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Reciprocal Two Stages Spectrum Sensor to Overcome the Noise Uncertainty

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A B S T R A C T

Noise uncertainty is the most crucial issue that affects the cognitive radio spectrum sensing process. The majority of robust wideband spectrum sensing approaches employ a fixed threshold determined by the amount of noise. These sensing approaches are not accurate since the noise is unpredictable. In this work, a novel spectrum sensing framework was proposed that enhances the detection results in the noise uncertainty (NU) presence, and decreases its effect. The proposed framework consists of two different stages; each has a specific rule, the first one is wavelet denoising (WD), the second stage is an adaptive threshold energy detector (AED). The noise information we get in the first sensing process will be used to make the energy detector adapt its threshold in order to overcome the noise uncertainty. The proposed model's detection performance beats a variety of conventional and hybrid techniques in the presence of noise uncertainty. That of energy detector (ED) on its own, and also the previous two-stages spectrum sensing techniques. The suggested model improves detection performance in the noise uncertainty presence, as it can increase the detection probability to 94% instead of 69% for the static threshold energy detector at SNR= -10 dB, Pfa=0.1 and NU=1dB, according to simulation findings, and the main goal of this accomplished and assessed effort is to not raise the computational cost.

1. Introduction

Service providers deal with the radio spectrum as a valuable resource that makes it available for wireless communication. There are several parts of the spectrum. The licensed spectrum is underutilized, and there are always gaps and possibilities in the spectrum. A spectrum hole occurs when a frequency band is empty. CR is being used to use the white gaps and make optimal use of the spectrum. Secondary users (SUs) can use unoccupied holes in a CR system if they are not employed by the primary user (PUs). Because interacting with other users is prohibited, the essential job of CR is spectrum sensing. Spectrum sensing is employed to determine the spectrum's occupancy condition. [1,2,3].

Spectrum sensing is used to create a comprehensive map of the whole spectrum. This map is used to find empty holes. Frequency-domain estimates of the signals available are frequently used in spectrum sensing. In the spectrum sensing procedure, a frequency hopping method is used. Spectrum sensing enables the addition of new wireless communication services to previously unserved areas. Fading, shadowing, and

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uncertainty difficulties at the receiver are all variables that can influence the quality of the spectrum sensing process.[1]

Noise uncertainty and performance deterioration are two key issues in spectrum sensing; for example, the probability of false alarm PFA rises while the detection probability PD declines. Furthermore, with noise uncertainty, an energy detection with static threshold technique gives reduced performance. This suggests that the adaptive threshold would perform better in the existence of noise uncertainty. [1,4]

The main contribution of this paper is presenting a reciprocal two stages spectrum sensor to overcome the noise uncertainty in CR systems. The suggested model composed of two stages: WD and ED. It exchanges between them according to the state of the sensing, it is turned down to a one stage for the re-sensing process executed during use the PU empty channel. It also satisfies the desired detection and false alarm probabilities with increased detection precision, despite the noise uncertainty presence.

The remainder of the paper is laid out as follows. Sect. 2 depicts the problem's related work. Sect. 3 introduces the sensing scheme's system model, the suggested reciprocal spectrum sensing model, and all of the mathematical analyses performed. Section 4 contains simulation results for assessing the proposed model's performance. Finally, the paper's conclusion is presented in the last part.

2. RELATED WORK

The PU existence or absence over a spectrum band of concern may be determined using a variety of spectrum sensing techniques The ED is a basic and uncomplicated approach since it does not demand any prior knowledge of signal properties making it simple and straightforward to execute. The ED works by calculating the samples' energy and examining it to a threshold. The PU signal is active if the energy is greater than this threshold; else, it is silent. However, it is unable to differentiate between noise and signal samples, resulting in a significant level of uncertainty. Furthermore, at low SNR levels, it has a poor detection performance. Sahai and Cabric in [5] and a slew of other developers employed this in CR for spectrum detection, with a slew of efforts to improve the ED method's accuracy.

