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Abstract—Spectrum underutilization has made cognitive radio a promising technology both for current and future telecommunications. This is due to the ability to exploit the unused spectrum in the bands dedicated to other wireless communication systems, and thus, increase their occupancy. The essential function, which allows the cognitive radio device to perceive the occupancy of the spectrum, is spectrum sensing. In this paper, the performance of modern adaptations of the four most widely used spectrum sensing techniques namely, energy detection (ED), cyclostationary feature detection (CSFD), matched filter (MF) and eigenvalues-based detection (EBD) is compared. The implementation has been accomplished through the PlutoSDR hardware platform and the GNU Radio software package in very low Signal-to-Noise Ratio (SNR) conditions. The optimal detection performance of the examined methods in a realistic implementation-oriented model is found for the common relevant parameters (number of observed samples, sensing time and required probability of false alarm).

Keywords—Cognitive radio, dynamic spectrum access, GNU Radio, spectrum sensing.

I. INTRODUCTION

In the past decade, the number of applications which use Cognitive Radio (CR) has increased. The technology is being exploited to provide a method of using the spectrum more efficiently. That makes the area of spectrum sensing increasingly important and key to those applications. This requires that the overall system operates effectively and provides the required improvement in spectrum efficiency. The CR spectrum sensing system must be able to detect and identify any other transmissions and to inform the central processing unit within the CR so that the appropriate action can be taken.

The detection of Primary Users (PU) is performed based on the received signal at CR users. This approach includes methods, such as energy based detection [1], cyclostationary based detection [2], [3], matched filter based detection [4], eigenvalues-based detection [5], whose purpose is to detect the presence or absence of primary transmitter.

Kumar et al. [1] present some approaches for the energy detection technique and investigate the effect of different threshold selection methods on the spectrum sensing performance parameters. Banjade et al. [6] propose some approximations for performance of the energy detector, although offering computational ease, but not accurate for small sample sizes. In their work, Murty et al. [2] propose a cyclostationary based spectrum detection algorithm for Orthogonal-Frequency Division Multiplexing (OFDM) signals. The proposed architecture is hardware implemented in Field-Programmable Gate Array (FPGA) platform and its functionality and performance are verified with respect to conventional ones. Blad et al. [7] also consider spectrum sensing of OFDM signals and propose modifications to some state-of-the-art detectors, which are implemented using GNU Radio and USRP, and evaluated over a physical radio channel. Tani et al. focus on a low-complexity cyclostationary spectrum sensing of cognitive heterogeneous LTE-A network where the eNB represents the primary system. The third method, based on the matched filter technique, is characterized by a static sensing threshold. However, the noise is random, and [4] suggest a dynamic sensing threshold approach to increase the efficiency of the sensing detection. The eigenvalue-based method overcomes the highly vulnerable under noise uncertainty energy-based detection method, but the performance deteriorates at low SNR. To solve this problem, the optimum number of samples, the theoretical analysis and numerical formula for given SNR are proposed in [5]. The optimal threshold minimizes the total error rate over a WGN channel and [8], based upon the optimal threshold theory, propose dynamic threshold scheme to reduce average total error rate for local CR node with applied energy detector.

The majority of spectrum sensing research works is performed theoretically and verified via computer simulations [9], [10]. Sardana and Vohra [10] evaluated the two important parameters for the channel sensing performance of energy detection, cyclostationary detection and matched filter. This analysis reports the detection probability and the false alarm probability. In [9], only the performance of energy detector and matched filter are compared, which is a common and well established practice. There have also been many practical realizations of CR systems [7], [11], [12] with a different range of scientific contributions but they are much fewer in comparison to the works which present solutions verified only via simulations.

The rest of the paper is organized as follows. Section
II describes the common description of the PU signal and noise used in all of the experiments in this study, and the models of the four detectors. Then, Section III introduces the hardware platform and the software used for the implementation. The setting and conditions of the experiments are explained in Section IV. Section V discusses the results of the measurements in terms of detection performance for the examined algorithms. Finally, the conclusions of this study are given in Section VI.

