# Adaptive Threshold Technique for Spectrum Sensing Cognitive Radios Under Gaussian Channel Estimation Errors

Syed Affif Raza Naqvi[1], Aamir Zeb Shaikh[2(✉)], Krishan Lal Khatri[2], Altaf Ahmed Mugheri[2], and Shabbir Ahmed[2]

[1] MS Computer Networking, Ryerson University, Toronto, Canada
affifraza93@gmail.com
[2] Department of Electronic Engineering, NED University of Engineering & Technology, Karachi, Pakistan
{aamirzeb,krishan.lal}@neduet.edu.pk, mugherialtaf@live.com, shabbir_umrani@yahoo.com

**Abstract.** Spectrum sensing helps cognitive wireless users to gather RF information regarding presence or absence of spectral holes. These spectral holes are not permanent in nature. These are exploited by cognitive users in secondary fashion in such a way that they do not create harmful interference for primary users (PU). Thus, on sudden arrival of a PU, secondary user must vacate those bands for PU because they are high priority users in comparison to cognitive users. The receiver circuit of cognitive radio estimates the received signal and noise parameters and computes a test statistic. This statistic is compared with a pre-set threshold. However, under realistic scenarios, wireless communication channels behave as time-varying entities. Hence, received signal as well as noise varies significantly. The variation in estimated receiver parameters results in deteriorated detection performance for fixed-threshold sensors. In this paper, it is assumed that there are Gaussian estimation errors in received signal. Under this case, an adaptive threshold based testing rule is applied to explore the performance of spectrum sensing radios under adaptive threshold rule. The results clearly recommend the use of proposed algorithm for received signal with Gaussian channel estimation errors. The results show that the proposed method significantly improves the detection performance of the considered cognitive radio i.e. for a false alarm rate of 0.1, the detection probability of the proposed system improves more than 3 times in comparison to the classic cognitive radio under Gaussian Channel estimation errors. The proposed technique can be utilized for future intelligent radios for 5G wireless networks.

**Keywords:** Adaptive spectrum sensing · Collaborative spectrum sensing Gaussian channel estimation errors

## 1 Introduction

Evolution of new wireless standards and services require additional bandwidth. However, RF spectrum is almost packed as it is reserved to different users on permanent basis. Hence, the new standards can look towards exploiting unlicensed RF


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bands. These bands include both ISM and UN-II. However, due to license-exempt nature of these bands, they are also overtly congested [1]. This apparently poses a great threat to execution of 5G services as well, with one of the prime motive to increase traffic quantity and quality [2]. The spectrum occupancy evaluations by many researchers in various parts of the world [3–7] report that more than 75% of the spectrum remains unutilized. This spectrum can be utilized in secondary fashion to produce virtual unlicensed bands [8]. This suggests one possible way to cater the bandwidth requirements of 5G users. The notion of using RF spectrum in secondary fashion is also supported by Federal Communications Commission (FCC) and also issued a notice to implement the idea through opportunistic secondary usage [9, 10].

The successful implementation of the proposed technology depends on gathering RF information about unused spectral bands and then using those identified bands in opportunistic fashion. The RF information can be shared by a secondary Base Station (BS) or Spectrum Sensing Detection. In the first method, secondary BS collects the information about available white spaces and transmits to secondary users. And in the latter case, all the cognitive sensors sense the spectrum in a distributed fashion. RF sensing can be performed by various algorithms, including coherent detector such as matched filter, cyclostationary feature, energy, autocorrelation, multi-taper spectral estimation method, radio-identification method, waveform transform based estimation, time-frequency analysis, Hough transform and covariance [11, 12]. Of these algorithms, energy detection based spectrum sensing is one of the widely used methods for the case when you do not have the exact knowledge of PU [13, 14]. This is a blind algorithm that requires only the noise variance to compute the probabilities of detection and false alarm. It works faster than coherent sensors (i.e. matched filter) that require complete knowledge of PU to compute detection results.

Conventional detectors used to compare test statistic with fixed value of threshold. However, realistic wireless channels result in significant variation of noise power. Hence, the performance of conventional detectors is highly compromised under low SNR [15]. Because, the threshold depends on various factors that include sensing time [16–18], transmission power of PU [18, 19], and target error probabilities i.e. false alarm and missed-detection [18].

