A Study and Simulation of Spectrum Sensing Schemes for Cognitive Radio Networks

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***Abstract* - The under - deployment dilemma of the allocated radio spectrum has made the Cognitive Radio (CR) communications to evolve as a trustworthy and valuable solution. Spectrum sensing is one of the schema to accomplish the essential Quality of Service (QoS). Spectrum sensing offers the critical data to facilitate the interweave communications which does not authorize the primary and secondary to utilize the medium simultaneously. Cognitive Radio Networks (CRNs) in addition include the suppleness to amend its own transmission parameters in accordance with the requirements of multimedia services or applications. This paper concentrates on various schemes for spectrum sensing such as Energy Based Detection scheme, Autocorrelation Based Detection scheme, Euclidean Distance Based Detection scheme, Wavelet Based Detection scheme, Matched Filter Detection scheme for the Cognitive Radio Networks.**

***Index Terms* - Cognitive Radio, Cooperative Spectrum Sensing, Energy Detection, Autocorrelation Detection, Euclidean Distance Detection, Wavelet Detection, Matched Filter Detection.**

I. OVERVIEW OF COGNITIVE NETWORKS

A. Dynamic Spectrum Access:

The Conventional Wireless Networks uses the static spectrum access scheme and it is interchanged by the Variable Spectrum Access also called as Dynamic Spectrum Management (DSM) [1], giving raise to the concept of cognitive radio networks. The spectrum sensing operation is made reliable and smooths [1] [2], by the suppleness of the spectrum sharing which helps the cognitive users to utilize the holes in the spectrum also named as white spaces in the licensed spectrum. Cooperation from licensed users is also a key which evades the interference. The factors involved in DSA are spectrum sensing, interference improvement and spectrum usage analysis. The working principle of CRNs is completely dependent on the cognitive cycle. Spectrum sensing is conventionally characterized as a measure of the spectral contents, or measure of the radio frequency energy in a given spectrum; The cognitive radio is a further universal concept that engages obtaining the spectrum utilization attributes across compound aspects such as time, space, frequency, and code.

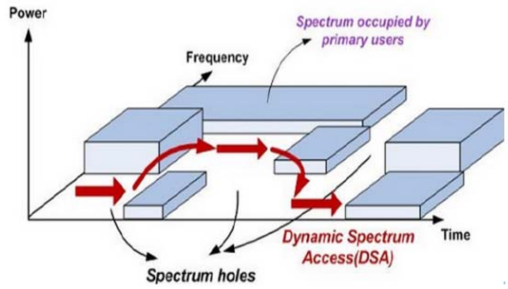

Figure 1: Diagram of Dynamic Spectrum Management

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B. Cognitive Cycle:

The complete spectrum sensing and spectrum allocation methods are classified into four main categories represented as cognitive cycle. Identifying the spectrum holes (white spaces) available in the spectrum by using different spectrum sensing techniques is the initial move in the cognitive cycle. The second step is the spectrum management, during which the interference provided to primary users is set aside at a bare minimum to sustain the secondary user communications in the licensed band. The third step is the sharing of the spectrum which is initially sensed & managed. In the scheme of spectrum sharing, the spectrum holes (white spaces) are utilized by using the following methods of the white space utilizations techniques such as underlay, overlay, or interweave method [3],[4]. The cognitive cycle i.e, the spectrum sensing, spectrum management, spectrum sharing and the mobility helps in the efficient usage of the spectrum.