II. SYSTEM MODEL AND PRIMARY USER SIGNAL DETECTION

The premise which is described in this section will be applied for all detection algorithms examined in this study. It consists of a PU which has to be detected and a secondary user (SU) which needs to determine whether the PU’s signal is present in the frequency band in question or not. They are both located in close proximity to one another as the scenario is relevant to indoor cellular networks or Internet of Things (IoT) system deployments. The signal of the PU is defined as an OFDM modulated data flow which is described as a Gaussian process and so is the noise. Due to the problem studied here, being detection of the PU signal, the input $y(k)$ of the receiver can be characterized in the following way:

$$y(k) = \begin{cases} n(k), & H_0 \\ s(k) + n(k), & H_1, \end{cases}$$

where $n(k)$ representing the noise with zero mean and variance $\sigma^2_n$, and $s(k)$ - the signal of the PU with zero mean and variance $\sigma^2_s$. There are, thus, only two possibilities for the content of the information received by the detector - hypothesis $H_0$ which signifies that the PU is absent from the band, and $H_1$ where the signal is present and needs to be detected accurately despite of it being corrupted by noise and channel imperfections. It is required by each detection algorithm to identify the presence of the PU with a sufficient probability $P_d$ while, at the same time, guaranteeing a desired probability of false alarm $P_{fa}$ which describes the likelihood of the detector perceiving that the signal is present in the spectrum when in reality, it is not. The probability of detection secures the transmission of the PUs from harmful interference while a low probability of false alarm guarantees a desired probability of false alarm $P_{fa}$.

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The performance of the detector is determined through the widely-used equation for $P_d$ [14], [15] which is applicable due to the PU signal and noise following a Gaussian distribution and the number of samples being more than a few hundred [1], [14], [15].

B. Cyclostationary Detection

This type of detector extends the capabilities of the spectrum sensing function by allowing better detection in low SNR and fading for much lower number of samples than the energy detection [3], [11], [12]. The algorithm utilizes the presence of characteristic cyclostationary features in the communications signals. Noise is differentiated from the PU signal by examining whether the test statistic includes these features or not. Their main advantage is that they remain present even if the noise level is much higher than that of the signal. The test statistic $T(y)$ chosen for the following comparison uses the Cyclic Autocorrelation Function (CAF) of the Single Cycle Detector with Sliding Correlation (SCD-SC) proposed in [3] due to its decreased computational complexity:

$$T(y) = \left| \overline{R_y}^{\alpha} (\tau) \right|^2$$

where $\overline{R_y}^{\alpha}$ is the CAF of the received signal $y$ which is examined for the two features of the PU signal – the cyclic frequency $\alpha$ and time lag $\tau$ [16]. $N$ is the number of observed samples and $M$ is the quantity of samples which are contained in the sliding window. The decision threshold for this cyclostationary detector is [3]:

$$\lambda = -\frac{2\sigma^4_n \ln (P_{fa})}{NM}.$$
\[ P_d \] [3]:
\[ P_d = \int_{\min(h)}^{\max(h)} Q_0 \left( \frac{2f}{\nu_f}, \sqrt{\frac{h^2}{\nu_f}} \right) e^{-\frac{h^2}{\mu}} dh^2, \]  
\[ \nu_f = \frac{\sigma^2_f + \sigma^2_h^2}{\sqrt{MN}}; \quad \gamma_f = \left| \hat{R}_y \right|^2 h^2. \]  

The integral is defined within the lowest and highest values of the channel estimation vector \( h \) and \( \mu \) is the mean of its distribution, \( Q_0(\cdot) \) being the Marcum Q function of first order [17] which can be computed using the algorithm proposed in [18].

\[ C. \text{ Eigenvalue-Based Detection} \]