The threshold, that can be constant or adaptive, has a significant impact on sensing accuracy. [6,7,8]. Employing dynamic thresholds, various methods have been suggested to increase the ED's detection performance. For example, Haykin [6] used a constant-false-alarm-rate technique to determine the threshold, which is based on constraining the false alarm probability and then continuously changing the threshold level to optimize the chance of detection. Joshi et al [7] in the noise existence, a discrete-Fourier-transform (DFT) filter bank approach was presented to adaptively set the threshold that reduces the defect in spectrum sensing. Furthermore, Muralidharan et al [8] on the basis of an image binarization methodology, an adaptive-threshold sensing approach was presented. This technique adaptively predicts the threshold based on past decisions and other factors such as the desired false alarm and detection probabilities, the samples number and the SNR.

Softened Hard Decision and Wavelet Denoising for Improved Cooperative Spectrum Detection in CR-Networks was suggested by G. Padmavathi and S. Shanmugavel in 2014 [9]. On a wide-band power spectrum, improved edge sensing methods based on continuous WT (CWT) and discrete WT (DWT) methodologies are suggested by Abhishek Kumar in 2018 [10].

Various two-stage spectrum sensing strategies have been developed to address the limitations of the single-stage ED methodology. These approaches have several advantages over their single-stage counterparts, including increased detection probability, shorter sensing times, and encouraging performance in low SNR situations. The performance of CR may be dramatically enhanced by utilizing the advantages of two-stage spectrum sensing approaches. Yan Xin and Honghai Zhang [11] proposed a simplified sequenced spectrum sensing method in 2009. In cognitive radio networks, Konstantinos Plataniotis invented two-stage spectrum monitoring in 2010 [12]. Minny Bhola and Rinkoo Bhatia then proposed a two-stage spectrum detection for cognitive radio employing energy detection and cyclostationary detecting in 2012. [13] After that, the notion of covariance detection and energy detection was established by Min Jia, et al in 2015. [14].

Khobragade and Raut showed a composite spectrum sensing approach for cognitive radio in 2017, combining five distinct spectrum sensing methodologies to create a hybrid sensing system founded on the notion of Centralized Organization, with infrastructure installed specifically for CR users. [15]. In 2019, Mahua Bhowmik and Malathi proposed and demonstrated a hybrid strategy for energy efficient spectrum detection in cognitive radio using a neural network forecasting approach. [16]. Fawzi, A. et al in 2020, an adaptable two-stage spectrum detection approach based on energy detection and wavelet denoising has been developed [2]. Abdulsatar, S. M. et al in 2020, a new method to enhance the sensing is presented and implemented, in this scheme eigen-values are obtained from the sample covariance matrix of the signal that received at the secondary user's receivers. Random Matrix Theory (RMT) derives the expression of the thresholds required for effective sensing [18]. Subhajit, C. et al in 2020, to improve the performance an adaptive Genetic Algorithm is proposed where operators and parameters are adaptive to the changing conditions of the spectrum [19]. According to prior research, the various two-stage spectrum sensing algorithms have a significant computing complexity, significant sensing expenditures, medium detecting sensitivity, and weak performance under noise uncertainty environments.

In this paper and in consideration of the ongoing endeavor to optimize spectrum sensing performance in the presence of noise uncertainty, and in terms of achieving a higher detection probability with a low risk of false alarm, for spectrum detection, a new reciprocal sensing approach is presented. This proposed model offers a very good performance in the noise uncertainty presence with the minimal computational cost.

3. SYSTEM MODEL

3.1 Spectrum Sensing Model

The detector has evaluated the following hypothesis in order to conduct spectrum sensing: The primary user signal is absent in H0, leaving just noise at the receiver input; but, in H1, both the primary user signal and noise are present at the receiver input. Considering that the primary user signal's bandwidth B and center frequency fc are defined, Down converting and sampling the input signal at the rate of Nyquist, fs = 2B, is required. The following two hypotheses discrete time model are tested in order to define the detection decision process in general [17]:

$$H_0: g_1 = z[k], k=1, ..., n \qquad \textit{signal absent} \quad (1)$$

$$H_1: g_2 = s[k] + z[k], k=1, ..., n \qquad \textit{signal present} \quad (2)$$

where n samples indicate a duration of observation that equivalent to the time of sensing. Signal g[k] was received by the secondary user. Both the signal s[k] and noise z[k] samples are represented as Gaussian independent random variables with a mean equal zero and variance σ_s^2 andσ_z^2, respectively.