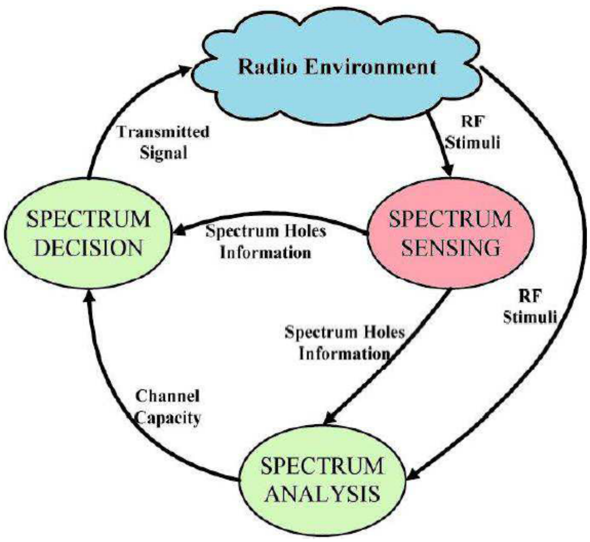

Figure 2: Block Diagram of Cognitive Cycle

II. SPECTRUM SENSING:

The spectrum sensing is classically carried out by means of two statistical hypotheses H_1 and H_0 which specify the existence or nonexistence of primary user signal in the licensed band [5], [20]. Generally spectrum sensing scheme (or method) are related with two probabilities value: detection probability value ($P_d = P[H_1\ H_1]$) that represents the probability of accurately detecting the existence of primary signal when the signal is truly available and probability of false alarm ($P_f = P[H_1\ H_0]$) that represents the probability of wrongly declaring the existence of primary signal if the signal is truly absent.

Larger numerical values of P_d and smaller numeric values of P_f are forever preferable for SUs, since larger P_d value guarantees the least likelihood of intrusion to PU transmission and smaller P_f numeric value offers enhanced likelihood of throughput to be obtained by SUs. Hence the sensing routine characteristics of a SU is controlled by the values of P_d and P_f which in turn is reliant on the characteristics of the licensed spectrum band.

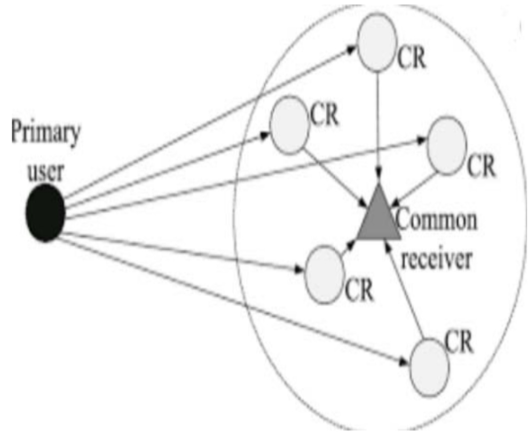

Figure 3: Diagram of Spectrum Sensing

II. REPRESENTATION OF SPECTRUM SENSING :

The spectrum sensing model is represented as:

$$y(n) = \begin{cases} w(n) & \mathrm{H_0}\text{: PU absent} \\ h * s(n) + w(n), & \mathrm{H_1}\text{: PU present} \end{cases} \qquad (1)$$

where n =1….N, N is the total samples, y(n) indicates the cognitive signal, s(n) represents the primary user, w(n) indicates the additive white Gaussian noise (AWGN) with zero mean and variance δ^2_W and h designates the complex channel gain of the sensing channel. H_0 and H_1 symbolize the non availability and the availability of the primary user signal respectively. The detection of primary user signal is carried out with the help of one of the spectrum sensing methods to take a decision among the two hypotheses H_0 and H_1. The detector output, which is otherwise named as the test statistics, is finally compared with the value of threshold for taking a sensing decision regarding the availability of the main user signal.

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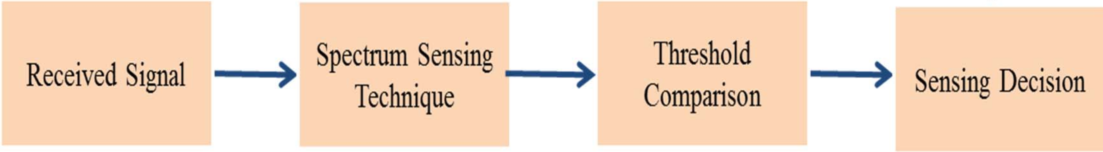

Figure 4: Model of Spectrum Sensing

The sensing decision is performed as:

$$\begin{cases} \text{if } T \geq \gamma, & H_1 \\ \text{if } T < \gamma, & H_0 \end{cases} \qquad (2)$$

in which T represents the test statistics involved in the detector and γ represents the threshold value of sensing. When the main user signal is not present, cognitive user will have a capability of right to use the PU channel. The literature has proposed a large number of sensing methods which are categorised as two major classifications namely: cooperative scheme of sensing and non-cooperative method of sensing [6] as given in Figure 5.

