Autocorrelation Average Based Sensing Technique for Cognitive Radio Networks

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***Abstract*—The increasing sophistication in the technological requirements of modern life has created intractable problems in controlling and managing the limited sources of frequency bands. While all modern wireless systems mainly propose to reconsider novel methods of exploiting these frequencies. Cognitive radio network techniques required both spectrum sensing and dynamic spectrum access to solve the problem of resources management. Where, the spectrum sensing aspect provide all information about the utilization stat of frequency bands. The secondary users get actions according to this information by adopting the Dynamic Spectrum Access (DSA). Those unlicensed users get the permission to use the frequency bands of primary/licensed users when it was free. This approaches had many difficulties citing the unpredictable communication conditions first, and secondly, the amount of damage caused by any wrong sensing detection. This paper presents the detection capabilities using a novel idea based on the signal correlation proprieties. This novel technique use the average of the three first correlation lags as a statistic parameter. Starting by presenting the optimized detector parameters and its efficiency in simulation environments. Ultimately, the practical implementation serves to validate the detection capabilities of the technique within an authentic FM Radio broadcasting setting. This involves utilizing the Register Transfer-Level Software Defined Radio (RTL-SDR) dongle to capture the FM signal, while leveraging the GNU Radio software platform to both showcase the efficacy of the technique and highlight its limitations.**

***Index Terms*—Spectrum sensing, Cognitive radio networks, Radio Spectrum, Correlation function**

I. INTRODUCTION

Recent statistical data reveals significant congestion in frequency utilization, prompting scientific investigation into strategies for managing frequency resources. Cognitive Radio (CR), introduced by [7], addresses spectrum scarcity through Spectrum Sensing (SS) and Dynamic Spectrum Access (DSA), enabling secondary users (SUs) to opportunistically reuse unoccupied bands. Various spectrum sensing techniques exist, yet none fully overcome real-world limitations. Energy detection, highlighted by [3] proves efficient for narrowband sensing. It compares received signal power against a threshold to identify primary user signals. Despite simplicity, susceptibility to low Signal-to-Noise Ratio (SNR) drives exploration of alternatives. Methods comparing signal statistics with established knowledge offer efficacy, but with higher complexity. Matched filters [6] and cyclostationary techniques [11] use signal pattern databases, while [2] suggest autocorrelation for weak signal detection. [8] propose an autocorrelation-based statistic using Lag_1 and Lag_0 values. Similarly, Sharma et al. [10] advocate the sum of the first two autocorrelation lags. Correlation Sum (CorrSum) outperforms other techniques. Reyes et al. [9] explore autocorrelation-based sensing, comparing correlation detection, Euclidean distance, and energy detection for cognitive radio networks. The authors in [4] suggest utilizing the variance of autocorrelation coefficients as a statistical parameter, demonstrating its strong performance in spectrum sensing. Despite the array of solutions available, they fall short since Dynamic Spectrum Access (DSA) requires the utilization of a spectrum sensing technique that can operate effectively in practical real-world implementations for both narrow and wideband channels, even in the absence of prior knowledge, and yield commendable performance outcomes.

In practice, multiple sensing parameters are employed to evaluate the robustness of each detector. Notably, the probability of detection is a pivotal metric reflecting a detector's capabilities, often assessed through analysis of Signal-to-Noise Ratio (SNR) variations to elucidate sensing limitations. Another crucial parameter is the probability of false alarm, representing unnecessary frequency band consumption when the detector is utilized. Instances of false alarm declarations treat a channel as occupied, even if it remains available. Conversely, the probability of miss detection pertains to misclassifying an occupied channel as vacant, potentially leading to communication interference and operational disruptions between licensed and unlicensed users.

The wish list and the desired enhancements encompassed a range of anticipated features, notably a streamlined version of the spectral detection system to aid practical real-time implementation. The primary aspiration was to achieve a notably high detection probability, coupled with an acceptable false alarm probability, ensuring the dependable administration of spectral resources and preventing undesirable interference between licensed and non-licensed users. In our research, we suggest utilizing specific correlation characteristics of received signals as statistical measures. Notably, autocorrelation values tend to quickly converge to zero when noise is present,

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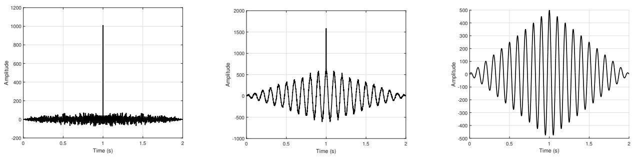

(a) (b) (c)

Fig. 1: Autocorrelation function of the noise signal (a) and a noisy signal (b) and a periodic signal (c)

whereas this trend is more gradual in other scenarios. Incorporating these insights, calculating the average of the first three lags results in a more pronounced distinction between scenarios involving noise and those with a noisy signal. Typically, beyond the fourth lag, the discrepancies in magnitude between lag values become more consistently aligned. The aim of this approach is to assess a novel, straightforward, and blind technique that can achieve a prominent position among conventional spectrum sensing methods.