In this case, further accuracy and robustness to noise is sought by exploring a more complex mathematical derivation of the test statistic [5]. It is expressed by the ratio of the maximum \( \gamma_{\text{max}} \) and minimum \( \gamma_{\text{min}} \) eigenvalue of the covariance matrix \( R_Y \) formed by performing the following operations. First, the vector of \( N \) received samples is split into \( L \) (\( L \) is the smoothing factor) equal parts and a matrix \( Y \) with shape \( L \times N_L \) is formed, where \( N_L = \frac{1}{L} \). Finally, \( R_Y \) is obtained [11]:
\[ R_Y = \frac{1}{N_L} Y Y^*. \]  

The threshold \( \lambda \) is defined as [5], [11]:
\[ \lambda = \frac{\chi^2}{\delta^2} \left( 1 + \frac{\chi^{-2/3}}{(N N_L)^{1/6}} F_2^{-1} (1 - P_f) \right), \]  
\[ \chi = (\sqrt{N_L} + \sqrt{NN_L}), \quad \delta = (\sqrt{N_L} - \sqrt{NN_L}) \]  
\[ F_2^{-1}(\cdot) \] is the inverse Tracy-Widom distribution of second order [19] which is used in the case of complex samples as it is in this study. To determine the performance of the EBD, the expression for \( P_d \) derived in [5] is used:
\[ P_d = 1 - F_2 (\kappa), \]  
where
\[ \kappa = \frac{N}{\sigma^2} \left( \lambda \gamma_{\text{min}}(R_n(N_L)) + \lambda \rho_{\text{min}} - \rho_{\text{max}} \right) - \psi \]
\[ \psi = (\sqrt{N_L} - 1 + \sqrt{L})^2, \]
\[ \phi = (\sqrt{N_L} - 1 + \sqrt{L}) \left( \frac{1}{\sqrt{N_L} - 1 + \sqrt{L}} \right)^{1/3}. \]

The parameters \( \gamma_{\text{min}}(R_n(N_L)), \rho_{\text{min}} \) and \( \rho_{\text{max}} \) are the minimum eigenvalue of the covariance matrix of the noise, the minimum and maximum eigenvalues of the covariance matrix of the PU signal. They are all computed in the same way as the covariance matrix of the received samples and its eigenvalues (\( \gamma_{\text{max}} \) and \( \gamma_{\text{min}} \)). \( F_2(\cdot) \) is the Tracy-Widom distribution of second order which is calculated using tabular data found in [20]. As taken from [5], \( L \) is set to 5.

\[ D. \text{ Matched Filter Detection} \]

The detector based on the MF is characterized by achieving optimal performance in case the probability density function (PDF) of the PU signal is known (as it is in the present study) [21]. That is due to the use of specific information about the signal which needs to be identified. This is the main disadvantage of the MF. The information is usually in the form of the pilot signal \( x_p \). Thus, the test statistic and the decision threshold have the form [4], [21]:
\[ T(y) = \sum_{k=0}^{N-1} y(k) x_p^*(k) \]
\[ \lambda = Q^{-1}(P_f) \sqrt{E \sigma_n^2}, \]  
where \( E \) is the energy of the PU pilot signal and \( Q^{-1}(\cdot) \) is the inverse Q-function defined as \( Q^{-1}(u) = \sqrt{2} \text{erfc}^{-1}(2u) \), \( \text{erfc}^{-1} \) being the inverse complimentary error function. The probability of detection which characterizes the efficiency of the algorithm is [4], [21]:
\[ P_d = Q \left( \frac{\lambda - E}{\sqrt{E \sigma_n^2}} \right), \]  
where \( Q(.) \) is the Q-function which is expressed as
\[ Q(u) = \frac{1}{\sqrt{2\pi}} \int_u^{\infty} e^{-\frac{v^2}{2}} dv. \]

III. MEASUREMENT EQUIPMENT AND SOFTWARE

For the purpose of our experiment, the GNU Radio software development toolkit and two ADALM-PLUTO Software-Defined Radios (SDRs) were used. GNU Radio provides signal processing blocks to implement SDR and also contains the Companion, a graphical user interface similar to Simulink for creating signal flow graphs and generating flow-graph source code [22]. In our scenario, various blocks provided by GNU Radio are directly utilized in our Python source code without using the Companion.

