Performance of the LAD Spectrum Sensing Method in Measured Noise at Frequency Ranges between 10 MHz and 39 GHz

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***Abstract*—Spectrum sensing is a low-complex and interesting way to find unused white spaces for secondary users transmission in cognitive radio. Because radio frequencies are strategic resource, their reallocation is required to ensure enough capacity for future communication devices. In addition to commonly used frequencies, millimetric waves have been proposed to be used for communication to fulfill upcoming needs. Because of broad operating area, adaptive spectrum sensing methods are needed to manage in different noise environments. For that reason, noise measurements were performed at several frequency areas between 10 MHz and 39 GHz. The goal was to study the noise properties in different frequency areas. Statistical properties of measured noise areas were analyzed and compared also with theoretically generated noise. The results show that histograms, PSDs and CDFs are almost equal. However, it was noticed that there is a huge difference between the noise levels, so sensing method that adaptively sets the detection threshold is required. The localization algorithm based on the double-thresholding (LAD) method was used as a blind and adaptive sensing method. The LAD method is based on the assumption that the noise is Gaussian. The probability of detection and false alarm were studied. It was shown that the LAD method operates well in all studied frequency areas.**

Keywords–noise measurement, cognitive radio, spectrum sensing, millimetric waves.

I. Introduction

In the modern information society, radio spectrum is a basic and essential element. The demand of more frequencies because of developing communications requires effective and improved resource allocation as well as novel way of thinking. More capacity is required, so existing frequency bands should be used more efficiently. One possibility is to utilize cognitive radio systems (CRS) [1][2][3][4]. In CRS, secondary (S) users can temporarily use unused white spaces aka holes in time/frequency domain where primary (P) users are non-active. In addition, more band is required. Future solution for wider frequency band demand is to use higher frequencies like millimetric waves, i.e., bands from 10 GHz-70 GHz. However, those bands require a lot of investigation and possible whole new technologies.

In CRS, unused white spaces in the spectra can be found using spectrum sensing. Even though there are also other techniques as databases, sensing is very attractive because it can be done blindly and easily. Even though the Federal Communication Commission (FCC) has decided that sensing is not required defining TV white spaces [5], sensing has a future, for example, in other frequency areas and in wireless local area network (WLAN)-type solutions when the distances between the transmitter and receiver are short and transmit power are small. In addition, public safety applications when infrastructure is down and there is no connection to databases, sensing may be needed.

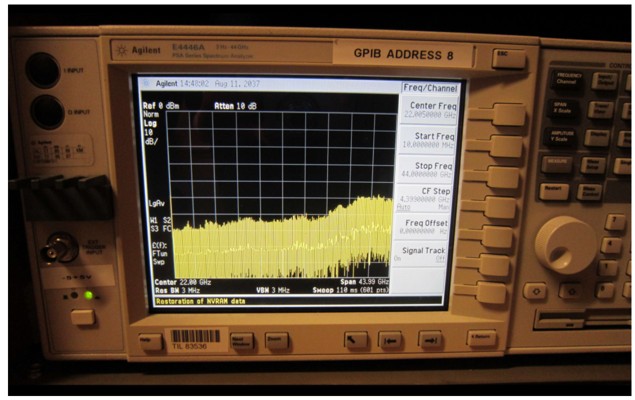

Figure 1: Agilent E4446A spectrum analyzer.

Spectrum use measurements are very important to characterize white spaces for CRS. In many cases, these spectrum use measurement campaigns have used conventional spectrum analyzer as, for example, in [6][7]. The classification into signal and noise has been done with a non-adaptive single (power) threshold. The performance of this signal classification is decreased when the noise spectral density is not flat inside investigated frequency range. In some cases, radio frequency (RF) sensor has been used [8]. In the future, possible frequencies for CRS operation cover from megahertz to tens of gigahertz. The problem is that noise properties vary in different frequency areas. Thus, a critical issue to deal with that wide operating area is to adapt parameters in the different environments. Inside of broad operating frequency range there is a quite large variation in internal noise level of a conventional spectrum analyzer and an RF sensor. For example, in some sensor applications the aim is to get consistent group delay, which is a requirement for good Time Difference of Arrival (TDOA). The downside is that the noise floor inside of a receiver is not flat inside wide operating frequency range. In Fig. 1, the internal noise level of spectrum analyzer as a function of frequency is shown. It can be seen that there is

 ISBN: 978-1-61208-360-5

over 20 dB difference between the internal noise levels at low frequency compared to noise level at higher frequencies. It is also seen that there is some noise level fluctuation also inside of much narrower bandwidth. This noise fluctuation decreases the performance of sensing if this fluctuation is not taken into account.