To improve the detection performance under realistic variable-noise environments, many authors have recommended proposals to shift the attention to dynamic threshold setting in comparison to fixed threshold sensing. In [20], authors present an adaptive double threshold based spectrum sensing algorithm to improve detection performance. The decision region is divided into two regions. One that produces confirmed results of 1 and 0 and the other is marked as confused region. Through simulation results, it is shown that double threshold based detection outperforms the conventional energy spectrum detector as well as cooperative spectrum sensor. In [21], authors proposed a multi-threshold spectrum sensing scheme based on phototropism. It is shown that the proposed multi-threshold driven energy detection algorithm performs better than fixed-threshold energy detectors. In [22], authors proposed a three-threshold based energy detection algorithm. The performance of the proposed detector for cognitive radios is compared with conventional CFAR detector as well as adaptive double threshold detector that do not take the account of confused region of operation. In [23, 24], authors optimized the detection threshold of the spectrum sensing algorithms. In [25], authors propose adaptive threshold algorithm for multichannel cognitive radio and in [26] for wideband cognitive radio applications. Additionally, an excellent recursive estimator based spectrum sensor is utilized under cluttered environments to improve performance of the sensing equipment [27].

In this paper, we assume the cognitive sensor to result in sensing values of SNR with Gaussian channel estimation errors. The proposed model considered in this paper is introduced by [27]. We incorporate adaptive threshold based detection rule to improve the performance under estimation errors. The simulation results reveal that the proposed setup gives improved values of detection probability in comparison to the conventional methods.

The Rest of the paper is organized as follows: System model of the proposed setup is presented in Sect. 2 of the paper. Section 3 presents the performance evaluation of the proposed algorithm under IEEE standard for TV White Spaces. Section 4 presents the conclusion of the paper.

## 2 System Model

Consider, the spectrum sensing framework introduced by [27]. This setup includes the operation of a cognitive sensor under unlicensed RF band. The proposed setup includes one PU and k secondary users. These secondary users are located at the same distance from PU. It is assumed that the wireless channel between PU and sensing node is both fast and slow fading i.e. Rayleigh and Lognormal Shadowing [27]. Authors in [27] use fixed threshold based detection algorithm for detection of spectral holes. We incorporate adaptive detection threshold into the proposed framework and analyze its impact for the performance improvement of the sensing device.

Assuming, the received signal follows simple binary hypothesis i.e. $H_0$ representing occupied channel and $H_1$ representing spectral hole. Thus, CR user is only allowed to operate if the sensor results in $H_1$.

$$y(n) = \begin{cases} \eta(n); & H_1 \\ x(n) + \eta(n); & H_0 \end{cases} \tag{1}$$

In the above equation, $\eta(n)$ represents additive white Gaussian noise while x(n) represents the power transmission by PU. Under null hypothesis, the CR senses the presence of a PU, hence it avoids transmitting on the band, while under alternative hypothesis; it detects the presence white space, hence exploits the RF band in secondary fashion.

Using the derived results of [27], the probabilities of detection and false alarm can be given by

$$\mathrm{P_d} = \mathrm{Q}\left(\Delta\mu \cdot \frac{\sqrt{\mathrm{n}}}{\sqrt{\sigma^2 + \frac{100}{\mathrm{N}\,\ln^2 10}}} + \mathrm{Q}^{-1}(\mathrm{p_{fa}})\right) \tag{2}$$

$$P_{fa} = Q\left(\frac{\lambda - \sigma_n^2}{\sigma_n^2/\sqrt{N/2}}\right) \quad (3)$$

In the above equations, $\sigma_n^2$ represents the noise variance. Q(.) is the Gaussian Q function defined by (4)

$$Q(y) = \frac{1}{\sqrt{2\pi}}\int_y^{\infty} e^{-\frac{t^2}{2}}dt \quad (4)$$

$\Delta\mu$ in Eq. (2) represents the difference between the mean values of received signal samples under $H_1$ and $H_0$ hypotheses; n shows the number of samples. Under both hypotheses, the variance of signal is represented by $(\sigma^2 \sum + \frac{100}{N \ln^2 10} I)$ [27]. Where ln(.) represents the natural logarithm operation, $\sum$ represents the covariance matrix of **y** and **1** is the n × n identity matrix and the $\frac{100}{N \ln^2 10}$ is the Cramer-Rao Lower Bound (CRLB) [27, 28]. Equation (4) shows the Gaussian Q Function. Probability of miss detection is computed as $P_{md} = 1 - P_d$. The higher value of missed detection results in lower chances of exploiting the RF spectrum in secondary manner and higher values of false alarm results in producing harmful interference for PU activity. In the proposed setup it assumed that cognitive sensor periodically senses the noise variance of the channel and incorporates those values in computing threshold of detection. This feature enables the cognitive user to perform better in noise-varying environments. Additionally, based on the estimated data the sensor modifies the threshold ($\lambda$) for detection accordingly on periodic basis. Thus, under the proposed setup the detection performance of the sensor results in improved performance as compared to fixed threshold energy detection rule.

