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Gaussianity Testing as an Effective Technique for Detecting Discontinuous Transmission in 5G Networks

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ABSTRACT The paper investigates statistical distribution testing-based detection methods in an intermittent signal detection scenario. The relevance of the research is driven by 5G networks based on packet transmission, incorporating the concept of cognitive radio and adapting spectrum detection methods from Long Term Evolution (LTE) Licensed-Assisted Access (LAA). The conducted study refers to the recently proposed methods based on testing goodness-of-fit (GoF) of statistical distributions, which are compared with a conventional energy detector. The authors examine the applicability of well-known GoF methods in intermittent transmission, as they require reconsideration in 5G communication systems, and investigate the behavior of the innovative energy-based GoF. The experiments are carried out for different transmitter activity factors, i.e., channel occupancy and signal-to-noise ratio (SNR), demonstrating the superiority of the GoF-based methods in general and particularly the invented GoF test over other energy-based detectors for discontinuous signals detection.

INDEX TERMS Gaussianity testing, energy detection, discontinuous transmission.

I. INTRODUCTION

In recent years, many technologies have been developed for wireless systems based on the IEEE 802.15.4 and IEEE 802.11 standards. These technologies work primarily in the unlicensed 2.4 GHz and 5.725 GHz Industrial, Scientific, and Medical (ISM) frequency bands, which are shared among different networks. In the meantime, the mobile industry has requested to adapt the unlicensed spectrum, in particular, the 5.725 GHz ISM band, to meet the emerging demand for additional spectrum for mobile broadband applications. With the spread of wireless devices and systems, ISM bands are becoming increasingly crowded, and interference between the devices is becoming more problematic. Therefore, operating in the unlicensed band requires careful planning of coexistence to avoid or minimize interference between users.

A complex solution to this problem is introduced by the 5G network in the concept of New Radio-based access to Unlicensed spectrum (NR-U), which incorporates cognitive radio to efficiently utilize unlicensed spectrum bands [1], [2]. The NR-U introduced in 5G, describes an optional listen-before-talk procedure preceding an attempt to seize a random access channel (RACH). However, NR-U has to be designed in accordance with the regulatory requirements of the corresponding bands. In the case of the 5 GHz and 60 GHz bands, the regulation mandates the use of LBT in Europe [3]. Therefore every user equipment must perform a LBT operation for transmission over RACH. The operation of NR in 5 GHz and 6 GHz bands assumes the LBT procedure defined in Long Term Evolution (LTE) Licensed-Assisted Access (LAA) as a baseline [4], [5]. Therefore in 5G systems, the spectrum sensing procedure continues to refer to energy detection as one of the main measures of assessing radio channel occupancy [5], [6].

Energy detection is a simple and effective method of detecting the presence of a signal in which the energy measured during a detection period is compared with a certain threshold value [7]–[9]. A conventional energy detection scheme is based on the assumption that the signal is present throughout the entire duration of the sensing period. Such detection has limited performance in more realistic scenarios in which the pulse signal can dynamically switch between

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active and inactive states, e.g., in sporadic data packet transmissions [10]–[12]. When using energy detection in intermittent transmission, the instantaneous signal energy is outstretched in the average energy measured over the entire detection window. Adaptation for discontinuous transmission is considered in [12]–[15] by redesigning the energy detection algorithm. As a result, the correct operation of a modified energy detector in a dynamic radio channel requires prior gathering of information on transmitter activity, such as average and current signal duration, channel occupancy, and signal and noise parameters, such as noise variance and signal-to-noise ratio (SNR). In this case, the energy detector, which was intended as a light and simple solution, is excessively overloaded with the determination of auxiliary parameters. Consequently, it cannot be further considered as a simple, blind detector dedicated to unknown signals.

The solution to the problem of a blind and yet simple detector that remains sensitive to intermittent transmission is to use detection techniques based on statistical distribution analysis also called goodness-of-fit (GoF) testing. The main principle for this group of methods is the examination of empirical distribution of the received samples and assessment of their compliance with the expected distribution. Due to insufficient distortion of the expected Gaussianity introduced by signal-with-noise samples filling the entire detection window, the above solutions have been omitted so far in many review studies (e.g., [16], [17]). As the sum of two Gaussian distributions still remains Gaussian [18], the addition of a Gaussian-distributed signal and noise results in a Gaussian distribution also for signal-with-noise samples, which precludes the effective use of GoF tests. However, when considering intermittent transmission, the subject of detection is a certain proportion of signal-with-noise and noise-only samples. Thus, the resulting distribution is strongly disturbed and expected to be no longer Gaussian [19]. Although so far rejected due to low efficiency, Gaussianity testing methods can find wide applications in modern telecommunication networks, i.e. 5G wireless systems based on intermittent transmission. Moreover, as a group of techniques operating on a single assumption of the expected noise distribution, they meet the requirements of unknown signals detection. In such a case, the use of GoF and in particular Gaussianity and normality testing methods needs to be reconsidered. To meet new challenges, the authors introduced the foundations of a novel, energy-based Gaussian fitting test [20]. The described solution is based on a weakly dependent, empirical energy distribution of the received signal, which allows simple implementation and potentially high efficiency. Although the proposed test is theoretically refined, it is based on some assumptions that may not correspond to the actual radio noise in 5G networks, hence the need for further research using real experimental data.

In this paper, we examine and compare the effectiveness of discontinuous signal detection using known statistical fitting methods in general and the method developed in [20] in particular. Method described in [21], which uses a fundamentally different basis of detection, is a benchmark adopted in the conducted research. The research covers the most frequently referenced GoF tests, indicated as those with high efficiency and superiority to other similar, i.e., Jarque-Bera (JB) [22]–[24] and higher-order statistics (HoS) [25], [26]. As we evaluate them as an alternative to solutions based on an energy detector, in a comparative study we combine the above techniques with the adaptation of energy detection to intermittent transmission proposed in [21].