In this paper, several 100 MHz noise measurements at broad spectrum range from 10 MHz to 39 GHz were performed and the characteristics of measured noise at different frequency areas were analyzed. Theoretically generated noise following Gaussian distribution was used as a point of comparison. Histogram, power spectral density (PSD) and cumulative distribution function (CDF) were studied. In addition, the blind and adaptive spectrum sensing method called the localization algorithm based on double-thresholding (LAD) method [9] was used to find signals present. The LAD method is based on the assumption that the noise is Gaussian, and it determines the noise level. Here, we studied how the LAD method is able to operate in all measured noise areas. Probability of detection and false alarm were studied for measured noise areas as well as for theoretically generated noise.

This paper is organized as follows. In Section II, the LAD method is presented. Section III presents measurement setup. Noise measurement results are presented in Section IV and conclusions are drawn in Section V.

II. The LAD method

The LAD method [9] uses two forward consecutive mean excision (FCME) thresholds [10]. The adaptive FCME algorithm calculates the detection thresholds using pre-determined threshold parameter that is calculated based on the distribution of the noise. It is assumed that the noise is white Gaussian process with the one-sided power spectral density N_0. Thus, the threshold parameter T_{CME} can be found solving [11] [12]

$$P_{FA,DES} = e^{-(T_{CME}M)} \sum_{i=0}^{M-1} \frac{1}{i!}(T_{CME}M)^i, \tag{1}$$

where $P_{FA,DES}$ is the desired false alarm probability like in constant false alarm rate (CFAR) systems at M element antenna array. Note that it does not depend on the variance [11]. Here, $M = 1$, so (1) reduces to $P_{FA,DES} = e^{-(T_{CME})}$, from which we get that

$$T_{CME} = -ln(P_{FA,DES}). \tag{2}$$

Let us assume that there are N samples x_i arranged into an ascending order from smallest to largest so that $x_1 < x_2 < \ldots < x_N$. Signal samples are found iteratively searching the smallest k, $k \geq round(0.1N)$ so that [12]

$$y_{k+1} \geq T_{CME} \sum_{i=1}^{k} y_i = T, \tag{3}$$

where $y_i = |x_i|^2$ (=energy). In the first iteration, $k = round(0.1N)$ so that $\sum_{i=1}^{k} y_i$ includes 10% of the smallest samples (so called initial set assumed to consist only noise samples). Now, energy of the noise samples y_i follow the central chi-square distribution with $2M = 2$ degrees of freedom. In general, the probability density function for the chi-squared distribution with r degrees of freedom is [11]

$$P_r(x) = \frac{x^{\frac{r}{2}-1} e^{\frac{-x}{2}}}{\Gamma(\frac{1}{2}r)2^{\frac{r}{2}}}, \tag{4}$$

where Γ is a gamma function. If (3) holds, y_{k+1} and values above that are decided to be from signal(s) and y_k and values below that are from the noise, i.e., the FCME algorithm estimates the noise level (Fig. 2). Thus, the samples have been divided into two sets using the threshold T:

$$y_1, \ldots, y_k \rightarrow \text{ noise samples}$$
$$y_{k+1}, \ldots, y_N \rightarrow \text{ signal samples}$$

Because of the initial set assumption, the FCME algorithm assumes that at least 10% of the samples are from the noise, so at most 90% of the samples can be from the signal(s). However, the less signal samples the better the FCME algorithm operates [13].

