An Effective Adaptive Threshold Based Compressive Spectrum Sensing in Cognitive Radio Networks

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Abstract-Spectrum sensing is playing a vital role in Cognitive Radio networks. Wideband spectrum sensing increases the speed of sensing but which in turn requires higher sampling rate and also increases the complexity of hardware and also power consumption. Compression based sensing reduces the sampling rate by using Sub-Nyquist sampling but the compression and the reconstruction problem exists. In compression based spectrum sensing, noise uncertainty is one of the major performance degradation factor. To reduce this degradation, compressive measurements based sensing with adaptive threshold is proposed. In this technique compressed signal is sensed without any reconstruction of the signal. When the nodes are mobile in the low SNR region, the noise uncertainty degrades the performance of spectrum sensing. To conquer this problem, noise variance is estimated using parametric estimation technique and the threshold is varied adaptively. In the low SNR region, this proposed technique reduces the effect of noise and improves the spectrum sensing performance.

Keywords-*Compressive measurements based sensing, Noise variance estimation, Adaptive threshold, Low SNR region.*

1. Introduction

In wireless communications, the spectrum scarcity problem arises because of the tremendous growth of the utilization of wireless devices and services. On the other hand, a large portion of the spectrum of the licensed user remains underutilized. To overcome these two problems FCC (Federal Communications Commission) proposes a new paradigm such as Dynamic Spectrum Allocation (DSA) [1]. In DSA or cognitive radio networks, the idle spectrum of the licensed users is opportunistically utilized by the unlicensed users without causing any harmful interference to the licensed users. In order to use the idle spectrum of the licensed users, Cognitive Users(CU) should perform spectrum sensing. Spectrum sensing is the process in which the SUs can detect the presence or absence of the PUs and identify the available white spaces in the spectrum. The spectrum sensing can be performed by using various sensing techniques such as Energy detector, Cyclo-stationary detector matched filter detector etc. During spectrum sensing, the speed and accuracy requirements should not be harmful to the PUs [1], [2][5][6]. Broadly, spectrum sensing can be classified as narrow band and wideband sensing. Wideband sensing techniques sense multiple channels simultaneously [6]. But in wideband sensing, there are some problems such as high sampling rate, need of complex front end and fast digital signal processing [9]. To overcome these problems either sub Nyquist sampling or compression based sensing can be used. In compression based sensing, compression and reconstruction has to be performed.

In [8] an optimal multiband time-adaptive joint wideband spectrum sensing technique was proposed. In this technique multiple frequency bands were sensed collectively. The spectrum sensing performance is good when the number of channels to be sensed is small but the complexity increases when the channel size increases.

In [3] Taha. A khalaf et.al proposed compression measurements based spectrum sensing in which spectrum sensing was performed based on the compressive measurements without performing the decompression operation. In order to improve the performance of this technique in the noisy low SNR region, we propose adaptive noise variance based compressive measurements sensing. In this technique threshold of energy based sensing is varied adaptively based on the variation of the noise variance. This

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

technique improves the spectrum sensing performance even in the noisy low SNR region by increasing the probability of sensing and reducing the probability of false alarm. In this proposed work, section I briefly explains about this adaptive sensing technique. Section II discusses about the

compressive measurements with adaptive threshold based sensing and Section III describes the performance of this adaptive sensing technique. Section IV concludes and gives the future scope of this sensing technique.

2. System Model

In this proposed work the primary network is considered as WRAN IEEE 802.22 and the PU signal is transmitted using Orthogonal Frequency Division Multiplexing (OFDM). The channel model considered is AWGN.The received signal at the SU is given by

$$x(t)= s(t)+n(t) \quad : \quad H_1$$

$$x(t) = n(t) \quad : \quad H_0 \qquad (1)$$

Where s(t) is the signal at the PU with bandwidth W and n(t) is the AWGN with zero mean. H_1 indicates the presence of the PU and H_0 is the null hypothesis meaning that there is no PU present. The received signal is sensed using compressive sensing in which the sampling rate is the sub Nyquist rate. It is given as follows,

$$Y= Ax \qquad (2)$$

Where Φ is MXN sensing matrix (M<N), x is the Nyquist rate samples of x(t) with size Nx1 and Y is compressed measurements vector with size 1xM.