3.2 Energy Detector

Because of their minimal implementation complexity and fast performance, energy detector-based techniques, also termed as radiometry, are the spectrum sensing most prevalent technique. The traditional form of ED comprises of a Nyquist sampling A/D converter, followed by a Fourier transform Nf-FFT to turn the signal to the frequency domain. As a result, the PSD is estimated using the signal's squared and averaged values; after that, the sensor examines the PSD peak to a specified threshed expression. The decision statistic for the energy detector gathered energy throughout n samples [4-17]:

$$\varepsilon(g) = \sum_{m=1}^{n} g[m]^2. \qquad (2)$$

The conventional threshold of sensing λ can be obtained in terms of detection probability as:

$$\lambda = \sqrt{2N}(1+\gamma)(Q^{-1}(P_D) + \sqrt{\frac{N}{2}}), \qquad (4)$$

Or can be obtained in terms of false alarm probability as:

$$\lambda = \sigma_z^2.\left(Q^{-1}\left(P_{fa}\right)\sqrt{2N} + N\right) \tag{5}$$

where the received PU Signal-to-Noise-Ratio (SNR) is $\gamma = \sigma_s^2/\sigma_z^2$, The samples number N can be evaluated as N= 2t B, where B is the bandwidth of PU signal and t indicate the sensing time. P_D represents the detection probability, P_{fa} false alarm prob. and $Q^{-1}(\cdot)$ is the inverse of the Q-function which is complementary distribution function of the standard Gaussian

3.3 Wavelet Denoising Detector

For noise reduction, single-level WD is utilized since it is simple. In signal denoising applications, wavelet transformation is commonly used. The CR must always handle the sampled signal inside the authorized user's band. Energy sensing's goal is to determine whether H0 or H1 is correct by measuring the energy of the signal y, which is provided by Equation 3. A relatively short detection interval is required for energy sensing. Equations 1 and 2 simplify the system model as follows [9-10]:

$$g_1 = z(k), \tag{6}$$

$$g_2 = s + z(k). \tag{7}$$

The received signal's wavelet transform is expressed as follows:

$$[ay, dy] = Wg = W(s+z) = Ws + Wz \tag{8}$$

where W is the DWT's left invertible transformation matrix. In the wavelet transformation domain, the detail information dy includes the details that make up the majority of the noise power. The required signal may be recovered via the inverse wavelet transform with reduced noise effect while thresholding the detail information to improve the ED process.

3.4 Proposed Model

In this paper, considering the system model in Fig. 1, we investigate the proposed reciprocal model. The primary user signal is detected by a single non-cooperative secondary user, whereas the licensed band PU connection and the opportunistic spectrum SU link are the prime spectrum access links.

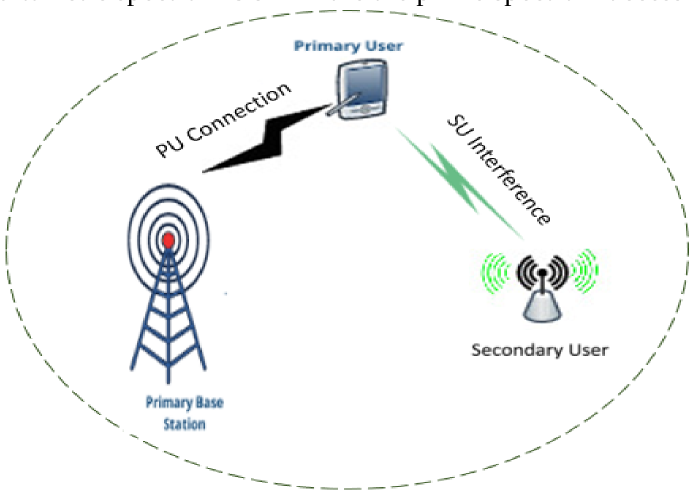

Fig.1. The proposed System Model.

The proposed frame work consists from two different stages, each has a certain rule, the first one is wavelet denoising, the second stage is an adaptive threshold energy detector, as shown in Fig. 2.

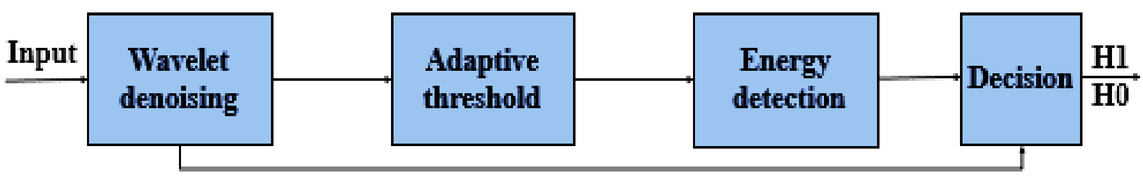

Fig.2. The proposed reciprocal two-stage sensing paradigm is depicted as a block diagram.