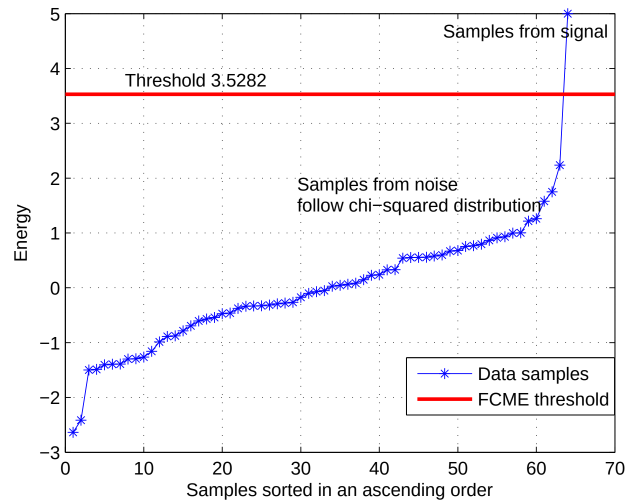

Figure 2: An example of the FCME algorithm. Impulsive signal, noise and FCME threshold. $N = 64$ samples.

The LAD method [9][13] calculates two FCME thresholds using two different threshold parameters T_{CME}. After that, all the adjacent samples above the *lower* threshold are grouped together to form a group G_i, $i = 1, \ldots, h$, where $h < N$. If at least one sample of each group G_i exceeds also the *upper* threshold, the group is accepted to be from the signal. If not, the group is from the noise and rejected. The number of accepted groups is $l \leq h$. The computational complexity of the FCME and LAD methods is of the order of $N \log_2 N$ [14]. An example of the LAD method is presented at Fig. 3.

III. Measurement Setup

In the noise measurements, we used high-performance spectrum analyzer (Agilent E4446A) [15]. The input signal was downconverted and digitized with 14 bit analog to digital

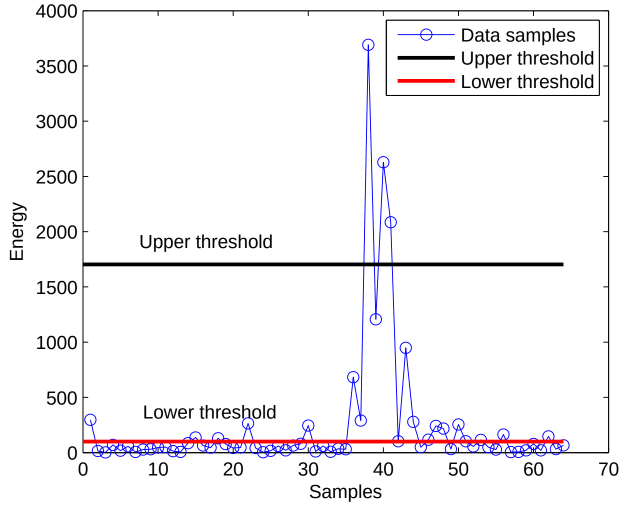

Figure 3: An example of the LAD method. BPSK signal with SNR=5 dB and BW=10%, noise and LAD thresholds. $N = 64$ samples.

converter (ADC). All the signal processing was performed digitally. Spectrum analyzer was connected to a computer. Instrument Control Toolbox was used to connect Matlab to the spectrum analyzer. This enabled direct results analysis. Six measurements at six different frequency areas were performed from 10 MHz to 39 GHz. Considered frequency ranges were 10-110 MHz, 1-1.1 GHz, 2.5-2.6 GHz, 9-9.1 GHz, 17-17.1 GHz and 39-39.1 GHz. The parameters are presented at Table I. There were 1601 frequency points and 1 000 or 10 000 sweeps in time domain. Energy of the samples was measured, i.e., $|x_i|^2$. The internal noise level of spectrum analyzer was measured in two ways. In the first way, internal noise level was measured when the 50 ohm wideband load was connected to the input of the spectrum analyzer (cases a-d). In the second way, broadband antenna was connected to the input. In this way, noise level is caused by the analyzer internal noise and noise coming from the antenna (cases e and f).