The tests of applicability and usability evaluate the algorithms in terms of probability of detection (P_d) with respect to decreasing SNR, increasing probability of false alarm (P_f), and variable transmitter activity. The assessment is based on a semi-experimental configuration that combines simulated radio-pulse transmission and environmental background distortions from radio frequency (RF) noise traces recorded using software-defined radio (SDR) by National Instruments, model USRP-2900.

The paper is organized as follows. Section II presents the system model and describes the detection methods. Section III presents a simulation and numerical results, which are followed in Section IV by a discussion on the performance of the methods. Finally, the paper is concluded in Section V.

II. SYSTEM MODEL AND DETECTION METHODS

A detection system dedicated to unknown signals can be described as a binary decision model distinguishing between two states

$$x(n) = \begin{cases} w(n) & H_0 \\ s(n) + w(n) & H_1, \end{cases} \tag{1}$$

where $x(n)$ is the received signal, $s(n)$ is an unknown, deterministic signal and $w(n)$ is additive white Gaussian noise (AWGN). The main issue of detection when concerning unknown signals is to define a decision rule $\Lambda(x)$ that indicates the current state of the radio channel: H_0 when only noise is present or H_1 when both signal and noise are present. The decision rule $\Lambda(x)$ with respect to the adopted decision threshold γ can be described as

$$\begin{cases} H_0 & \text{for } \Lambda(x) < \gamma \\ H_1 & \text{for } \Lambda(x) \geq \gamma. \end{cases} \tag{2}$$

In the considered scenario, the receiver collects signal samples $x(n)$ for $n = 1 \ldots N$, with sampling frequency $f_s = \frac{N}{T}$ in detection intervals of equal duration T. The burst signal as a subject of detection is assumed to be dynamic, switching at random moments between active (H_1) and inactive (H_0) states. The duration of the signal and following transmission breaks are assumed to be independent of the detection intervals and have exponential distributions with mean values τ and η, respectively [13]. Such a scenario is illustrated in Figure 1 in the form of a sequence of burst signals buried in noise.

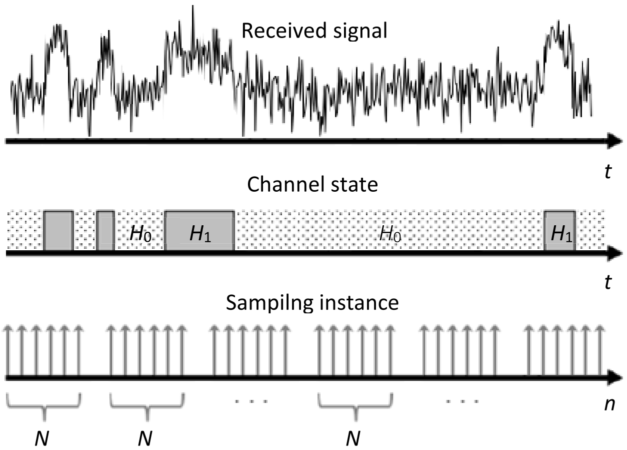

FIGURE 1. Illustration of discontinuous transmission with marked channel states and detector sampling periods.

A. ENERGY-BASED DETECTORS

In a real system, supporting opportunistic access, information about the signals and transmission parameters often remains inaccessible to competing users. Therefore, one of a few available strategies for the successful execution of the LBT procedure is energy-based detection. The main decision criterion is the energy value obtained by direct measurement in a finite time. The simplicity of the implementation, low hardware requirements and speed supporting effortless real-time processing cause a wide application of the energy-based methods in the detection of unknown signals.

1) CONVENTIONAL ENERGY DETECTOR

In the most common implementation of energy detection, the test criterion is the average value of a squared amplitude of the samples measured during a specified observation window. For the collected samples $x(n)$, the decision statistics can be described as

$$\Lambda(x) = \frac{1}{N}\sum_{n=1}^{N}|x(n)|^2. \quad (3)$$

With a large enough number of samples (N) in the sensing interval, the distribution of the noise energy test statistic can be approximated as Gaussian $\mathcal{N}\left(N\sigma_w^2, 2N\sigma_w^4\right)$. Therefore, the detection threshold can be formulated as

$$\gamma = \sigma_w^2\left(Q^{-1}\left(P_f\right)\sqrt{2N}+N\right), \quad (4)$$

where Q^{-1} represents an inverse Q-function for a tail distribution of the standard normal distribution [7]–[9]. The equation shows that the proper thresholding of Gaussian-distributed energy requires *a priori* knowledge of the mean and deviation and therefore of the noise variance σ_w^2. Despite the disadvantage of requiring σ_w^2, energy detection is widely used and still developed.

2) SHORT WINDOW-BASED ENERGY DETECTION

As an example of recent adaptation, one can refer to [21], which presents a short window-based energy detection, adapted to intermittent transmission. The scheme proposed in [21] divides the sensing interval into shorter windows with the length of LSW samples each. Thus, the sensing interval is composed of N/LSW non-overlapping short windows. The proposed scheme selects the maximum energy of a short window and compares it with a pre-determined γ. The test statistic given in [21] is described as

$$\Lambda(x) = \frac{1}{L_{sw}}\max\left\{\sum_{n=1}^{L_{sw}}|x(n)|^2,\ldots,\sum_{n=N-L_{sw}}^{N}|x(n)|^2\right\}. \quad (5)$$

Since $\Lambda(x)$ is the maximum average energy selected from N/LSW short windows, to satisfy the assumed P_f, threshold γ is obtained as

$$\gamma = \frac{2\sigma_w^2}{L_{sw}}\Gamma^{-1}\left(L_{sw},\left(1-\left(1-P_f\right)^{\frac{L_{sw}}{N}}\Gamma\left(L_{sw}\right)\right)\right), \quad (6)$$

where $\Gamma(\cdot)$ and $\Gamma^{-1}(\cdot,\cdot)$ denote the complete and inverse incomplete gamma functions, respectively.