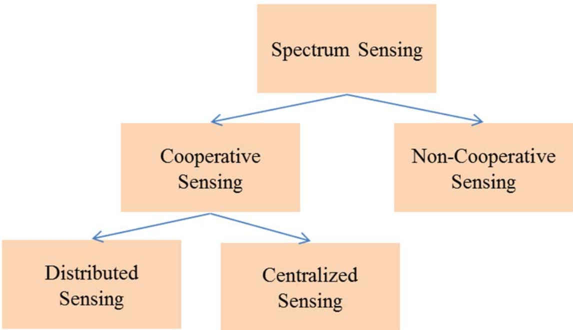

Figure 5: Categories of Spectrum Sensing

In the non-cooperative sensing method, which is otherwise named as local technique for sensing, every SU requests for its own access and do not consider the decisions taken by various SUs involved. Since there is no transfer of information or collaboration that exists among the various secondary users which senses the identical band of frequency, decision on the sensing of the spectrum is executed locally [8]. But the non cooperative scheme in turn it is prone to errors because of the following parameters such as shadowing, interferences due to fading, and the uncertainty in the noise etc. These techniques are primarily utilized if and only if there is a single sensing terminal existing.

In the cooperative spectrum sensing schema, the SUs work in partnership. This collaboration among the varied SUs is categorised as the following two schemas: one is centralized and the other is distributed schema [7]. In the distributed schema, SUs share its local interpretation along with the sensing details. Considering the details from various other secondary users sensing the identical frequency band, its own decision is made by every SU. This schema does not necessitate any general network for making the ultimate decision in which the detection is completely inhibited by the secondary users. However in the centralized schema, each and every SUs transmit its sensing details to a vital central entity, named as fusion center, as given in Figure 6.

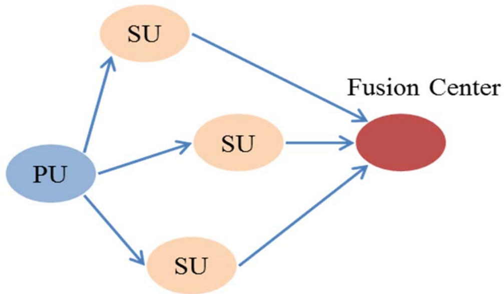

Figure 6: Representation of Centralized Cooperative Spectrum Sensing

A. System Requirement Specifications:

The competence of the entire spectrum sensing algorithm is calculated depending on the subsequent important evaluation statistics: Detection, probability, false alarm probability, misdetection probability and the signal-to noise ratio. The evaluation of the detection is calculated via an AWGN channel with the help of MATLAB simulation tool.

IV. SIMULATION SPECIFICATIONS:

MATLAB (R2014a), a sophisticated language tool, is utilized to design the algorithm for sensing the spectrum. The Primary User produces an input which is Quadrature Phase Shift Keying (QPSK) modulated. The secondary signal is received through the channel where the modulated signal gets added with the noise of the channel (AWGN).

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The energy performance metric is evaluated by comparing the signal that is received to a predestined value, at a characterized false alarm probability.

PU Signal	QPSK
Noise added in the channel	AWGN
Samples count/Fast Fourier Transform Size	128, 256, 512, 1024, 2048
SNR	-25 dB to 0 dB
False Alarm Probability	0 to 1
Required Detection Probability	0.9
Required False Alarm Probability	0.1
Iteration Performed	10000

Table 1: Simulation Specifications

V. ANALYSIS OF SPECTRUM SENSING TECHNIQUES:

A CRN is defined as a network containing the combination of many CR enhanced nodes (secondary users) along with the licensed nodes (primary users), in which the CR enhanced nodes utilizes the communication of the licensed spectrum bands by exploiting the spectrum holes (White Spaces) available. The Sensing of spectrum holes available in the licensed bands by the cognitive users also called as secondary users (SUs) is important for the accomplishment of CRN and this terminology is named as Spectrum Sensing. In CRN, SUs are enriched with CR facilities such as frequency agility, adaptive modulation which enables the CRN to dynamically to deal with the performance of spectrum sensing.