IV. Noise Measurement Results

Results were analyzed using Matlab simulation software. The purpose was to study the statistical properties of noise in different frequency areas, and performance of the LAD method in the presence of measured noise. As a point of comparison, theoretical zero mean Gaussian distributed noise generated from Matlab simulation software was used. Matlab-generated noise was used because Matlab is widely used in the computer simulations, and the performance of the LAD method has already been studied in the presence of Matlab-generated noise. In this way, these measurement results are directly comparable to the earlier results. Energy of those samples was considered, so the used Matlab-generated noise followed chi-squared distribution. Because of the different scales between the measured and simulated energies, energies were normalized.

TABLE I: Measurement parameters. In all cases there were 1601 frequency data points.

Case	Frequency Range	Bandwidth	Sweeps	Antenna
a	$10 - 110$ MHz	100 MHz	10 000	No
b	$1 - 1.1$ GHz	100 MHz	10 000	No
c	$17 - 17.1$ GHz	100 MHz	10 000	No
d	$39 - 39.1$ GHz	100 MHz	1 000	No
e	$2.5 - 2.6$ GHz	100 MHz	1 000	Yes
f	$9 - 9.1$ GHz	100 MHz	1 000	Yes

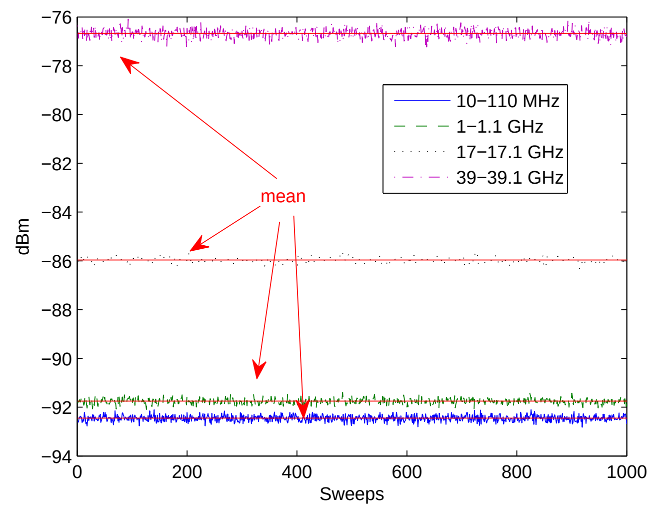

Figure 4: Measured noise energy at different sweeps at different frequency areas.

A. Noise level

From Fig. 4 can be seen that the measured noise levels [dBm] vary a lot at different frequency levels. For example, there is about 15 dB difference between 10-110 MHz and 39-39.1 GHz areas. Thus, adaptive method that is able to estimate the noise level is required when operating at different frequency areas. Instead, methods that use fixed thresholds are not able to operate in all frequency areas without measuring the noise level and defining used threshold based on that information.

B. Histogram

Figs. 5 – 8 present the elements of data into 10 bars that are equally spaced. Number of elements in each container is presented. Cases a, d and e are presented. Therein, the number of elements in each bar is presented. This describes the distribution of energies. Number of time domain sweeps is in y-axis. In Fig. 5, Matlab-generated chi-square distributed noise is used as a reference. For example, first bar consists of about 950 of total 1000 samples. It can be seen that the shapes of histograms are almost equal, so the energies are almost equally-type distributed.

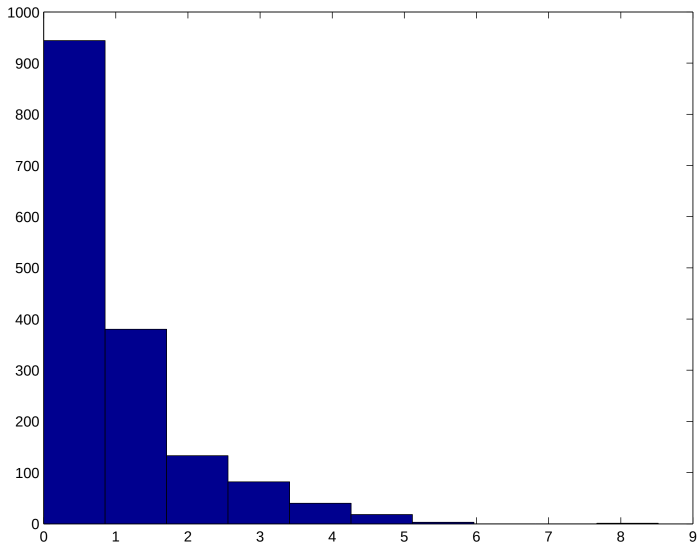

Figure 5: Histogram for Matlab noise.