B. GOODNESS-OF-FIT TESTING

Assume noise samples $w(n)$ follow Gaussian distribution $\mathcal{N}\left(\mu_w, \sigma_w^2\right)$, while the unknown signal samples $s(n)$ can be modeled as a random variable with distribution $\mathcal{N}\left(\mu_s, \sigma_s^2\right)$. If $w(n)$ and $s(n)$ are independent random variables, their sum is also Gaussian-distributed, with the mean being the sum of the two means, and the variance being the sum of the two variances, i.e., $\mathcal{N}\left(\mu_w+\mu_s, \sigma_w^2+\sigma_s^2\right)$, which for clarity of description will be further indexed as $\mathcal{N}\left(\mu_{w+s}, \sigma_{w+s}^2\right)$. Continuous transmission therefore precludes the use of goodness-of-fit tests, as these methods are based on the assumption that the distribution of mixed signal and noise is different from the sole distribution of noise [25]. In the case of intermittent transmission, however, the receiver collects not only signal-with-noise samples from $\mathcal{N}\left(\mu_{w+s}, \sigma_{w+s}^2\right)$, but also a certain proportion of noise-only samples from $\mathcal{N}\left(\mu_w, \sigma_w^2\right)$. Depending on the activity factor of the transmitter, the LBT evaluation will be held for a mixed distribution resulting from the combined distribution of signal-with-noise and noise-only samples, as illustrated in Figure 2.

1) JARQUE-BERA NORMALITY TEST

There are several statistical methods for analyzing the distribution of measured samples, e.g., Kolmogorov-Smirnov, Anderson-Darling or Shapiro-Wilk tests. One of the more commonly used methods, however, is the Jarque-Berra test, which exhibits superiority over other tests in its sensitivity to distortions of normal distribution [22]. The method is based on kurtosis and skewness, therefore it only requires the determination of the mean value and variance of the empirical distribution of received samples. JB test statistics

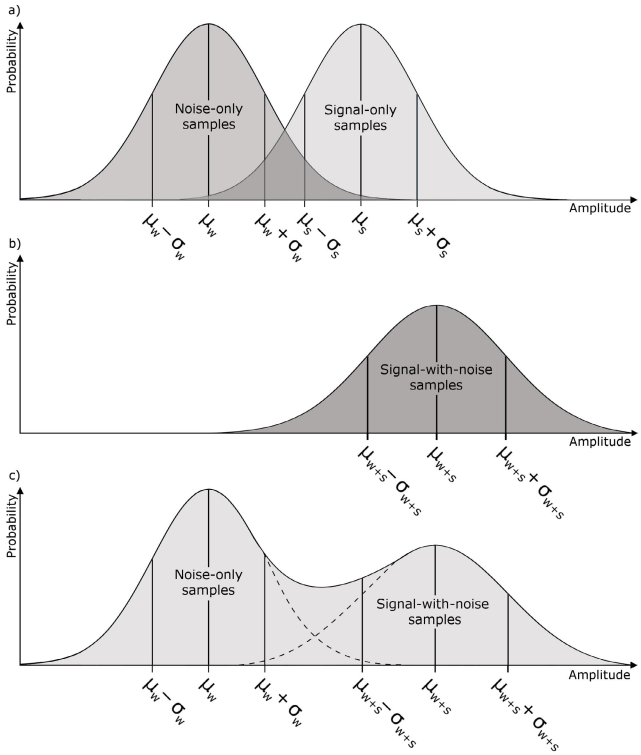

FIGURE 2. a) Gaussian distributions of signal-only and noise-only samples; b) Gaussian distribution of signal-with-noise samples for continuous transmission; c) mixed distribution of noise-only and signal-with-noise samples for discontinuous transmission.

are defined as

$$\mathrm{JB} = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right). \tag{7}$$

where N is the number of samples, S is the sample skewness and K is the sample kurtosis. The skewness of a data set is a measure of the degree of asymmetry of its distribution from the mean value, defined by

$$S = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3}{\left(\frac{1}{N}\sum_{i=1}^{n} x_i - \bar{x})^2\right)^{3/2}}, \tag{8}$$

and the kurtosis is a measure of matching the tails of a distribution, defined as a normalized form of the fourth central moment

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left(\frac{1}{N}\sum_{i=1}^{n} x_i - \bar{x})^2\right)^{2}}. \tag{9}$$

In relation to the assumed goal, i.e., testing whether the empirical distribution function of the received signal is Gaussian or not, the skewness and kurtosis of AWGN should be taken as the reference value. If x follows the normal distribution, for any non-negative integer p, the plain central moments are defined as

$$\mathrm{E}\left(x^p\right) = \begin{cases} \dfrac{\sigma^p (p!)}{2^{\frac{p}{2}}\left(\frac{p}{2}!\right)} & p \text{ even} \\ 0 & p \text{ odd.} \end{cases} \tag{10}$$

Considering the above, for a normal distribution, skewness as a 3rd-degree moment should be close to 0, and kurtosis as a 4th-degree moment should be close to 3. To maximize the information for test statistics of a complex signal, both the real and imaginary parts are used

$$S = \frac{S(\mathrm{Re}(x)) + S(\mathrm{Im}(x))}{2}, \tag{11}$$

$$K = \frac{K(\mathrm{Re}(x)) + K(\mathrm{Im}(x))}{2}. \tag{12}$$

When only noise appears in the received signal, the real parts as well as the imaginary parts, will have Gaussian distribution. Therefore, JB test statistics will have a chi-square distribution with 2 degrees of freedom. For the threshold setting, we have to calculate the probability of a false alarm, as a right tail probability of $\chi^2(2)$

$$P_f = P\left(JB > \lambda\right) = \frac{1}{2}\int_{\lambda}^{\infty} \exp\left(-\frac{1}{2}x\right) dx. \tag{13}$$