The remainder of this paper is organized by detailing the following sections. The technique proposed system model is explained in Section II. Section III provides an exposition of the technique, encompassing its principles and the modeling of its detection methodology. The characterization of the correlation average sensing technique and its subsequent evaluation through simulation are expounded in Section IV. Utilizing a Software-Defined Radio (SDR) implementation on the GNU Radio platform, practical sensing outcomes are detailed in Section V. Concluding remarks are furnished in Section VI.

II. System model

In wireless communication systems the received signal X(n) always has some noise components W (n). In addition, the sensing technique procedure is used to detect the primary user signal S (n) presence or absence. All that makes the spectrum sensing process shortened as the following binary hypotheses test:

$$\begin{array}{lll} \mathrm{H}_0 & : & X\left(n\right) = W\left(n\right) \\ \mathrm{H}_1 & : & X\left(n\right) = S\left(n\right) + W\left(n\right) \end{array} \quad (1)$$

Where H_0 hypothesis means absence of the PU signal, and the inverse H_1 assumed that the PU signal is present. In this paper the PU signal is supposed M-PSK or M-QAM modulated signal in simulations and the noise is supposed Gaussian. However, in implementation, the received signal is a real received FM broadcasting signal undefined noise nature.

The detector principles based on comparing the statistic parameter T to a chosen threshold λ to differentiate between cases of PU signal presence or absence. The detector sets its outputs H_1 to 1 and fixes H_0 at 0 when the statistic parameter is greater than the threshold. However, in the opposite cases the parameters H1 and H0 are respectively fixed to 0 and 1, as it is mentioned in the following equation:

$$\left\{ \begin{array}{lllc} T & > & \lambda & H_0 \\ T & < & \lambda & H_1 \end{array} \right. \quad (2)$$

TABLE I: NUMERICAL SIMULATION PARAMETERS AND RESULTS.

Parameters	Values
Number of samples	1000
Sampling frequency	8000
Noise signal	$N\left(t\right) \sim \mathcal{N}(0,1)$
Periodic signal	$cos\left(100\pi t\right)$
Time domain	$\frac{1}{Fs}\left(1:1:1000\right)$
Statistic parameter T of the two first lags	0.89 periodic signal 0.61 noise
Statistic parameter T of the three first lags	**0.81** periodic signal **0.48** noise
Statistic parameter T of the four first lags	0.73 periodic signal 0.42 noise
Statistic parameter T of the five first lags	0.67 periodic signal 0.37 noise

$\mathcal{N}(\mu, \sigma^2)$ is a Gaussian distribution with μ mean and the variance σ^2.

III. Autocorrelation average sensing process

The autocorrelation is a continuous function represented by the integration of the product between a signal and its time-shifted version. The time instances at which the correlation function is evaluated are referred to as lags. Analyzing these lags provides deeper insights into the signal's behavior, revealing the degree of independence between the signal and its temporally shifted counterpart. At the origin, the autocorrelation function achieves its maximum value, which is equivalent to the signal's energy. Mathematically, for a continuous-time signal $x(t)$, the autocorrelation function at the origin $R(0)$ is expressed as follows:

$$R(0) = \int_{-\infty}^{\infty} x(t) \cdot x(t)\, dt = \text{Energy of the signal}$$

The maximum value of the autocorrelation function experiences rapid decline in the presence of noise signals, and a more gradual decrease for correlated signals or signals with noise interference. This intriguing variation has prompted researchers to explore leveraging these distinctive patterns to differentiate between noise and other types of signals.

Consider Figure 1, which portrays three distinct simulation scenarios. Figure 1a showcases an instance of an uncorrelated signal (Additive Gaussian White Noise - AGWN signal). On the other hand, Figures 1b and 1c illustrate the autocorrelation function of a signal with noise interference and a periodic signal, respectively (correlated signals). The figure visually demonstrates the slower convergence of the autocorrelation function to zero for periodic signals, and its notably faster convergence for noisy signals. Conversely, for noise signals, the autocorrelation values swiftly approach zero. Table 1 provides a concise overview of simulation parameters and the corresponding statistical parameter values for each of these scenarios.