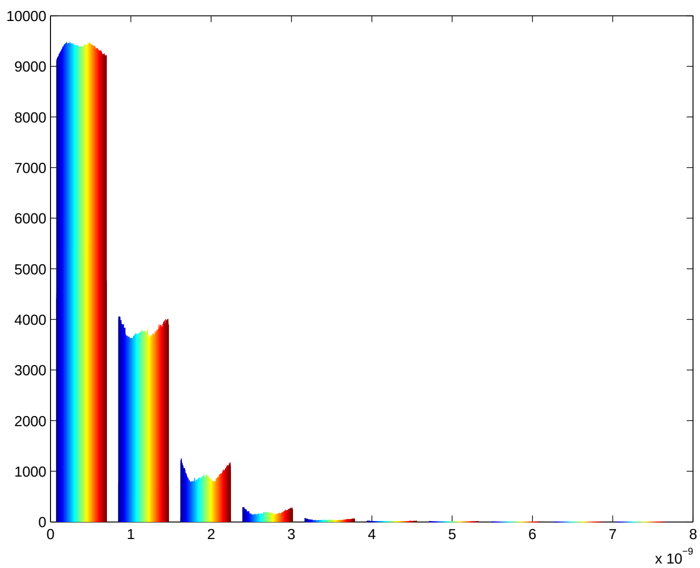

Figure 6: Histogram for 10-110 MHz noise.

C. Probability plot and CDF

The performance of the LAD method depend on the distribution of the noise. In the definition of the LAD method it is assumed that the noise is Gaussian, so variable $|x|^2$ (=energy of samples) follows the chi-squared distribution. Here, it is studied how well the measured noise follows that same distribution, i.e., is there differences between the simulated and measured noise. Fig. 9 presents the probability plots and Fig. 10 presents a plot of the cumulative distribution function (CDF) for the data in the vector x. Empirical CDF (=$F(x)$) can be defined as the proportion of x values less than, or equal, to x. Matlab-generated chi-squared noise was used as a point of comparison. From Figs. 9 and 10 can be seen that there is no differences between the probabilities and CDFs between the measured cases a-f and the Matlab-generated noise.

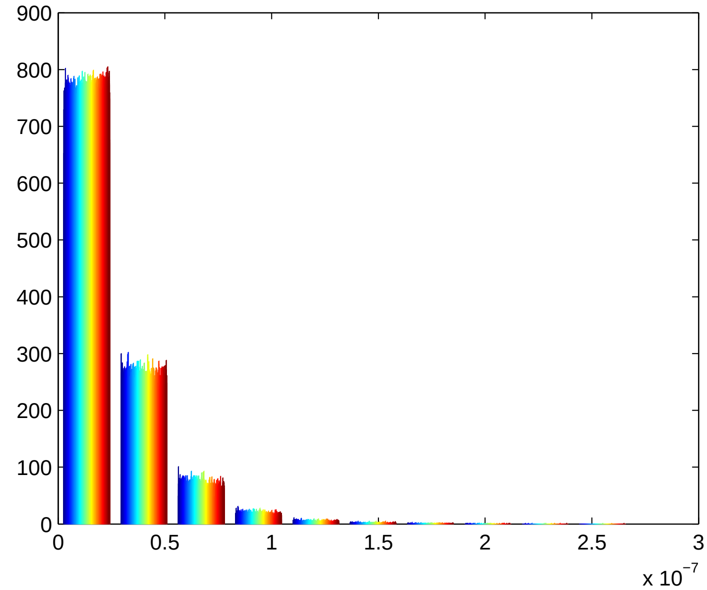

Figure 7: Histogram for 39-39.1 GHz noise.