2) HIGHER ORDER STATISTICS NORMALITY TEST

Cumulants-based detection represents statistical signal processing originated in pattern recognition for signals of different structure. The detection scheme proposed in [26] is based on a specific cumulants - so called joint cumulants of random variables of the fourth and sixth orders. All six (for 6-th order cumulants) and four (for 4-th order cumulants) variables used in the test statistics are considered to be the same, with the number of conjugate values used for these variables being three and two for 6-th order and 4-th order cumulants, respectively. As the authors of [26] point out, it is not the only possible combination of variables and their conjugates for higher order joint cumulants.

According to the joint cumulant generating formula, for a zero-mean random variable x with second-order cumulant $C_{21,x} = cum\,(x, x^*) = E\left(|x|^2\right)$, where x^* denotes the conjugate of x, the sixth order joint cumulants, labelled as $C_{63,x} = cum\,(x, x, x, x^*, x^*, x^*)$, are defined as [26], [27]

$$C_{63,x} = E\left(|x|^6\right) - 9E\left(|x|^4\right)E\left(|x|^2\right) + 12\left|E\left(x^2\right)\right|^2 E\left(|x|^2\right) + 12E^3\left(|x|^2\right). \tag{14}$$

The fourth order joint cumulants, labelled as $C_{42,x} = cum\,(x, x, x^*, x^*)$, are defined as [26], [27]

$$C_{42,x} = E\left(|x|^4\right) - \left|E\left(x^2\right)\right|^2 - 2E^2\left(|x|^2\right). \tag{15}$$

The normalized sixth and fourth order cumulants, $\hat{C}_{63,x}$ and $\hat{C}_{42,x}$, are defined as

$$\hat{C}_{63,x} = \frac{C_{63,x}}{E\left(|x|^2\right)^3}, \tag{16}$$

$$\hat{C}_{42,x} = \frac{C_{42,x}}{E\left(|x|^2\right)^2}. \quad (17)$$

For noise, modelled as AWGN, all joint cumulants of order larger than two are equal to zero. However, due to the limited accuracy of estimation, when considering a finite number of samples used to determine HOS, the cumulants may not be exactly zero. Therefore, a certain threshold must be set to decide if the samples belong to the signal or noise class. The IEEE 802.22 standard compares the higher-order cumulants with the power of second-order moment [28].

Let R be the number of moments (M_r) and cumulants (C_r) of the order r greater than two. For the evaluation step $0 < \sigma < 1$, e.g., $\sigma = 0.5/R$, and initial metric $p = 0.5$, the basis for the evaluation is the test condition

$$\begin{cases} p+\sigma & \text{for each } |C_r| < \gamma |M_2|^{r/2} \\ p-\sigma & \text{for each } |C_r| \geq \gamma |M_2|^{r/2}. \end{cases} \quad (18)$$

where γ is used to make a fine adjustment of P_f if needed, in most cases kept close to unity. If $p \geq 0.5$, then x belongs to the signal class.

HOS-based detection using 4-th to 6-th order cumulants has become the recommended sensing method for DTV signals in the IEEE 802.22 standard [25].

3) ENERGY-BASED GAUSSIANITY TESTING

The solution proposed in [20] uses the N-point fast Fourier transform (FFT) to obtain the power spectrum of the received signal after the necessary processing $|FFT\{x(n)\}|^2 \rightarrow Y(n)$. The M-point moving average creates a weakly dependent model, making the distribution of the noise-only power spectrum close to Gaussian. It is therefore important to select $M \ll N$. The test statistics of the proposed Gaussianity testing examine the field of tails of the obtained distribution

$$\Lambda(Y) = \frac{1}{N}\sum_{n=1}^{N}(|Y(n) - \bar{Y}| \geq \sigma). \quad (19)$$

The solution performs a Gaussianity test on the empirical distribution of weakly dependent energy samples obtained in short, overlapping windows, resulting from the use of a moving average. The energy analysis is a simple fit test, i.e., the spread of samples between the tails and center of the distribution. In the case of noise, the tails containing samples exceeding $\pm\sigma$ maintain a fixed ratio of approximately 0.317 of the field under the Gaussian curve. Due to processing performed on a finite number of samples, the authors provide an expression describing the fluctuations of the field of tails with respect to M and N, which follows the Gaussian distribution with parameters

$$\begin{cases} \mu = 0.317 \\ \sigma = \frac{3}{8}\left(erf\left(\frac{1+C}{\sqrt{2}}\right) - erf\left(\frac{1-C}{\sqrt{2}}\right)\right), \end{cases} \quad (20)$$

where

$$C = (1 - \sqrt{\lfloor N/M \rfloor / \chi^2_{[0.8145, \lfloor N/M \rfloor - 1]}})\sqrt{t_{[0.9, M]}}. \quad (21)$$

Determining threshold γ for $\Lambda(Y)$ is limited to a well-known problem of setting the threshold on the Gaussian distribution for the assumed P_f. In the above case, the following formula applies

$$\gamma = \mu - Q^{-1}\left(P_f\right)\sigma^2. \quad (22)$$

The proposed detection method eliminates σ_w^2 from the threshold equation, which by referring to the field and incorporating C depends only on N and M selected by the user. It is worth noting that for the assumed M and N, the threshold is determined only once and does not need to be updated even if the noise variance changes.

A clear comparison of energy-based and GoF-based detection methods in terms of information and performance requirements is presented in Table 1.