The proposed framework consists of two different stages, each has a certain rule, the process flow chart in Fig.3 shows that the first one is wavelet denoising, which has two different jobs, initially in the first sensing process it has to work as an ordinary signal detector and give us a decision about the primary user presence, but not only that job, the second job is to give us detailed information about the noise, which will we use it in the second stage. The second stage is an adaptive threshold energy detector, in the first sensing it has no rule, but the successive sensing process occurs during the secondary user usage of the empty band to make sure that the primary user is still idle.

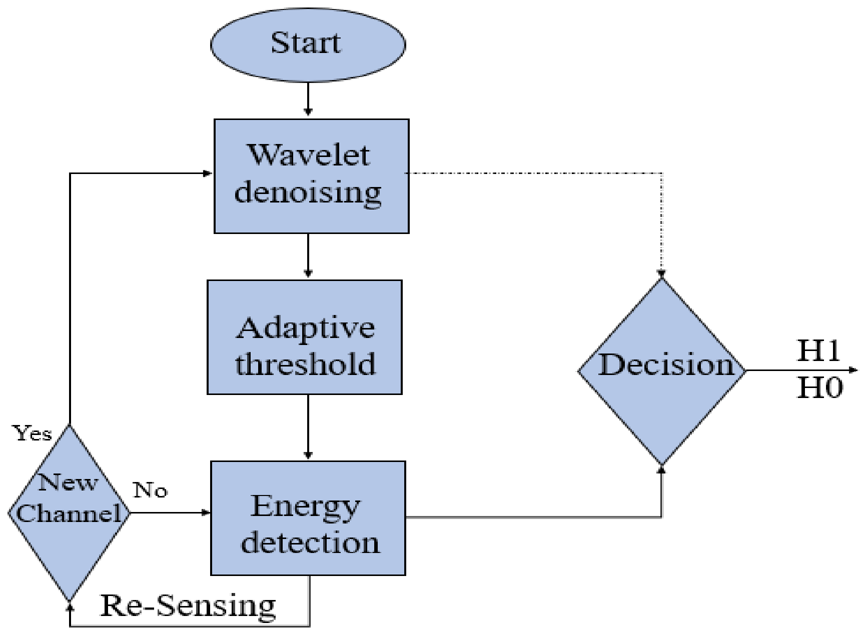

Fig.3. The suggested reciprocal two-stage sensing model's process flowchart.

From the process flow chart in Fig.3, it's clear that we can use the results we get from the WD stage to expect the noise variance σˆ_z^2and use it to adapt the threshold value of the second stage ED to overcome the noise uncertainty. We specified the threshold as follows depending on the expected noise variance and Eq. 6:

$$\lambda_r = \hat{\sigma}_z^2 (Q^{-1}\left(P_{fa}\right)\sqrt{2N} + N) \tag{9}$$

4. SIMULATION RESULTS AND DISCUSSION

In this part, MATLAB was used to evaluate the suggested reciprocal two-stage sensing model detection performance to the conventional energy performance in the existence of noise uncertainty. We carried out different scenarios, for example, studying P_{md} and P_{fa} in the absence and presence of noise uncertainty. the energy distributions in both situations with and without denoising at SNR=-15dB. All of these cases were utilized to evaluate the proposed method's detection accuracy in the existence of noise uncertainty.

Figure 4 illustrates the false alarm prob and the prob of missed detection of the conventional ED for various SNR at NU=0dB and NU=1dB noise uncertainty. It was discovered that the missed detection prob is higher in the case of NU=1 dB than in the case of NU=0, indicating that the sensing result using the conventional ED is affected by noise uncertainty, as well as the probability of false alarm.

In both PU presence and PU absence scenarios, the probability density function is employed to define the energy distribution. Figures 5 and 6 show the energy distributions in both situations with and without denoising at SNR=-15dB. The PU present and absence cases distributions get farther with WD, as seen in these graphs. As a result, the WD step improves the spectrum sensing model's discriminating capabilities.