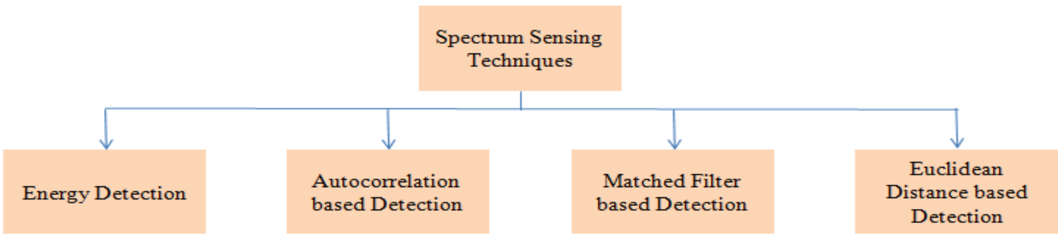

Figure 7: Types of Spectrum Sensing Methods

A. Energy Detection Scheme:

The easiest sensing method, which do not involve any data regarding the main signal for its operation is the Energy detection scheme. The detection is done by means of comparison of the arrived signal energy to a predefined value. The value of threshold is fixed depending merely on the value of the power of the noise. The decision metric of an energy detector is evaluated using the squared magnitude value of a Fast Fourier Transform which is averaged over N as given in Figure 8. The output of the detector is represented by

$$T_{ED} = \sum_{n=0}^{N} y(n)^2 \tag{3}$$

in which n=1…. N, N represents the total samples, and y(n) represents the SU, and T_{ED} represents the test metric. Therefore, the decision-based energy detection is represented as:

$$\begin{cases} \text{If } T_{ED} \geq \lambda, & \text{PU signal present} \\ \text{If } T_{ED} < \lambda, & \text{PU signal absent} \end{cases} \tag{4}$$

in which λ represents the threshold value for sensing and T_{ED} represents the received signal energy from the SU. A Gaussian random signal is used for the representation of the signal received. Consequently, the evaluation metric, T_{ED}, is represented in terms of Gaussian and expressed as

$$\begin{cases} H_0: T_{ED} \sim \mathcal{N}\left(N\delta_w^2, 2N\delta_w^4\right) \\ H_1: T_{ED} \sim \mathcal{N}\left(N(\delta_w^2+\delta_s^2), 2N(\delta_w^2+\delta_s^2)^2\right) \end{cases} \tag{5}$$

in which $\delta^2{}_S$ represents the primary user signal variance, $\delta^2{}_W$ represents the noise variance, with $\mathcal{N}$ representing the distribution which is normal. In the estimation metrics, the detection probability and the false alarm probability with an additive white Gaussian noise (AWGN) channel is represented as:

$$Pd = Q\left(\frac{\lambda - N((\delta_w^2+\delta_s^2))}{\sqrt{2N((\delta_w^2+\delta_s^2))^2}}\right), \quad Pfd = Q\left(\frac{\lambda - N\delta_w^2}{\sqrt{2N\delta_w^4}}\right) \tag{6}$$

where Q(.) symbolizes the Q-function with λ representing the value of threshold for sensing [7]. The formula for both the metrics is written as a function of signal to noise ratio (SNR) as follows:

$$P_d = Q\left(\frac{\bar{\lambda} - N(1+\gamma)}{\sqrt{2N(1+\gamma)^2}}\right) \quad , \quad P_{fd} = Q\left(\frac{\lambda - N\delta_w^2}{\sqrt{2N\delta_w^4}}\right) \quad (7)$$

in which γ represents the SNR and λ represents the average value of the threshold, $\bar{\lambda} = \lambda/\delta_w^2$. Consequently, the threshold value of sensing which is based on the power of the noise is represented for a target P_{fd} as [8]:

$$\lambda = (Q^{-1}(P_{fd})\sqrt{2N} + N)\delta_w^2 \quad (8)$$

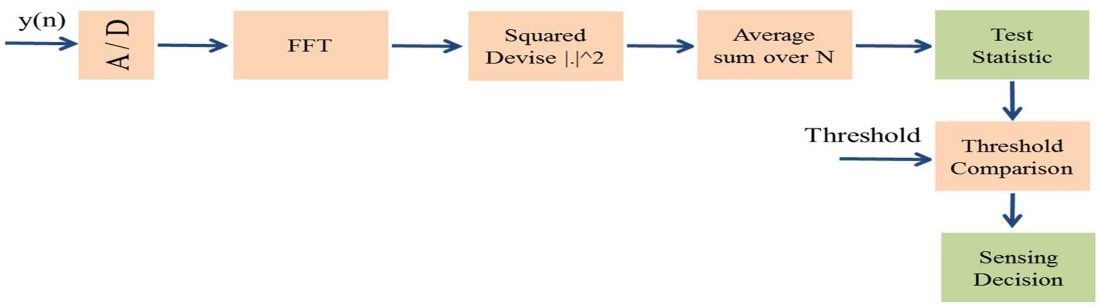

Figure 8: Block Diagram of Energy Detection Model

Every value of threshold denotes a pair of (Pd, Pfd), representation said as the receiver operating curve (ROC). ROC characterizes the plot corresponding to accurate rate of detection which is expressed as a function of the wrong rate of detection with various values of threshold. Energy detection is simple to employ and do not necessitate any previous data regarding the PU signal, that enables it to be used as a general method. Nevertheless, this is extremely responsive in the presence of noise in addition it do not discriminate among the signal & noise if the power of the signal is little. Additionally, the value of threshold for sensing of energy detector is also a significant parameter. If the detector does not amend the threshold value appropriately, then its capability of the spectrum sensing will be reduced.

The below given Matlab simulation result shows that the results of energy detection for different numbers of CRs over Additive White Gaussian Noise channel for an SNR n = -10 dB. It is observed that the false alarm probability is increased to a great extent while the probability of detection is increased.

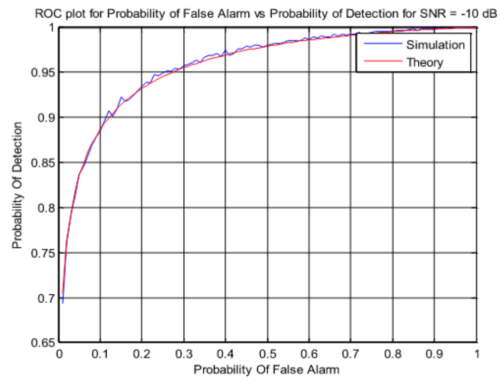

Figure 9: Simulation result of Complementary ROC of Cooperative Sensing Under AWGN Channel

B. *Autocorrelation Based Detection Method:*

Autocorrelation based sensing schema depends on the autocorrelation coefficient value of the received signal. It utilizes the available autocorrelation characteristics in the transmitted signal which will be available in the noise signal [9].

The autocorrelation function for any signal, s(t), is expressed as:

$$R_{s,s}(\tau) = \int_{-\infty}^{+\infty} s(t) * s^*(t-\tau)\, dt \quad (9)$$

in which τ represents the time lag, t represents time, and s* indicates the conjugate of the signal. In the perspective of sensing of spectrum, the superiority of sensing is altered by presence of the noise level and the interpretation of the Gaussian noise affected signals become difficult. In reality, the autocorrelation of the uncorrelated white noise contains a sharp spike at zero lag. Figure 10.

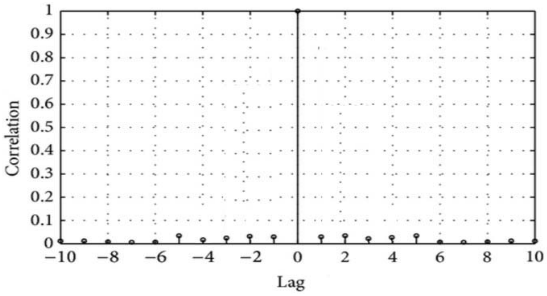

Figure 10: Diagram of White Noise Autocorrelation Function

The transmitted signal which is a concurrent signal; the zero lag along with the first lag are extremely near each other as given in Figure 11.