III. SIMULATION AND NUMERICAL RESULTS

The basis for further considerations is a comparison of conventional energy detection, short windows-based detection as its adaptation to packet transmission, Jarque-Bera normality test, HoS normality test and the Gaussianity test proposed by the authors as the main subject of the research.

In the implemented semi-experimental simulation framework, the object of analysis for each method are non-overlapping time frames. Each frame contains N complex noise samples, collected in an urban area using the National Instruments USRP-2900 [29]. The measurements contain RF background noise recorded in an unoccupied 5 kHz ISM band centered at 2.4 GHz with the average noise power −109.6 dBm. The receiver digitizes RF samples with sampling frequency f_s = 10 kHz using direct downconversion to baseband. To each noisy frame, an artificial radio pulse is added. The position of the pulse in the frame is set randomly, i.e., independently of the beginning of the detection period. In the simulated transmitter activity dependencies, the duration of pulses follows an exponential distribution, with the average value τ being swept from $0.1\frac{N}{fs}$ s to $0.9\frac{N}{fs}$ s in order to obtain the intended average occupancy rate ranging from 10% to 90%, respectively. In simulated SNR dependencies, the SNR level is regulated by adjusting the amplitude of the pulse signal, while maintaining the power of the recorded noise and constant average occupancy rate.

In the adopted model, the transmission corresponds to a random signal with time-varying statistics, which at the receiver location can be described as

$$x_m(n) = \alpha(m) \cdot \Pi\left(\frac{n - \beta(m)}{e(\tau, m)}\right) + w(n) \quad (23)$$

where $x_m(n)$ defines the n-th sample in the m-th observation, $\alpha(m)$ is the regulated pulse amplitude, $\Pi(n)$ is a rectangular pulse function, $\beta(m)$ is the start of transmission modeled as a random variable from a uniform distribution in the range $0\ldots N$, $e(\tau, m)$ is the transmission duration modeled as a random variable from the exponential distribution with the

TABLE 1. Comparison of energy-based and normality testing-based detection methods.

Parameter	Method		
	Energy-based detection	GoF-based detection	Proposed energy-based GoF
Noise knowledge	Noise variance σ_w^2	Gaussian distribution	Gaussian distribution
Signal knowledge	Not required for conventional energy detection Requires τ for optimal short windows-based detection	Not required	Not required
High performance requirements	High SNR and low noise uncertainty	Long observation window	Suitable size of the moving average

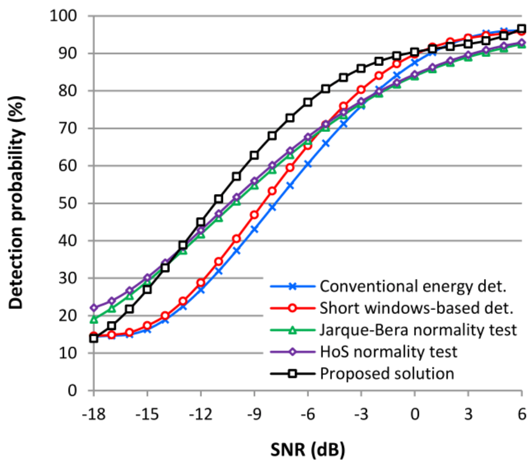

FIGURE 3. P_d**(SNR) function for the observation window size of** $N = 1024$ **samples, average transmitter activity** $\tau = 30\%$**, and type I error probability** $P_f = 10\%$**.**

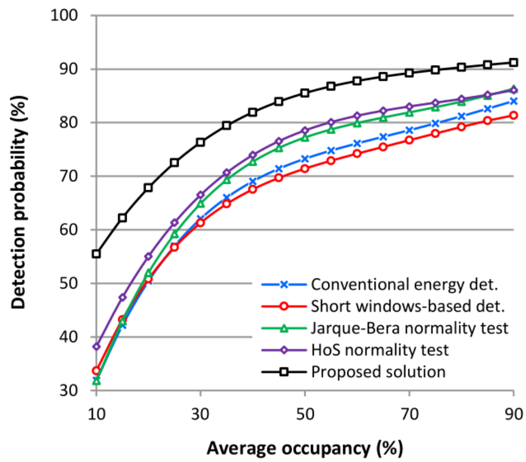

FIGURE 5. $P_d(\tau)$ **function for the observation window size of** $N = 1024$ **samples, type I error probability** $P_f = 10\%$**, and SNR =** $-6dB$**.**

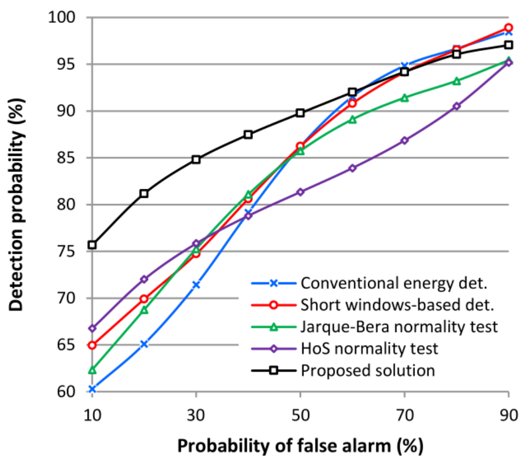

FIGURE 4. $P_d(P_f)$ **function for the observation window size of** $N = 1024$ **samples, average transmitter activity** $\tau = 30\%$**, and SNR =** $-6dB$**.**

mean τ and $w(n)$ is a downconverted additive white Gaussian noise.