A. Compressive Measurement Based Energy Detection Algorithm

The presence of the PU is identified with compression measurements based energy detection in which the received signal x(n) in the SU is compressed and detected from the measurements. In this sensing method the reconstruction of compression is not at all performed. Therefore, it reduces the hardware complexity and time. Compression sensing is performed with Discrete Cosine Transform (DCT) sensing matrix. CT is a simple compact and less energy consuming compression algorithm. The location of the sensing matrix at k the row and at ith column is given as follows [3],

$$(k,i)= c(k)\cos(\frac{\pi(2i+1)k}{2N}) \qquad (3)$$

Where k= 0,1, 2. M-1, i = 0,1, 2,N-1

$$c(k) = \begin{cases} \sqrt{\frac{1}{N}}, & k = 0 \\ \sqrt{\frac{2}{N}}, & k \neq 0 \end{cases}$$

The energy of the signal from the compressed signal is given as follows,

$$\xi_{yM}=\sum_{k=0}^{M-1} (\frac{y_k}{\sqrt{N01W}}) \qquad (4)$$

Then the energy detector decision variable ξ_{yM} is compared with the estimated adaptive threshold from the adaptive threshold algorithm as follows,

$$\xi_{yM}= \frac{H0<}{H1>} \gamma k(n)_{adapt} \qquad (5)$$

Where $\gamma_k(n)_{adapt}$is the adaptive threshold of energy detection, which is adaptively varied from the estimated, noise variance. Theadaptive threshold $\gamma_k(n)_{adapt}$ expression is given section B.

B. Estimation of Adaptive Threshold

When the secondary users are moving then the estimated noise variance also will vary and it will not be constant. Due to the variation of noise variance the spectrum sensing performance will be affected with the increased probability of false alarm and missed detection. To overcome this problem, the threshold of spectrum sensing is adaptively varied. The threshold is varied depending on the estimated noise variance. The noise variance is estimated from the contaminated received signal using Yule walker parametric estimation method.

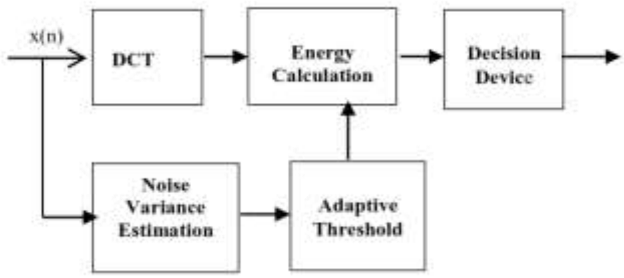

Fig.1: Block diagram of Enhanced Compression Based Spectrum Sensing.

The expression for noise variance is given as [4],

$$\sigma(k)_v^2)=\frac{\sum_{j=1}^{p} a_j^{(k)}\{R_x^{(k)}(j)+\sum_{i=1}^{p} a_i^{(k)} R_x^{(k)}(|j-i|)\}}{\sum_{j=1}^{p} a_j^{(k)2}} \qquad (6)$$

Thus, this adaptive threshold based spectrum sensing reduces the effect noise in spectrum sensing and improves the sensing performance by increasing the probability of detection and reducing the probability of false alarm and missed detection.

Noise variance is estimated based on the received signal whenever there is a change in the received signal. In adaptive threshold based spectrum sensing the threshold is varied depending on the variation of noise variance when the SU nodes are in motion. In order to reduce the probability of false alarm and improve the probability of detection the threshold of

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

spectrum sensing has to be varied according to the variation of the noise level in the received signal. The proposed adaptive threshold algorithm first estimates the noise variance and changes the threshold of sensing whenever the change of noise variance is more than some allowable limit.

The expression for adaptive threshold for the kth channel is given as follows [4]

$$\gamma_k(n+1)_{adapt} = \gamma_k(n)_{,adapt}(n) - \mu_k \nabla E^{(k)}(n) \qquad (7)$$

Where $\nabla E^{(k)}(n)$ is the spectrum sensing error.

The Adaptive threshold is calculated using the adaptive threshold algorithm which is given below.