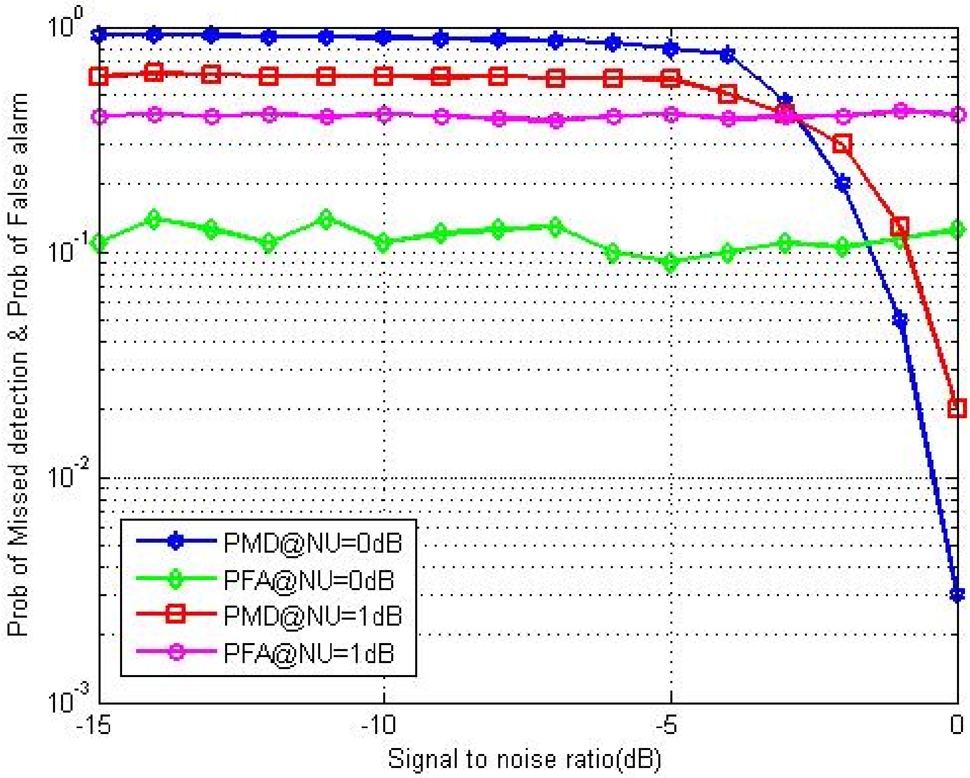

Fig.4. False alarm and Missed detection probabilities of the conventional ED for NU=0dB and NU=1dB noise uncertainty for different SNR