The conducted study includes two sets of characteristics for the short and long observation windows, respectively. Figures 3–5 show the results of a comparative analysis for each observation window containing $N = 1024$ samples. Figures 6–8 show the results for N increased to 16384, recognized as a number of samples large enough to clearly show the differences in the behavior of the tested methods, when processing long samples series. Both sets of characteristics consist of three charts presenting the following dependencies:

- Probability of detection as a function of average signal strength – P_d(SNR). Study of the constant false alarm rate (CFAR) scenario simulated assuming P_f of 10%, and random transmitter activity resulting in the average channel occupancy τ of 30% of the observation window.
- Probability of detection as a function of the probability of false alarm – $P_d(P_f)$. Evaluation of the receiver operating characteristic curve (ROC), simulated assuming random transmitter activity resulting in the average channel occupancy τ equal to 30% of the observation window, and arbitrarily selected SNR equal to -6 dB.
- Detection probability as a function of transmitter activity – $P_d(\tau)$. Investigation of the effectiveness of detection methods in intermittent transmission, simulated with the assumption of random transmitter activity resulting in the average channel occupancy τ in the range of 10%–90% of the observation window. The simulation performed while maintaining an arbitrarily selected SNR of -6 dB and constant P_f of 10 %.

Each comparison point in Figures 3–8 is obtained after averaging 1000 observations, generated according to point parameters. Due to the variability of transmitter activity, each SNR is determined as the average value obtained for all observations with the assumed constant pulse amplitude set in relation to the average noise amplitude and average pulse duration. Moreover, to eliminate inaccuracies in threshold estimation, for each value of P_f used, a corresponding threshold is set based on 1000 *a priori* observations.

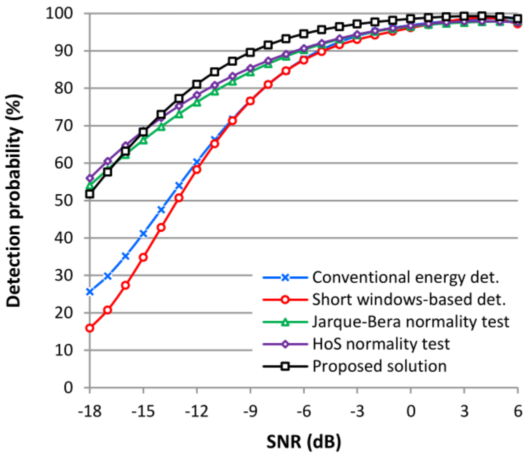

FIGURE 6. P_d(SNR) **function for the observation window size of** $N = 16384$ **samples, average transmitter activity** $\tau = 30\%$**, and type I error probability** $P_f = 10\%$**.**

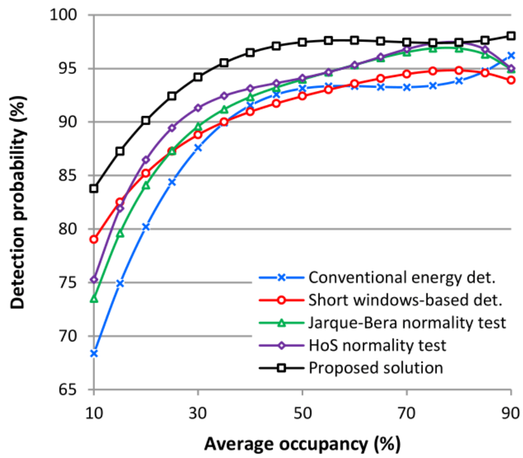

FIGURE 8. $P_d(\tau)$ **function for the observation window size of** $N = 16384$ **samples, type I error probability** $P_f = 10\%$**, and SNR** $= -6dB$**.**

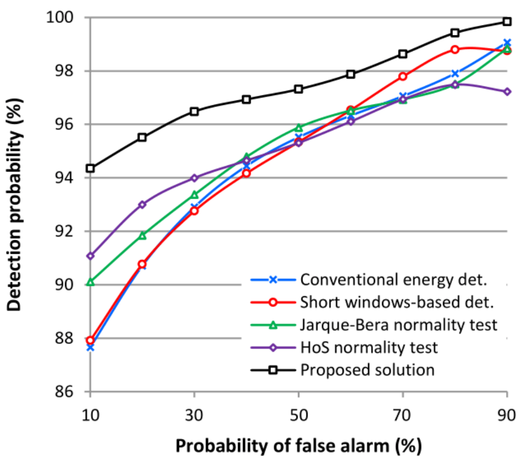

FIGURE 7. $P_d(P_f)$ **function for the observation window size of** $N = 16384$ **samples, average transmitter activity** $\tau = 30\%$**, and SNR** $= -6dB$**.**

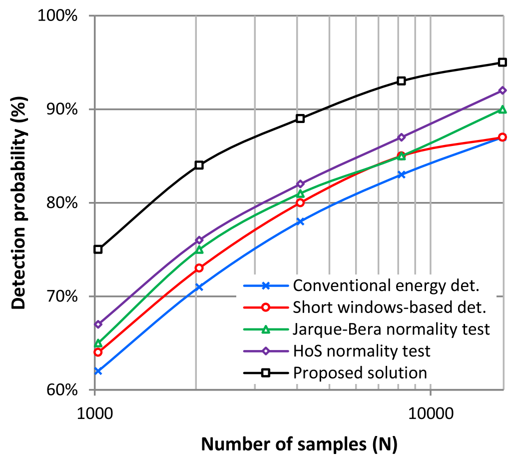

FIGURE 9. $P_d(N)$ **function for average transmitter activity** $\tau = 30\%$**, type I error probability** $P_f = 10\%$**, and SNR** $= -6dB$**.**

To complete the comparison, it is also tested how the probability of detection changes in the function of increasing observation window $Pd(N)$. Window size N is increased exponentially as 2^i, for $i = 10, .., 14$. The simulation assumes constant P_f equal to 10%, SNR equal to -6 dB and the average occupancy of the channel τ equal to 30% of the observation window. The simulation results are shown in Figure 9.