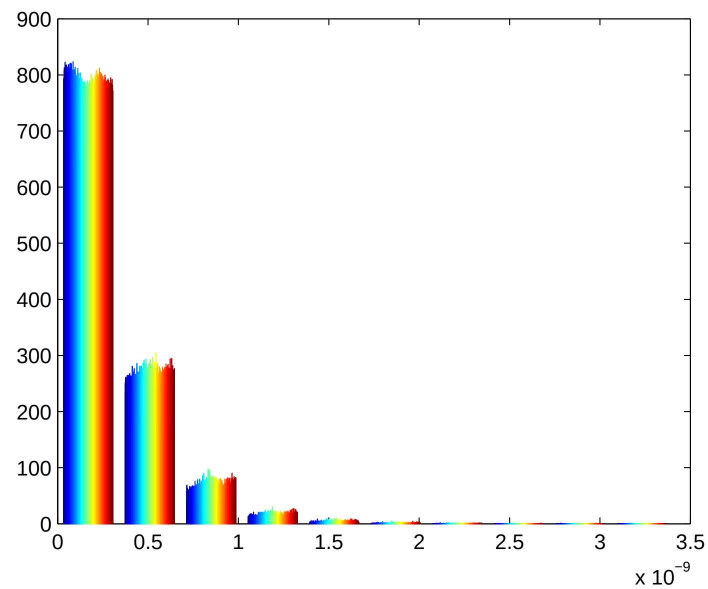

Figure 8: Histogram for 2.5-2.6 GHz noise.

D. Analysis

In this section, the goal is to investigate how the noise at difference frequency areas affect to the probability of detection P_d and probability of false alarm P_{fa} of the LAD method. Also here, Matlab-generated noise is used as a reference. The goal is

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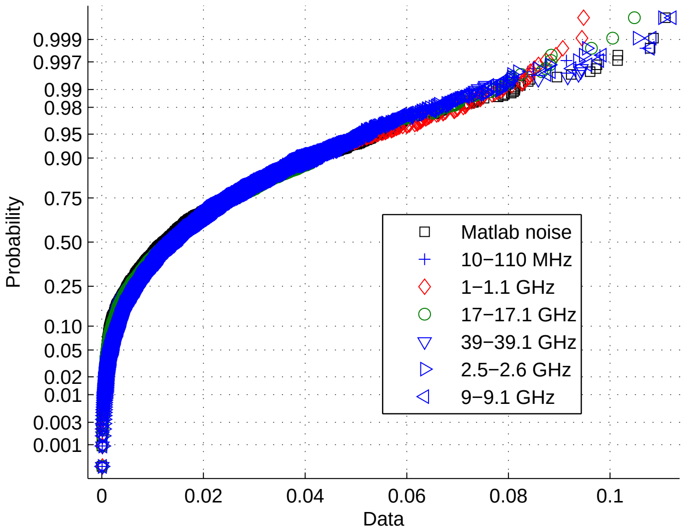

Figure 9: Probability plots for Matlab noise and cases a-f.

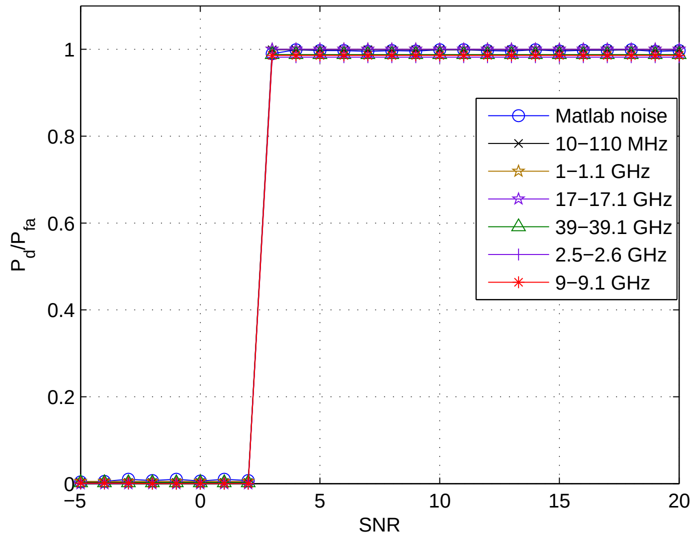

Figure 11: Probability of detecting the signal vs. SNR.