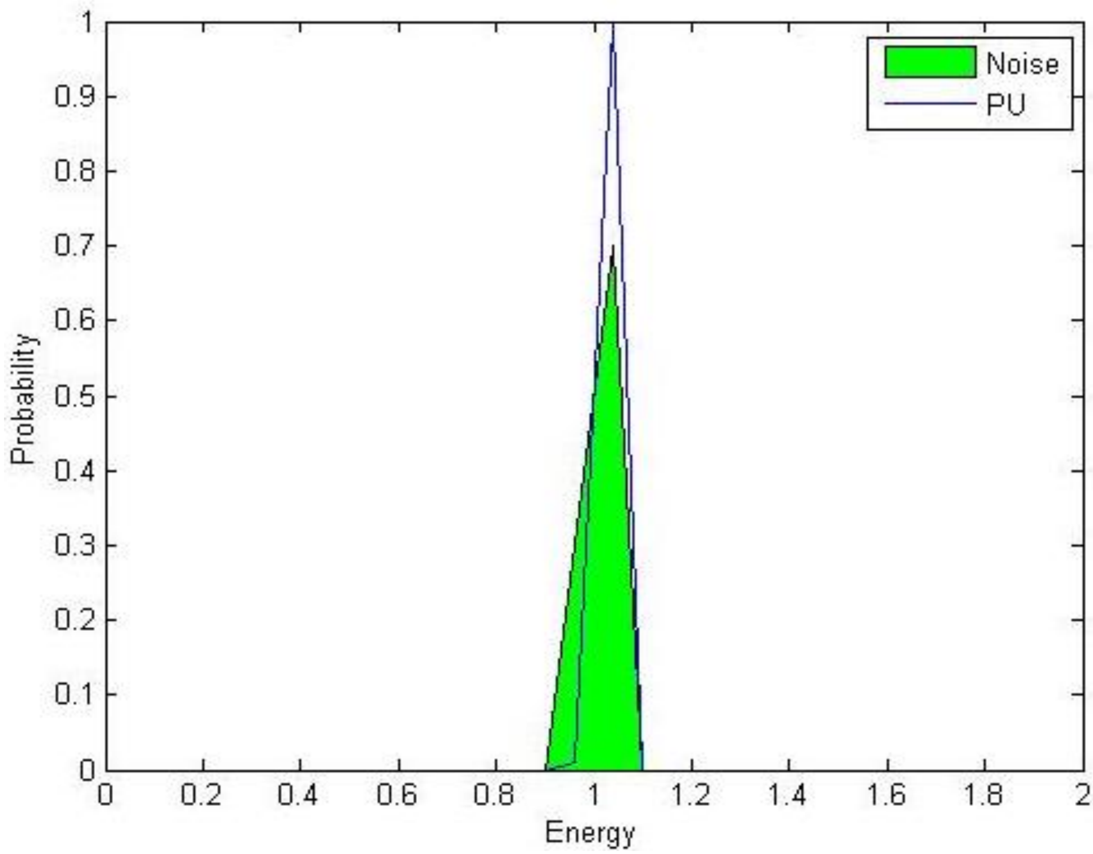

Fig.5. Without denoising, energy distribution at SNR = -15 dB.

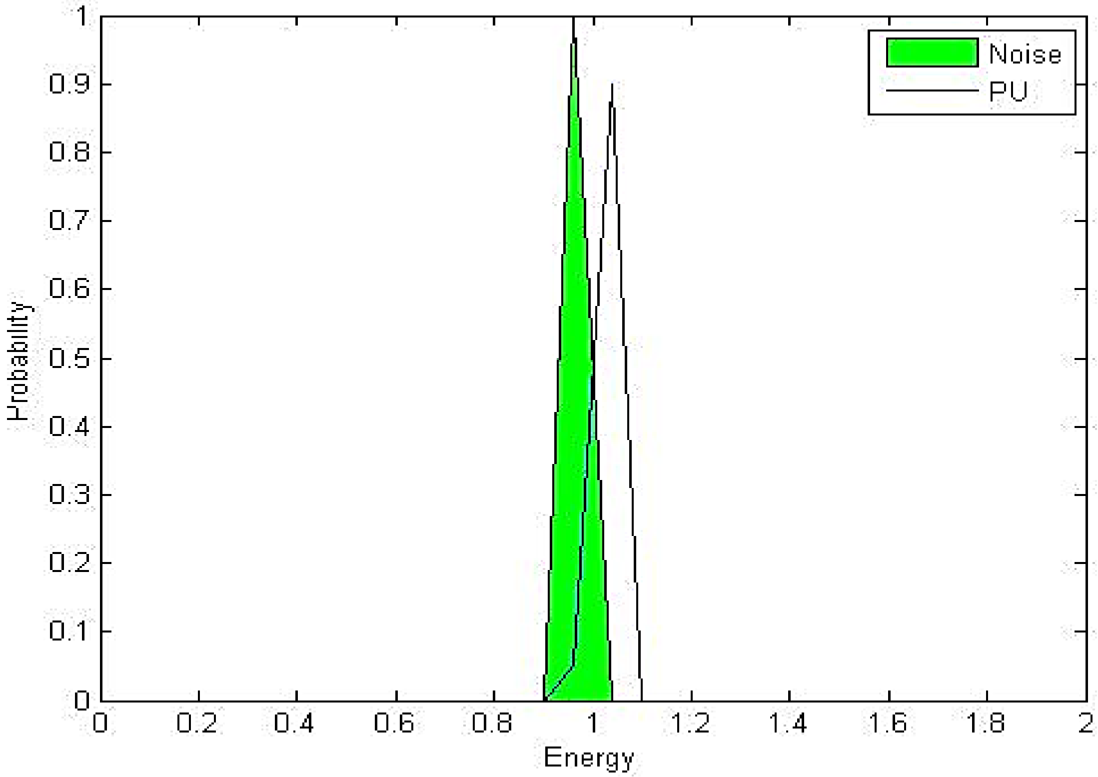

Fig.6. With denoising, energy distribution at SNR = -15 dB

We perform a study to determine the appropriate adaptive threshold values to account various levels of noise uncertainty encountered in various operational conditions. The findings of this investigation are shown in Figure 7, where increasing the noise uncertainty lowers the Adaptive threshold. The sensing node will save time in the subsequent operating stages by having previous knowledge of these values from the startup process.

