radios, leading to an efficient utilization of control channel resources. Additionally, in [7], for instance, results show that an increase in the number of SUs occurs in a diminishing return fashion of performance improvement; $n = 300$ samples to achieve the targeted performance metrics; SNR $= -10$ dB, considering a low SNR regime operation system; fraction of noise variations, $\rho = 0.5$, which was arbitrarily chosen to model variations in thermal noise power; path-loss exponent, $\eta = 2.5$, chosen to fit a typical urban scenario; normalized coverage radius, $r = 1$ m; reference distance for path-loss calculation, $d_0 = 0.001r$; $P_{\rm tx} = 5$ W, adapting to practical requirements of power for real PU transmitters; and random Rice factor, with $\mu_\kappa = 1.88$ dB and $\sigma_\kappa = 4.13$ dB, considering urban area [18]. The parameters related to the Laplacian noise have been calculated and generated as described in Section II. The values of p for each of the evaluated detectors can be retrieved from Table I.

Fig. 3 shows $P_{\rm d}$ versus the exponent p of Norm-based detectors in the absence and presence of impulsive noise. A reduction, to varying extents, is observed in the values of $P_{\rm d}$ as the value of the exponent p increases in both scenarios. For values of p less than 2, there is a certain stability and optimality in performance for the former scenario, as expected, since $p = 2$ corresponds to the optimal detector in the presence of pure AWGN. The curve starts to gradually decline from this value. The latter scenario presents a steeper decrease for lower values of p, returning a stable and quite significant sensitivity for $p > 2$. It is observed that, in the presence of Laplacian impulsive noise, higher p values tend to perform poorly. In contrast, lower p values, despite significant performance variation, outperform higher p values. The reason, according to [13], is that the FLOM properties present in lower values of p can mitigate heavy-tailed behavior of impulsive noise by adjusting p as a value between 0 and 2, returning a better performance in terms of $P_{\rm d}$ when compared to the ones reached with higher values of p in this scenario.

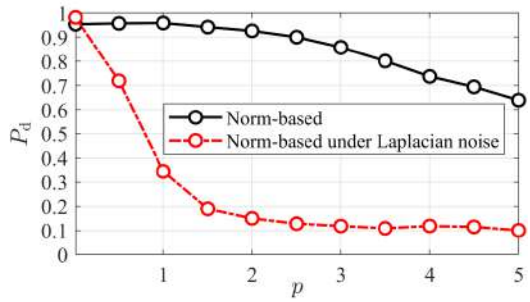

Fig. 3: Probability of detection, $P_{\rm d}$, versus exponent of Norm-based detectors, p, for SNR = -8.5 dB: system under both Gaussian and Laplacian noises. This figure is better viewed in color.

Fig. 4 shows $P_{\rm d}$ versus the k-th largest value selected after "Ordering and Selection" in Fig. 2. From Fig. 4a, considering pure AWGN, it can be seen that the ED tends to outperform the other detectors, as expected, being closely followed by the AVC, the L_4-Norm and the FLOM ($p = 0.5$). The performances of these detectors remain invariable since their test statistics use not only the k-th largest value, but all values. The COS Norm-based schemes show performance curves tending to worsen as a smallest value is selected, i.e, with the increase of k. The notable aspect is the proximity of the performance achieved by selecting only the maximum value, $k = 1$, to that one of conventional detectors using all values.

From Fig. 4b, considering the presence of Laplacian noise, one notices a maintenance of the curve patterns concerning the scenario with pure AWGN, except for the COS L_4-Norm detector, which showed high sensitivity to impulsive noise, not benefiting from the variation of k. It is also observed that the performance improvement is inversely proportional to the value of the exponent p for $p \leq 1$, with the FLOM ($p = 0.5$) unveiling a performance improvement more pronounced than that exhibited by the AVC. The ED and the L_4-Norm returned evident performance degradation, compared to the scenario with pure AWGN, with the latter showing poor $P_{\rm d}$. All Norm-based COS schemes, in the presence of Laplacian impulsive noise, showed either improved or decreased performance in line with their respective conventional detectors (without COS). Once more, the notable aspect is the proximity of the performance achieved by selecting the maximum value, $k = 1$, to that of conventional detectors using all values.

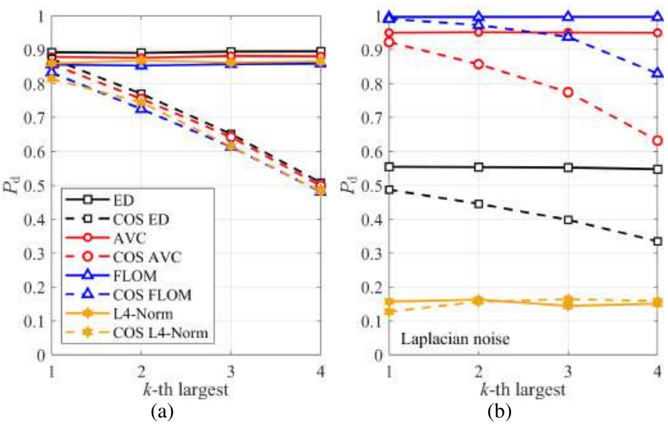

Fig. 4: Probability of detection, P_d, versus k-th largest value: system under Gaussian noise (left) and system under Laplacian noise (right). This figure is better viewed in color.

VI. Conclusions

This work has assessed the performance of centralized CSS with data fusion, under Laplacian impulsive noise. The performances of the Norm-based detectors ED, AVC, FLOM, L_p-Norm and COS Norm-based were compared under pure AWGN and under Laplacian noise models.

Norm-based detectors which use $p \leq 1$ tend to show excellent performances under Laplacian noise, specially as the value of p decreases. Conversely, the utilization of higher values of p return P_d worsening. Thus, FLOM ($p = 0.5$) and AVC ($p = 1$) detectors revealed great robustness against Laplacian noise, whereas the ED and the L_4-Norm behaviors have shown expressive sensitivity, mainly, the latter.

The use of the COS scheme accompanied by Norm-based detectors yielded two noteworthy outcomes: 1) Under Laplacian noise, as a smaller value was chosen at the output of the "Ordering and Selection" block provided in Fig. 2, that is, for a larger k, the performance degradation was less pronounced when compared to the pure AWGN scenario for all detectors, except for the COS L_4-Norm, which exhibited negligible performance for any k; 2) Selecting the maximum value ($k = 1$) yields performances very similar to conventional detectors that use all values. Consequently, one may assess the omission of the summing block in the COS scheme, using only the maximum value at the output of the sorter as the test statistic, thereby reducing some of its construction complexity.

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