Table 1 resumes many simulation parameters and outline some interesting statistical indices. The table values are illustrated from the autocorrelation functions presented the figure 1. This figure plots the three different simulation cases. Table 1 presents two main ideas. The effectiveness of utilization of the average of the three first lags as statistic parameter first, then a simple comparison between some statistical parameters to mention the purposes of limiting the average in the three first lags only. Generally, as much the difference between statistic parameter of the noise and the other cases is increased, the operation of choosing of the required threshold be easy.

Upon reviewing the contents of this table, the detection factors prominently demonstrate the innate sensing capabilities embedded within the proposed autocorrelation average-based sensing approach. In practical scenarios, the focal points regarding sensing capabilities frequently center on the straight-forwardness of the sensing algorithm and the feasibility of its implementation. These attributes collectively position this proposed method at a higher vantage point relative to all currently existing narrowband sensing techniques.

For instance, when utilizing solely the initial three lags for statistical computation, the most notable disparity between noise and periodic signal instances becomes apparent, resulting in reduced computational load. Taking these insights into account, a suitable threshold can be established within the range of 0.6 to 0.7 for the specified statistical parameter presented in the folowing equation:

$$T = \frac{\mathrm{lag}_0 + \ \mathrm{lag}_1 + \ \mathrm{lag}_2}{3\ \mathrm{lag}_0} \tag{3}$$

IV. Technique Characterization and Evaluation Results

In order to define the techniques characteristics and to evaluate its performances. Many simulations have been realized using MATLAB platform [1]. At first, the proposed technique was tested to outline the effect of variation of both the threshold and the number of sample on the P_{fa} values. This operation was stimulated to mention the appropriate P_{fa} target value according to these parameters. Secondly, the proposed technique was evaluated to guess its efficiency compared to those of the reference sensing techniques in two different environments. The first environment is when the treated signal is a 4-QAM modulated signal. However, the second one is when the received signal is an 8-PSK modulated signal.

Figure 2 illustrates the initial impact of the chosen threshold on the target values of P_{fa}. It is evident that an inverse correlation exists between these two parameters. As the threshold increases, the probability of false alarm diminishes. A stable phase of P_{fa} values emerges at 0.5, highlighting the constancy in these values despite fluctuations in the threshold selection. This stability underscores the efficacy of leveraging such statistical parameters, effectively discerning noise cases from noisy signals. The persistent stability of P_{fa} values at 0.5 indicates a substantial gap between the two distinct states, a crucial requirement for accurate differentiation. This gap serves as a safety margin to prevent high false alarm probabilities arising from incorrect threshold choices. Furthermore, the simulation reveals the influence of varying the number of processed points on both the optimal threshold and the probability of false alarm. Notably, an increase in the number of processed points reduces the range of impact that the selected threshold has on the target P_{fa}. The number of treated samples significantly affects sensing characteristics. As the number of processed samples rises, so does both the complexity of the technique and the sensing time, rendering the technique less feasible for implementation. In this study, we set the number of samples to 1000 and determined an optimal threshold value of 0.7. These selections ensure processing time aligns with network system requirements, where the desired probability of false alarm (P_{fa}) is maintained below 5%, the maximum acceptable value within network systems.

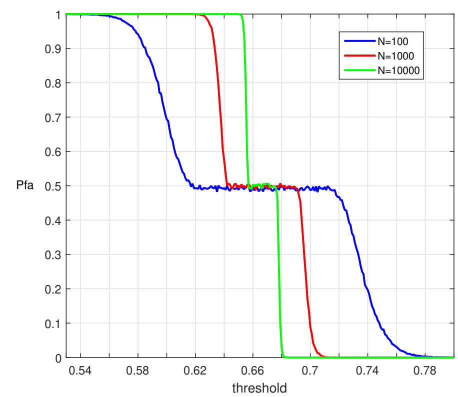

Fig. 2: The P_{fa} versus the selected threshold and for different number of samples in case of an 8-PSK modulated signal

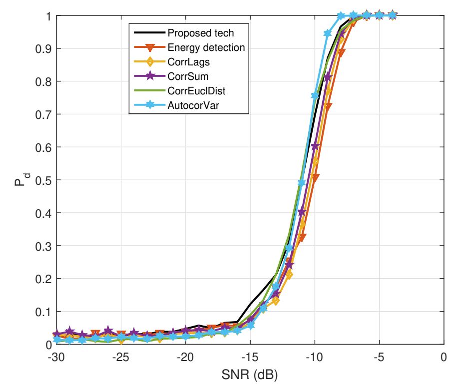

Fig. 3: The P_d versus SNR in case of a 4-QAM modulated signal when $P_{fa} = 0.01$.