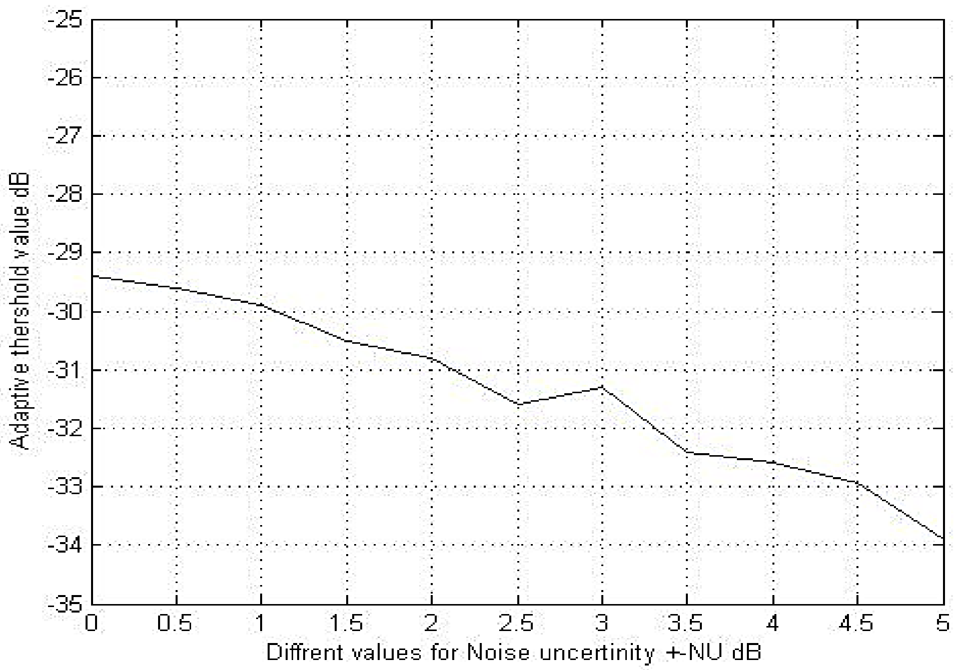

Fig.7. For different noise uncertainty level Adaptive threshold values.

For noise uncertainty NU=0dB and NU=1dB, the probability of missed detection is shown vs SNR using the conventional ED and Reciprocal, respectively. Furthermore, when the desired PFA is 0.1. When actual noise information is present, for noise power uncertainty NU = 0dB, both the conventional ED and Reciprocal perform similarly, as illustrated in Fig.8. When the predicted noise has an uncertainty of NU= 1dB, however, the conventional threshold performs worse than the adaptive threshold in comparison to the P_{FA} = 0.1 condition.