## 3 Performance Evaluation

The performance of the proposed spectrum sensing algorithm is presented in this section. We evaluate the performance of proposed adaptive threshold based collaborative spectrum sensing with Gaussian estimation errors. The proposed adaptive algorithm for spectrum sensing cognitive radios is simulated and analyzed under IEEE standard for TV white spaces i.e. IEEE 802.22. This standard provides useful data that can be incorporated by unlicensed users in broadcast bands for interference-free secondary transmissions. This standard opens up great opportunities for unlicensed wireless users to operate in license-exempt regime. Probability of false alarm is assumed to be 0.01, $\sigma$ = 2.5, N = 20 as presented by [27].

Figure 1 compares the performance of proposed adaptive threshold sensor with classic fixed detector under Gaussian channel estimation errors. Under fixed threshold energy detection rule, with false alarm rate of 0.1, the sensor results in 5% detection probability. However, adaptive detection threshold produces 25% detection probability. Similarly, for $P_{fa}$ = 0.4, fixed threshold scheme produces 15% detection probability and adaptive threshold rule produces 30%. This shows a consistently improved performance of proposed sensing scheme, producing double values of detection probability in

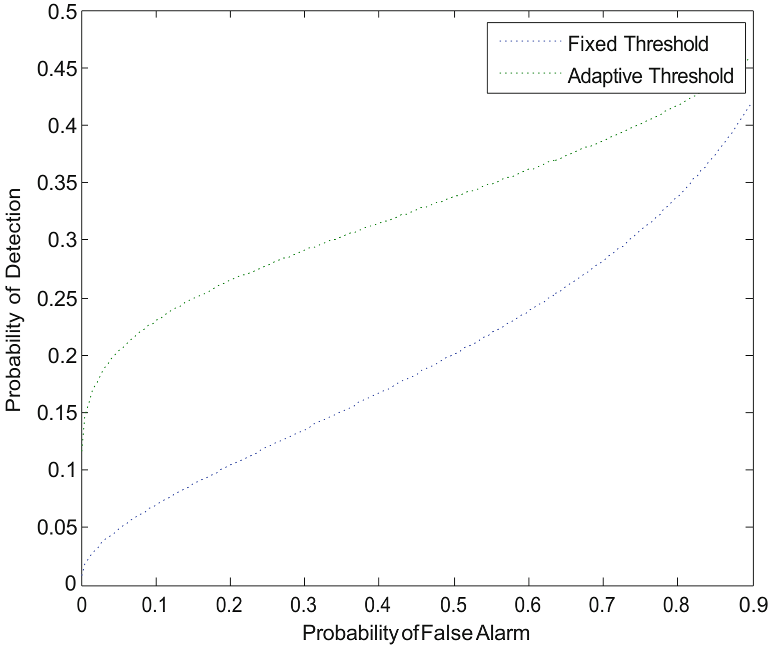


**Fig. 1.** ROC comparison between Adaptive and Fixed Threshold

comparison to fixed detection rule. This massive increase in detection probability will increase the chances of opportunistically exploiting the RF spectrum in secondary fashion.

## 4 Conclusion

Adaptive Threshold based detection rule is applied to a collaborative spectrum sensing algorithm with Gaussian channel estimation errors. This problem is incurred in a real wireless environment as compared to the perfect sensing results that is considered to be a theoretical or ideal sensing environment. The performance of the proposed algorithm shows a marked improvement over classical fixed threshold detection rule for sensing with Gaussian estimation errors. For a false alarm rate of 10%, the proposed technique performs more than 3 times better than the classic fixed threshold technique. The results are highly useful as the considered environment is IEEE standard for White Spaces. This environment allows the secondary unlicensed users to access the wireless spectrum in secondary fashion until they don't produce interference to the primary activity of the channel.

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