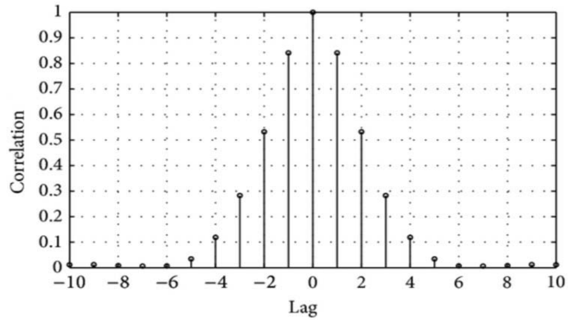

Figure 11: Diagram of Autocorrelation Function of the Signal

Consequently, the signal's autocorrelation is correlated at the same time as the autocorrelation of the noise is uncorrelated as given in the Figure 10 & Figure 11. The strength of the signal become larger as the measure of correlation is larger. As a result, the spectrum sensing is executed by utilizing the autocorrelation function so as to identify the main user availability during the existence of noisy signal as given in the Figure 12.

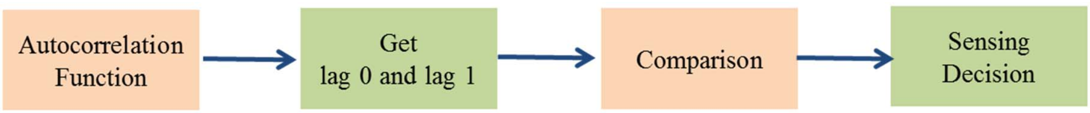

Figure 12: Block Diagram of Sensing Model Based on Autocorrelation

The decision on sensing is taken depending on the awareness of the numerical allocation of the autocorrelation function. The initial lag of the value of autocorrelation is extremely tiny even negative for a random noise, at the same time during the existence of signal the autocorrelation value at the first lag denotes a considerable value [10]. The decision on sensing is represented as:

$$\begin{cases} \text{if } lag0 \approx lag1 & \text{, PU signal present} \\ \text{if } lag0 >> lag1 & \text{, PU signal absent} \end{cases} \tag{10}$$

C. Euclidean Distance Based Detection Method:

A novel scheme for sensing was developed in [11] which is Euclidean distance based detection. It is principally dependent on the value of autocorrelation function of the signal from the SU. The detector achieves by evaluating the Euclidean distance among the autocorrelation value of the signal with the line of reference [3]. The received signal's autocorrelation value can be presented as

$$R_{s,s}(\tau) = \sum_{n=1}^{N} s(n) * s^*(n-\tau) \tag{11}$$

where $R_{S,S}(\tau)$ represents the autocorrelation at lag τ, s indicates the signal received, and N is the total samples. The line of reference is indicated by :

$$R = (\tfrac{2}{M})t + 1 \tag{12}$$

in which M synbolizes the lag counts of autocorrelation which ranges between $0 \le t \le \frac{M}{2}$, R symbolizes the line of reference. [12]

The Euclidean distance D, is represented as:

$$D = \sqrt{\sum (R_{s,s}(\tau) - R)^2} \tag{13}$$

It is defined as the difference calculated among the line of reference long with the signal autocorrelation [12]. The comparison of the above metric is done with a predefined threshold value for performing the sensing as given in the

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Figure 13.

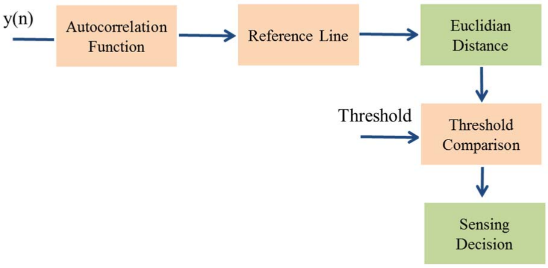

Figure 13: Block Diagram of Model of Sensing based on the Euclidean Distance

The decision on sensing is represented as:

$$\begin{cases} \text{If } D \geq \lambda, & \text{PU signal absent} \\ If\ D < \lambda, & \text{PU signal present} \end{cases} \quad (14)$$

in which λ represents threshold value of the sensing. The sensing based on Euclidean distance is very much competent compared to the autocorrelation based sensing with respect to the detection success rate [13].

D. Wavelet Based Sensing Method:

The sensing based on Wavelet, which is otherwise named as edge detection, depends on the value of continuous wavelet transform, that enables the calculation of the decomposed signal coefficients using the basis function[3], [13], [14]. It is represented by

$$f(s,u) = < x(t), \psi_{u,s} > = \int_{-\infty}^{+\infty} x(t)\psi_{u,s}^{*}(t)dt \quad (15)$$

where x(t) denotes the continuous wavelet function[15].