The ADALM-PLUTO Active Learning Module (PlutoSDR) is based on Analog Devices AD9363, a Radio Frequency (RF) 2 x 2 transceiver with integrated 12-bit Digital-to-Analog Converters (DACs) and Analog-to-Digital Converters (ADCs), and on Xilinx Zynq Z-7010 FPGA. The SDR offers one receive channel and one transmit channel which can be operated in full duplex, capable of generating or measuring RF analog signals from 325 to 3800 MHz, at up to 61.44 Mega Samples per second (MS/s) with a 20 MHz bandwidth. The transmit power output is up to 7 dBm and the receive Noise Figure is rated at < 3.5 dB. The PlutoSDR is widely supported under various software suites, including GNU Radio, MATLAB, Simulink, libiio, and offers Application Programming Interfaces (APIs) for C, C++, C#, and Python [23].

In our setup, each of the PlutoSDR units was connected to a host computer using the USB 2.0 interface and communicated via Ethernet over USB, through which complex I/Q samples were carried. The host computers for the transmitter and receiver units were running 64-bit Linux operating systems – Debian Stretch and Ubuntu Xenial, respectively. The PlutoSDR units run embedded Linux. The two units we used are depicted in Fig. 1.
The experiment was conducted in an indoor environment (in the premise of a room, see Fig. 2) using two PlutoSDRs, one being the transmitter (Tx) and the other - the receiver (Rx) which implements the detectors. In this way, a realistic scenario is represented due to the non-line-of-sight (NLOS) conditions and Rayleigh fading. Transmission is implemented by setting an array of busy and idle periods of the transmitter. Thus, a realistic one being the transmitter (Tx) and the other - the receiver (in the premise of a room, see Fig. 2) using two PlutoSDRs, distribution are.

The samples drawn from these distributions are the values of the PU signal. To emulate a realistic transmitter, the samples utilized for it are limited to 3000. That is necessary because it is generalized. For the CSFD, the amount of time.

The optimality of the MF-based detector is proven. This distinction holds.
due to the definition of the PU OFDM signal model which allows for generalization and does not require demodulation and feature extraction from a pilot signal. The paper [4] which describes the model further solidifies this observation because it shows that for high number of samples (as it is in this case), the detector reaches excellent performance. When it comes to the CSFD, it is evident that despite of it operating in very limited number of samples as stated in the previous section, has achieved fair efficiency even though it is worse compared to the other three detectors. The ED has shown significant performance surpassing the CSFD and EBD for SNR over -30 dB. This can be attributed to the large number of samples which naturally increase the SNR over -30 dB. This can be attributed to the large number of samples which naturally increase the $P_d$. Finally, the EBD statistic shows that the computation of the eigenvalues of the covariance matrix allow high discrimination of the signal from the noise even in very low SNR levels. It is however, unable to reach optimal detection in this setting. It is evident that all detectors achieve at least 50% efficiency at even -50 dB which is due to their characteristics and the large number of samples obtained by the receiver for the chosen sensing period (500 ms).

VI. CONCLUSION

This paper has presented a study of the implementation and comparison of the effectiveness of four contemporary detection algorithms. The details of the experimental procedures have also been described. Out of the four detectors, only ED and MF achieved the performance of 90% probability of detection at SNR of -20 dB, required in the CR standard. This underlines the necessity of algorithms which allow simple signal processing which allows for more samples to be observed. Due to the non-uniformity of areas where the signal detectors need to be applied within IoT, any of the examined types of detectors can be utilized depending on what information about the PU signal is known at the SU device, and how much computational power this device possesses. The examination conducted reveals their agility and potency for practical experimentation.

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