IV. DISCUSSION

The analysis of the P_d(SNR) relationship for a small number of samples (Figure 3) and strong signals, in the range of SNR above -3 dB, shows the superiority of methods based on energy detection over classical GoF solutions. Particularly interesting is the short windows-based detection, adopted for intermittent transmission, which provides an additional 1 dB gain compared to a conventional energy detector. Normality testing methods provide a detection gain greater than conventional energy detection only for very weak signals, i.e., SNR below -3 dB, and in the case of the short windows method, below -6 dB. In both cases, however, the detection probability is already below the usage values, i.e., 70%. Note that, e.g., for DTV systems, the required P_d should be greater than 90% [30].

The relationship between the methods changes as the number of samples in the observation window increases (Figure 6). The methods based on normality testing provide a shift of the 90% P_d threshold even by 1 dB towards weaker signals, and for the 80% P_d, even by 3 dB compared to energy-based solutions. Moreover, for longer observation windows, due to the reduction of uncertainty in noise measurements, the short windows method becomes less relevant and behaves similarly to conventional energy detection.

In the case of both small and large numbers of samples, the developed Gaussianity test is superior to both groups of methods. The superiority of the method results from combining the features of both groups. The distribution test is performed on energy samples obtained in short, overlapping windows, resulting from the use of a moving average. Although the proposed fit test is simple, i.e., it analyzes the spread of samples between the tails and the center of the distribution, it ensures satisfactory results and makes the test independent of changes in noise variance. The proposed method provides a profit comparable to the short window method for small observation windows, and significantly exceeds the other methods (by 4-5 dB) for long observation windows, when considering a 90% P_d. A noticeable, negative feature of the tested method is the observable, rapid decrease in efficiency for very low SNRs. In the case of the developed test, simplicity comes at a cost of obtaining the expected Gaussian distribution by the use of a small moving average. This results in intended noise averaging but also unfavorable averaging of very weak signals.

A separate analysis is required for those ROC curves which, through the slope of the $P_d(P_f)$ characteristic, show sensitivity of P_d to inaccuracies in the threshold γ determining P_f. It is of particular importance in CFAR scenarios, where, e.g., for DTV systems, the required P_f should be fixed at 10% [30]. For curves with a greater slope, error in threshold estimation results in a greater reduction of P_d. In both cases, the methods based on distribution analysis (which also include the proposed method) show lower susceptibility to changes in P_d due to fluctuations or mismatches of P_f. Although not very noticeable for short windows (Figure 4), the difference in the flattening of the curves becomes apparent for longer observation windows (Figure 7). Moreover, the proposed Gaussianity test appears to be the solution least prone to threshold mismatch.

A key factor in intermittent transmission is transmitter activity. In the study of the $P_d(\tau)$ characteristic, all methods show an increase in detection probability along with an increase in transmitter activity, and thus greater participation of signal-with-noise samples in the observation window. In this case, the proposed solution shows the highest detection gain for small channel occupancy. As signal participation increases, the profit over other solutions decreases. On the other hand, for short observation windows and high channel occupancy, methods based on classical GoF gain the most in detection efficiency (Figure 5). With longer observation windows, the difference between methods based on fit tests and methods based on energy detection becomes less noticeable (Figure 8).

The last analyzed characteristic is the probability of detection as a function of the observation window $P_d(N)$ (Figure 9). Once more, it can be seen that for short observation windows, although the differences are small, the proposed method provides the highest detection performance. The analysis of the shape of the curve slope shows that as the length of the window increases, the proposed test obtains an increase similar to the methods based on energy detection. However, the highest efficiency gains are recorded for methods based on classical normality tests.

V. CONCLUSION

The study presented in this paper reveals fundamentally different behavior of the analyzed groups of methods in the intermittent signal detection scenario. In the case of strong signals, the short window method, as low complexity, energy-based detection, performs at least as well as more advanced solutions. This predisposes the detection technique as the main method dedicated to intermittent transmission in time-critical applications and low-noise environments. In the case of weaker signals or longer observation windows, GoF-based methods exhibit better detection properties. At the same time, they show lower susceptibility to fluctuations in detection efficiency with inaccurate thresholding. The research proves that in modern telecommunications networks, which combines in discontinuous transmission noise-only and signal-with-noise samples, normality testing can be successfully used in detecting mixed distribution of even weak signals. Moreover, the developed Gaussianity test, evaluated in a real-data based, semi-experimental transmission scenario, appears to be a successful compromise between both groups of methods. Although more complex than energy-based detectors, provides good detectability for both strong and weak signals. It yields efficiency comparable to other methods for small observation windows and provides detection gain up to 5 dB for longer samples series. Furthermore, it remains less sensitive to thresholding errors than other GoF-based solutions and does not require the estimation of noise variance in changing environmental conditions.

REFERENCES

[1] F. Hu, B. Chen, and K. Zhu, "Full spectrum sharing in cognitive radio networks toward 5G: A survey," *IEEE Access*, vol. 6, pp. 15754–15776, 2018.

[2] A. Akhtar, F. Arif, and A. Siddique, "Spectrum decision framework to support cognitive radio based IoT in 5G," in *Cognitive Radio in 4G/5G Wireless Communication Systems*, S. Moghaddam, Ed. Rijeka, Croatia: IntechOpen, 2018, pp. 73–92.

[3] *Harmonised European Standard; Multiple-Gigabit/s Radio Equipment Operating in the 60 GHz Band; Harmonised Standard Covering the Essential Requirements of Article 3.2 of Directive 2014/53/EU, V.2.1.1 Ed.*, document ETSI EN 302 567, Jul. 2017.

[4] *Study on NR-Based Access to Unlicensed Spectrum*, document 3GPP TR 38.889, Technical Specification Group Radio Access Network, Jun. 2019.