Figure 3 illustrates a comparison among various sensing techniques' probability of detection (P_d) with respect to Signal-to-Noise Ratio (SNR) variation, while keeping P_{fa} fixed at 0.01 and the number of samples at 1000. The effectiveness of the proposed method is contrasted with energy detection, correlation at lag_1, the Correlation Sum (lag_0 and lag_1, CorrSum), and the technique based on the variance of the autocorrelation coefficients (AutocorVar). The figure initially highlights the stability of the proposed autocorrelation-based sensing detection through the convergence of P_d to the target P_{fa} value under extremely low SNR conditions.

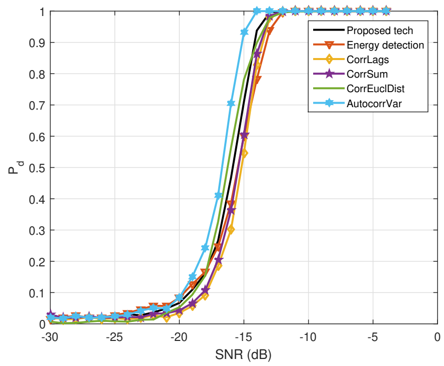

Fig. 4: The P_d versus SNR in case of a 8-PSK modulated signal when $P_{fa} = 0.01$.

Fig. 5: The practical experiment test-bed .

Figure 3 further emphasizes the superior detection capability of the proposed technique compared to all reference methods, with the exception of the technique based on the variance of autocorrelation function coefficients. This superiority is especially pronounced for the 4-QAM modulated signal. Importantly, across all communication system-required P_d values ($P_d \geq 0.9$), the SNR values corresponding to the proposed method consistently remain 1 dB lower than those associated with energy detection – a straightforward and extensively-used narrowband sensing approach.

Figure 4 illustrates the comparison between the probabilities of detection of the proposed method and those of the reference techniques as the signal-to-noise ratio (SNR) varies. The figure demonstrates that with increasing SNR, the detection probability (P_d) also increases. Furthermore, the figure highlights the superior detection performance of the autocorrelation average sensing technique compared to energy detection, correlation lags detection, and correlation sum-based sensing techniques. As an example, for all P_d values greater than or equal to 90%, the corresponding SNR values for the proposed method and energy detection are -14 dB and -13 dB, respectively, resulting in a detection improvement of 1 dB. Nevertheless, the AutocorVar approach exhibits the highest detection probability (P_d) when contrasted with all of these sensing methodologies. It is important to acknowledge that this method calculates a second-order statistical parameter derived from another second-order process, specifically the autocorrelation function.

V. Results and Evaluations

This section provides the practice evaluation of the GNU Radio implementation of the proposed autocorrelation average based sensing technique. Where this method is implemented the radio FM broadcasting receiver and another floor for estimating the SNR.

A. *Experimental test-bed setup*

To validate the practical efficiency of the technique, experiments were conducted using a laptop equipped with the GNU Radio platform, along with an RTL-SDR dongle serving as a wireless receiver. The implementation of the SDR test-bed was designed to evaluate the technique's sensing capabilities in real-world scenarios [5]. Figure 5 illustrates the configuration of the experimental setup for the proposed SDR test-bed. Leveraging the capabilities of the GNU Radio platform, wireless communication networks can be simulated and designed to closely resemble real systems. Additionally, the flexibility of the GNU Radio platform allows for the integration of various hardware components, including the RTL-SDR dongle, which is utilized in this implementation as an FM broadcasting receiver [12]. The RTL-SDR receiver was consistently tuned to a central frequency, providing coverage of the entire FM bandwidth ranging from 88 MHz to 108 MHz.

The system's implementation is structured across three tiers, as illustrated in Figure 6. The initial tier encompasses the reception and processing of radio broadcast signals, culminating in audio output via the loudspeaker (Audio Sink block). This stage also facilitates the adjustment of the central reception frequency of the RTL-SDR device, while enabling signal categorization into radio broadcast channel signals, radio broadcast side signals, or noise.