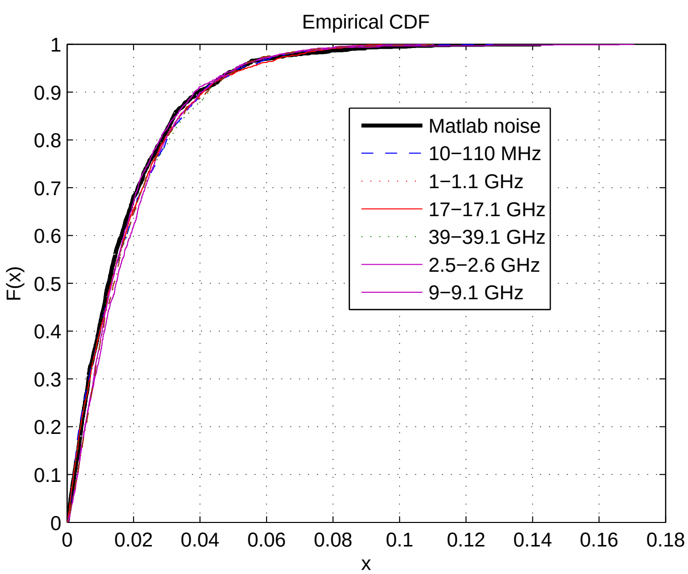

Figure 10: CDF plots for Matlab noise and cases a-f.

not to study the performance of the LAD method, which has already been done, see, for example, [16] and references therein. Here, the purpose is to find out does the measured noise cause any performance degradation compared to Matlab-generated noise. In Fig. 11, P_d vs. SNR is presented. Narrowband (0.3% of the studied bandwidth) theoretical information signal was used as a detected signal. The used LAD threshold parameters were 6.9 (upper) and 2.66 (lower) [16]. It can be noticed that P_d values are approximately on the same level. Note that using smaller upper threshold parameter, signal is found at 0 dB, but there will be more falsely detected signals.

TABLE II: Achieved P_{fa} values. Desired $P_{FA,DES} = 0.01$

Case	Frequency Range	P_{fa}
Matlab noise	-	0.0132
a	$10 - 110$ MHz	0.0064
b	$1 - 1.1$ GHz	0.0062
c	$17 - 17.1$ GHz	0.0061
d	$39 - 39.1$ GHz	0.0072
e	$2.5 - 2.6$ GHz	0.0070
f	$9 - 9.1$ GHz	0.0070

Probability of false alarm results are presented in Table II in the noise-only case. The LAD thresholds were selected so that the desired false alarm probability $P_{FA,DES} = 0.01$, i.e., the upper and lower threshold parameters were 4.6. It means that when there is only noise present, $0.01 = 1\%$ of the samples is above the threshold. Here, 1% corresponds to 16 samples. There is some difference between the desired noise $P_{FA,DES}$ and measured noise P_{fa} values, that is, the measured ones are slightly lower than the desired one. However, the difference is only about 0.003, i.e., 5 samples out of a total of 1601 samples. Performance differences are mainly caused by implementation restrictions of hardware. Noise properties in the analog part of spectrum analyzer may slightly vary in different frequency ranges. In addition, quantization noise affects to the noise properties.

V. Conclusion

Noise measurements were performed at several frequency areas between 10 MHz and 39 GHz. The goal was to study the statistical properties of measured noise in different frequency areas. The measurement results depend on the used equipment. Measured noise characteristics were analyzed and compared also with Matlab-generated noise. It was noticed that as the probability plots were almost equal, there was a great

 ISBN: 978-1-61208-360-5

difference between the noise levels. Thus, adaptive spectrum sensing is needed. The LAD spectrum sensing method that is based on the assumption that the noise is Gaussian was studied under the measured noise. It was noticed that the noise had only small effect to the probability of detection and probability of false alarm.

ACKNOWLEDGMENT

The research of Johanna Vartiainen was funded by the Academy of Finland.

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 ISBN: 978-1-61208-360-5