Adaptive Threshold Algorithm

- Calculate the average energy of the detector. (Using equation (4))
- compute the unbiased estimate of the autocorrelation coefficients $R_x^{(k)}$ (j), From the received noisy signal.[4]
- Using Least Square procedure, evaluate the AR parameters [4].
- Compute noise variance from AR model (Using equation (6)).
- If the difference between the computed threshold in the current time instant and the lost time instant value is greater than the reference threshold, then update the threshold and the gradient values else keep the old values.

C. Probability of Detection and False Alarm

The probability of detection is the presence of primary user during spectrum sensing. The expression for probability of detection is given by,

$$Pd = P(\xi_{yM} \geq \gamma k(n)\text{adapt}_{/H1})$$

The probability of detection from the DCT measurements is given as follows [3],

$$Pd = \frac{1}{2}\int_{\gamma_k(n),adapt}^{\infty}\left(\frac{\xi}{\mu k}\right) \qquad (8)$$

The probability for the false alarm is expressed as,

$$P_f = \frac{1}{2^{M/2}\Gamma(\frac{M}{2})}\int_{\gamma_k(n),adapt}^{\infty} \xi^{\frac{M}{2}-1} e^{-\xi/2} d\xi \qquad (9)$$

The spectrum sensing error is calculated from the probability of false alarmand the probability of missed detection as follows [4],

$$E^{(k)}(\gamma_k(n)) = \delta p_{fa}^{(k)}(\gamma_k(n)) + (1-\delta)p_{md}^{(k)}(\gamma_k(n) \qquad (10)$$

Where P_{fa} and P_{md} are the probability of false alarm and missed detection respectively.

3. Performance Evaluation

In this work, the primary network considered is IEEE 802.22. The PU signal is considered as OFDM with the carrier frequency of 54MHz and 4.45Mbps data rate. The payload modulation is 16 QAM and the size of the FFT is 2048.The simulation is performed for an AWGN channel. The probability of false alarm is considered as 0.01 and the value of N is taken as 128 and M = 16. The performance of this adaptive threshold based compressive sensing is verified for low SNR region and high SNR regions. For adaptive threshold estimation the reference threshold ε is taken as0.01.The performance of this adaptive sensing is examined for these three parameters such as probability of detection, probability of false alarm and spectrum sensing error.

Figure2. gives the probability of detection performance comparison of fixed threshold, compressive based sensing and adaptive sensing for low and high SNR regions. In this adaptive sensing technique, the probability of detection is improved in the low SNR region compared to other two techniques.

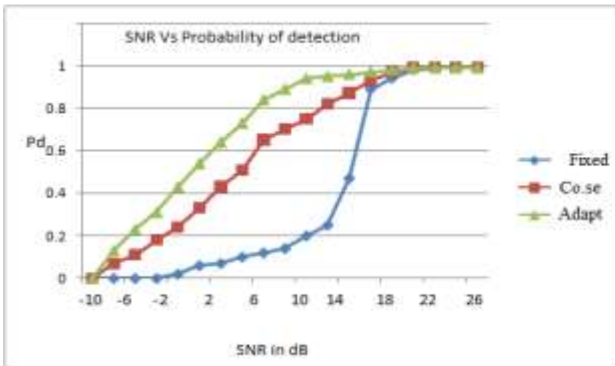

Fig.2: SNR Versus Probability of detection for low and high SNR regions.

Figure3 compares the probability of false alarm for fixed, compressive and adaptive sensing techniques. For this adaptive spectrum sensing, the rate of decrease of false alarm is faster even in the low SNR region compared to the other two techniques. This indicates that the spectrum sensing performance has been improved even in the low SNR region.

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

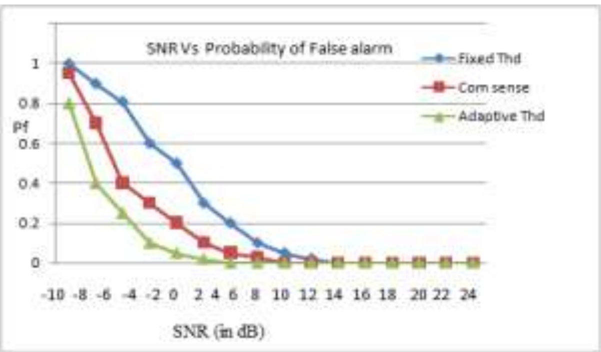

Fig.3: SNR versus Probability of False Alarm P_f for low and high SNR regions.