The second tier is dedicated to the sensing process, involving signal reception from the RTL-SDR dongle and subsequent processing through the sensing block (correlation avrlag block). The sensing block computes the average of the first three lags of the autocorrelation function for each 1000-sample set. This computed statistical parameter is then compared to a predefined threshold, yielding three outputs: the statistical parameter (lags mean), the threshold value, and the decision (1 or -1) denoting the presence or absence of a primary user signal.

Finally, the third tier focuses on estimating the signal-to-noise ratio (SNR), primarily utilizing the MPSK SNR Estimator block from the GNU Radio library. This stage aids in the analysis of detection results obtained through the proposed method. Notably, the presence of high-energy received signals does not guarantee accuracy, as these signals could originate from distortions. Conversely, low-energy received signals might exhibit high SNR values due to minimal interference.

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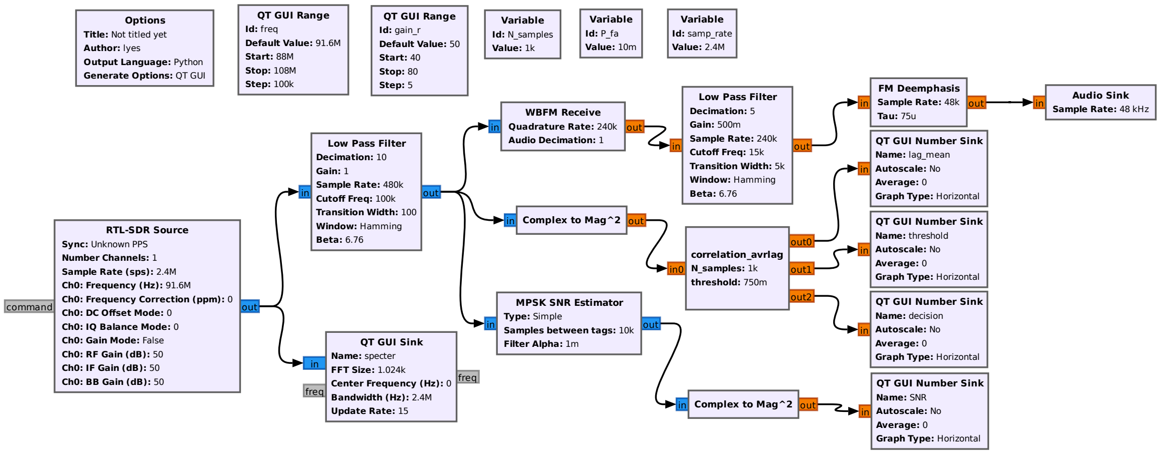
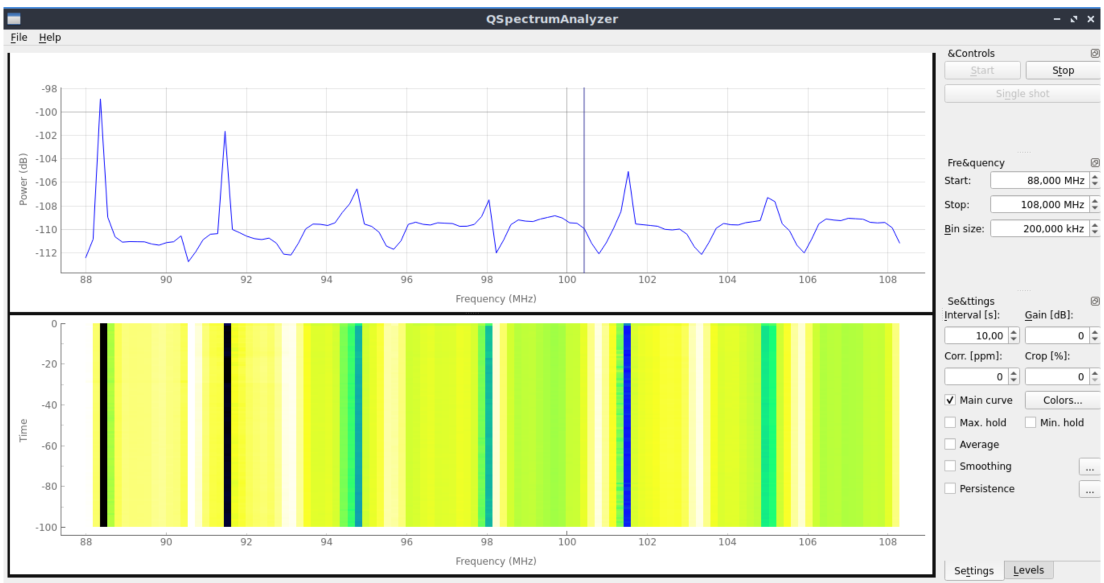
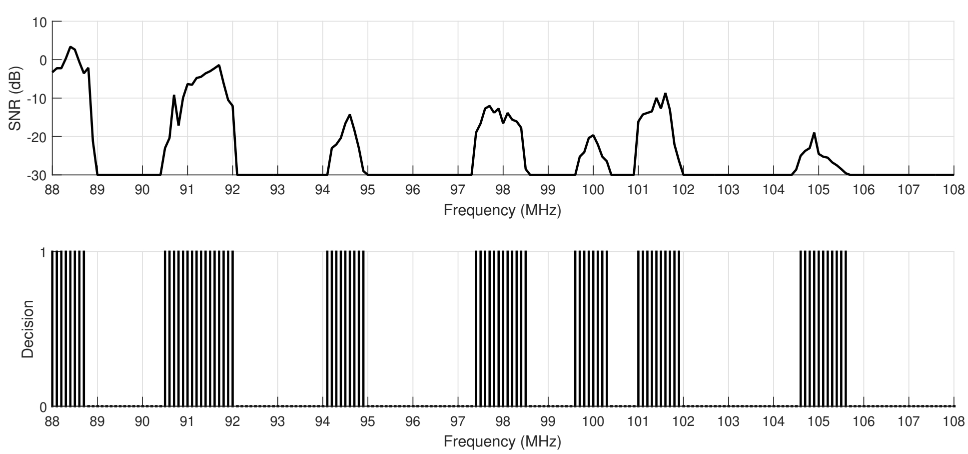