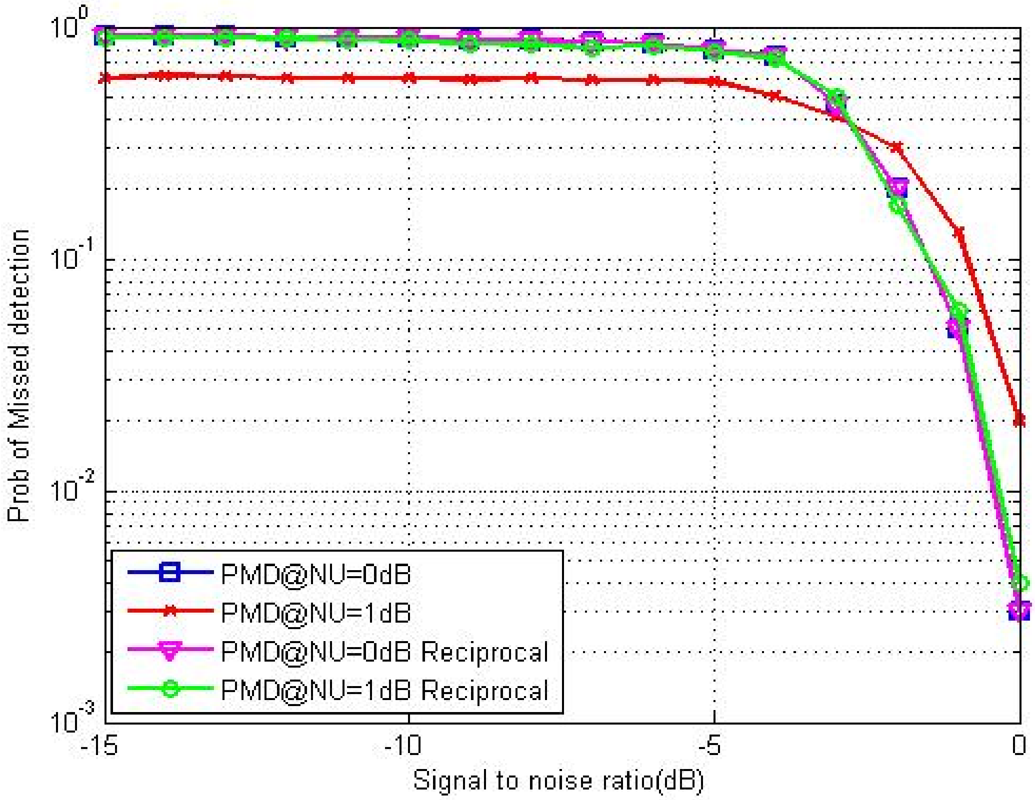

Fig.8. Missed detection probability for the conventional ED at NU=0dB and NU=1dB noise uncertainty, as well as the Reciprocal at NU=0dB and NU=1dB noise uncertainty, for various SNR.

Table 1. Numeric comparison between The proposed Reciprocal model to prior comparable spectrum sensing approaches, At SNR=-10dB

Spectrum sensing techniques	*Pd*	*Pd at NU=1dB*	*Sensing time (ms)*
ED [4]	0.90	0.69	20
CD [4]	0.94	0.76	60
MME [4]	0.93	0.82	100
WD [2]	0.95	0.81	70
ED and WD [2]	0.99	0.84	65
ED and MME [4]	0.99	0.86	128
ED and CD [5]	0.98	0.8	40
Proposed Reciprocal model	0.99	0.94	26.7

As shown from Table 1, compared with other previous techniques, at the SNR of −10dB, PFA = 0.1 and NU=1dB, the proposed model achieves the highest probability of detection and low detection time for large number of sensing samples in the presence of NU. The proposed model improves the detection probability better than the traditional related two-stage spectrum sensing techniques by 8%.

Table 2 shows the proposed Reciprocal model is compared to prior comparable spectrum sensing approaches. A tradeoff between the sensing accuracy, sensing time, performance in the noise un certainty presence and computational cost. Which shows that the proposed model offers a very good performance in the noise uncertainty presence with the minimal computational cost which is an additional advantage.

Table 2. The proposed Reciprocal model is compared to prior comparable spectrum sensing approaches**.**

Spectrum sensing techniques	Appearance			
	Sensing accuracy	Sensing time	Performance in Noise uncertainty presence	Computational cost
ED [4]	Good	Low	Low	Low
CD [4]	High	Medium	Medium	High
MME [4]	High	High	Good	High
WD [2]	High	Medium	Good	High
ED and WD [2]	High	Medium	Good	High
ED and MME [4]	High	High	Good	High
ED and CD [5]	High	Low	Good	High
Proposed Reciprocal model	High	Low	Very good	Low

5. Conclusions and Future Work

In this paper, for cognitive radio, we presented a reciprocal two-stage spectrum sensing approach to boost efficiency of spectrum sensing in the existence of noise uncertainty. The proposed frame work consists from two different stages, each has a certain rule, the first one is wavelet denoising, the second stage is an adaptive threshold energy detector. The first one used to get a detailed information about the noise to help in adapting the threshold of the second stage. Which shows that the proposed model offers a very good performance in the noise uncertainty presence as it can increase the detection probability and outperforms the ED and the previous related two-stage techniques by 25% and 29% respectively, at the SNRs of -10 and -5dB, with the minimal computational cost which is an additional advantage.

Some future work might be done based on this research, such as in a cooperative sensing scenario, employing the proposed reciprocal model and examining its influence on cooperative sensing performance. Modifying the suggested reciprocal model in order to assess its conduct in the MIMO sensing situation and analyzing its effect on sensing performance is another potential path that might be researched.

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