Figure 4 and 5 have compared the threshold versus spectrum sensing error for two particular SNR values such as -3dB and +3dB. The spectrum sensing error is very less for the adaptive spectrum sensing compared to the other two sensing techniques.

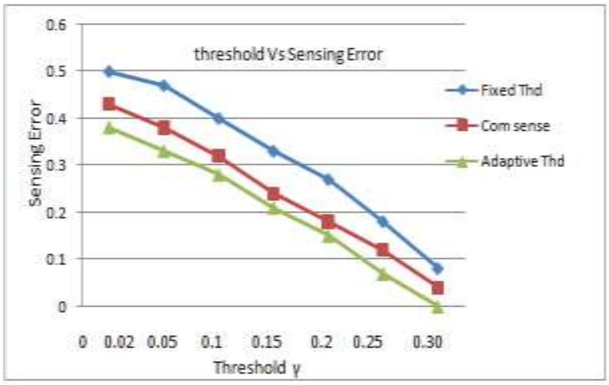

Fig.4a: Threshold versus spectrum sensing error for (SNR= -3dB)

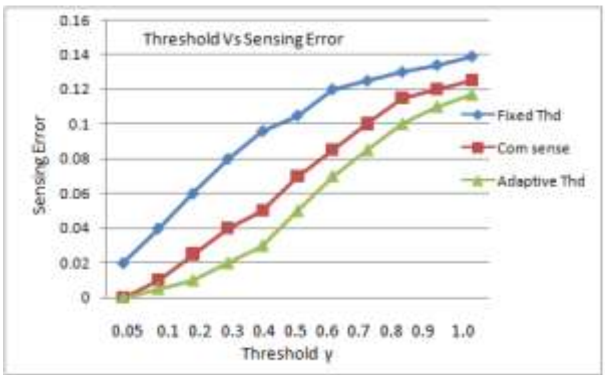

Fig.4b: Threshold versus spectrum sensing error for (SNR= -3dB).

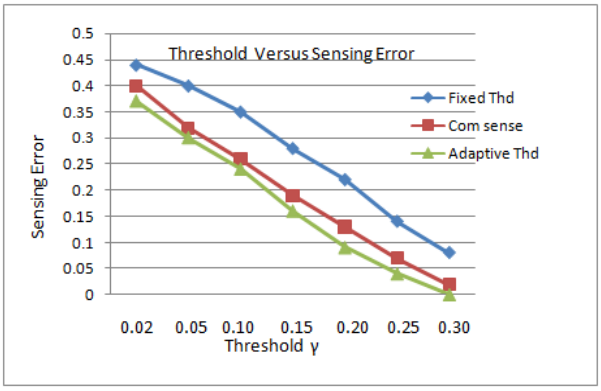

Fig.5a: Threshold Versus Spectrum sensing error for (SNR= 3dB).

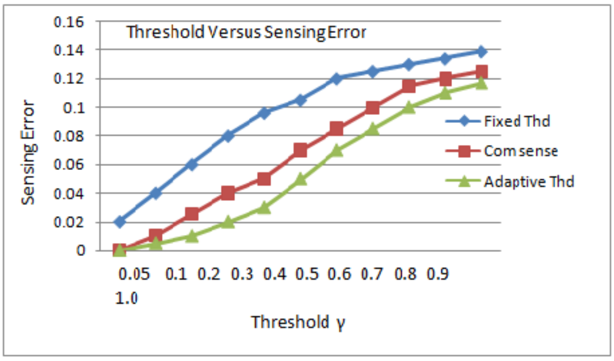

Fig.5b: Threshold Versus Spectrum sensing error for (SNR=3dB).

4. Conclusion

In this proposed adaptive spectrum sensing technique, the threshold of sensing is adaptively varied based on the estimated noise variance. This has increased the spectrum sensing performance such as probability of detection and decreasedthe spectrum sensing error and the probability of false alarm and missed detection. The amount of decrement of the probability of missed detection and false alarm are much more in the low SNR region compared to high SNR region.Therefore, this adaptive sensing technique can be used in mobile scenario to improve spectrum sensing performance in the noisy low SNR region.

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ISSN (Print): 2204-0595
ISSN (Online): 2203-1731