Fig. 6: GNU Radio flow-graph of the proposed autocorrelation average based sensing technique with the FM Receiver [4]



(a) The power spectrum density representation



(b) Sensing results

Fig. 7: The power spectrum density representation of the Radio FM broadcasting and the sensing decision for each FM channel

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B. Practical results analysis

Figure 7 provides a comprehensive overview of the experimental results, encompassing Radio FM band spectrum scanning and analysis, SNR estimation, and practical sensing decisions. Subfigure 7a visually represents the energy intensity of received signals across the entire Radio FM spectrum, enabling the identification of varying energy levels within 200 KHz-wide FM channels.

Subfigure 7b comprises two significant curves. The first curve illustrates the signal-to-noise ratio (SNR) across all channels, determined through the MPSK SNR Estimator block. SNR values below -30 dB are capped at -30 dB, highlighting the characteristics of received signals and differentiating high-energy distortions from medium-to-low energy signals with comparatively higher SNR values. The second curve highlights practical sensing decisions, with a (1) denoting the presence of FM broadcasting in the respective channel, and a (0) indicating an unoccupied channel. This analysis reinforces the effectiveness of the correlation average-based sensing technique in detecting FM broadcasting activity.

While Subfigure 7a might suggest occupancy in only 6 frequency bands initially, a more detailed scrutiny of the SNR curve reveals the existence of 7 distinct frequency bands. These findings correlate with the detection outcomes of the proposed method. Notably, FM broadcasting activity around 100 MHz is less prominent in Subfigure 7a due to low received energy signals. However, this activity becomes evident in the curves of Subfigure 7b, despite the relatively weak SNR in this range. The audibility of this false broadcast activity from the loudspeaker (Audio Sink block) on the first tier further validates its presence.

VI. Conclusion

In this paper, a novel approach to spectrum sensing was presented, utilizing the average of the initial three autocorrelation lags. The aim was to tackle the issue of spectrum sensing limitations. The technique underwent preliminary simulations to both assess its sensing capacity and recognize its potential constraints. The simulation outcomes underscored the technique's exceptional detection proficiency, particularly in scenarios characterized by low Signal-to-Noise Ratio (SNR), outperforming various benchmark sensing techniques. However, it was worth noting that a notable limitation of this method lied in formulating the mathematical relationships required to establish an appropriate threshold, ensuring an acceptable level of probability of false alarm.

Furthermore, the simulations affirmed the superiority of the proposed approach by 1 dB compared to energy detection, both in environments involving (8-PSK) modulation and 4-QAM modulated received signals. Concluding the investigation, the implementation of the autocorrelation average-based sensing technique was demonstrated using the GNU Radio platform and the RTL-SDR dongle. The implementation underscored the simplicity of the technique and its efficient capability, as evidenced by the minimal sensing time required to detect rapid variations in radio FM broadcasting signals.

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