[5] *Revised WID on NR-based Access to Unlicensed Spectrum*, document 3GPP RP-191575, Qualcomm, Jun. 2019.

[6] *Feasibility Study on Licensed-Assisted Access to Unlicensed Spectrum*, document 3GPP TR 36.889, Technical Specification Group Radio Access Network, Jun. 2015.

[7] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proc. IEEE*, vol. 55, no. 4, pp. 523–531, Apr. 1967.

[8] H. Jiang, S. Atapattu, and C. Tellambura, *Energy Detection for Spectrum Sensing in Cognitive Radio* (Conventional Energy Detector). New York, NY, USA: Springer, 2014.

[9] D. M. Martínez and Á. G. Andrade, "Adaptive energy detector for spectrum sensing in cognitive radio networks," *Comput. Electr. Eng.*, vol. 52, pp. 226–239, May 2016.

[10] M. C. Barela and J. S. Marciano, "An empirical study on the performance of a spectrum sensing scheme for cognitive radio," in *Proc. Int. Symp. Wireless Pers. Multimedia Commun. (WPMC)*, Sydney, NSW, Australia, Sep. 2014, pp. 474–479.

[11] S. Dikmese, P. C. Sofotasios, T. Ihalainen, M. Renfors, and M. Valkama, ''Efficient energy detection methods for spectrum sensing under non-flat spectral characteristics,'' *IEEE J. Sel. Areas Commun.*, vol. 33, no. 5, pp. 755–770, May 2015.

[12] S. MacDonald, D. C. Popescu, and O. Popescu, ''Analyzing the performance of spectrum sensing in cognitive radio systems with dynamic PU activity,'' *IEEE Commun. Lett.*, vol. 21, no. 9, pp. 2037–2040, Sep. 2017.

[13] F. Penna and R. Garello, ''Detection of discontinuous signals for cognitive radio applications,'' *IET Commun.*, vol. 5, no. 10, pp. 1453–1461, Jul. 2011.

[14] W. K. Saad, M. Ismail, R. Nordin, and A. A. El-Saleh, ''Spectrum sensing schemes for dynamic primary user signal under AWGN and Rayleigh fading channels,'' *J. Commun.*, vol. 11, no. 3, pp. 231–241, 2016.

[15] T. Duzenli and O. Akay, ''A new method of spectrum sensing in cognitive radio for dynamic and randomly modelled primary users,'' *IETE J. Res.*, pp. 1–9, Jun. 2019.

[16] Y. Arjoune and N. Kaabouch, ''A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions,'' *Sensors*, vol. 19, no. 1, pp. 1–32, 2019.

[17] B. Aneja, K. Sharma, and A. Rana, ''Spectrum sensing techniques for a cognitive radio network,'' in *Advances in System Optimization and Control*. Singapore: Springer, 2019, pp. 133–144.

[18] D. Lemons, *An Introduction to Stochastic Processes in Physics*. Baltimore, MD, USA: Johns Hopkins Univ. Press, 2002, p. 34.

[19] J. Ameijeiras-Alonso, R. M. Crujeiras, and A. Rodríguez-Casal, ''Mode testing, critical bandwidth and excess mass,'' *Test*, vol. 28, no. 3, pp. 900–919, Sep. 2019.

[20] J. Nikonowicz and M. Jessa, ''A novel method of blind signal detection using the distribution of the bin values of the power spectrum density and the moving average,'' *Digit. Signal Process.*, vol. 66, pp. 18–28, Jul. 2017.

[21] H. Oh and H. Nam, ''Energy detection scheme in the presence of burst signals,'' *IEEE Signal Process. Lett.*, vol. 26, no. 4, pp. 582–586, Apr. 2019.

[22] C. F. de, J. Rocha, W. Lopes, and M. Alencar, ''A spectrum sensing algorithm based on statistic tests for cognitive networks subject to fading,'' in *Proc. 22nd Eur. Signal Process. Conf. (EUSIPCO)*, Lisbon, Portugal, 2014, pp. 850–854.

[23] A. Subekti, N. Rachmana, S. Sugihartono, A. B. Suksmono, ''A blind spectrum sensing for cognitive radio based on Jarque-Bera normality test,'' *Int. J. Electr. Eng. Informat.*, vol. 8, no. 2, pp. 402–412, Jun. 2016.

[24] D. Reddy and Y. Ravinder, ''Novel receiver diversity combining methods for spectrum sensing using meta-analytic approach based on P-values,'' *J. Eng. Sci. Technol.*, vol. 13, no. 9, pp. 2883–2897, 2018.

[25] A. Subekti, N. R. Syambas, A. B. Suksmono, ''A HOS-based blind spectrum sensing in noise uncertainty,'' *J. ICT Res. Appl.*, vol. 9, no. 1, pp. 20–38, Jun. 2015.

[26] R. Bozovic and M. Simic, ''Spectrum sensing based on higher order cumulants and kurtosis statistics tests in cognitive radio,'' *Radioengineering*, vol. 27, no. 2, pp. 464–472, Jun. 2019.

[27] V. Orlic and M. Dukic, ''Automatic modulation classification algorithm using higher-order cumulants under real-world channel conditions,'' *IEEE Commun. Lett.*, vol. 13, no. 12, pp. 917–919, Dec. 2009.

[28] *Contribution 22-07-0359-00-0000*, IEEE Standard 802.22-07/0359r1, 2007.

[29] (2017). *Specifications USRP-2900 Software Defined Radio Device*. National Instruments. Accessed: Nov. 6, 2019. [Online]. Available: http://www.ni.com/pdf/manuals/374924c.pdf

[30] S. Shellhammer, ''Spectrum sensing in IEEE 802.22,'' in *Proc. IAPR Workshop Cogn. Inf. Process.*, Santorini, Greece, 2008, pp. 9–10.

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