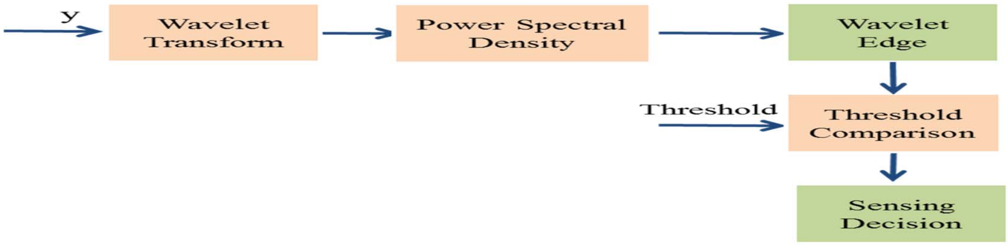

Figure 14: Block Diagram of Wavelet Based Sensing Model

in which s denotes the parameter of translation, u represents the parameter of scaling which is large, and $\psi_{U,S}(t)$ corresponds to the basis. The investigation could be executed at frequency corresponding to the factor s, at the time interval corresponding to factor u [3]. The sensing dependent on wavelet is carried out by evaluating the wavelet transform of the continuous signal to achieve the required PSD. The comparison of the highest value of the PSD which is represented by the edge, with the threshold value is done to make decision regarding the spectrum possession as given in the Figure 14.

The decision on sensing is represented as:

$$\begin{cases} \text{If } e \geq \lambda, & \text{PU signal absent} \\ If\ e < \lambda, & \text{PU signal present} \end{cases} \quad (16)$$

in which e indicates the wavelet edge and λ represents the value of threshold for sensing. The wavelet edge is utilized for taking judgments on sensing since the density of the power of any signal is represented by a single spike at the desired frequency despite the fact that it is represented by multiple spikes if noise is included as given in the Figure 15 and 16.

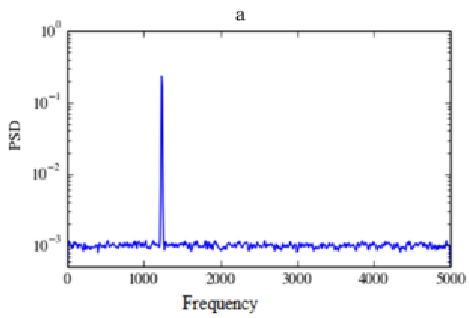

Figure 15: Diagram of Power Spectral Density of Noiseless Signal

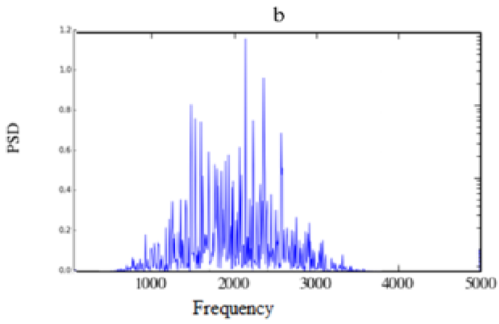

Figure 16: Diagram of Power Spectral Density of Noisy Signal

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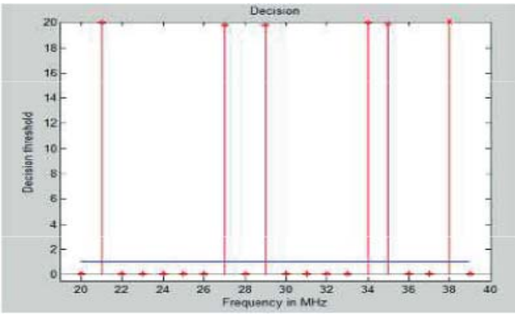

Figure 17: Simulation Result of Wavelet Based Detection

The above Matlab simulated result shows the plot of wavelet based detection in which frequencies with values zeros indicate the spectrum holes and the frequencies with values indicate the spectrum occupancy.

E. Matched Filter Detection Method:

It is one of the most favourable filters that necessitate the former information of the Primary User signals. This sensing scheme is the finest preference under the situation where certain knowledge regarding the Primary User signal are already existing at the Secondary User receiver. With an assumption that the Primary User transmitter transmits a pilot data sequence concurrently along with the data, the secondary user gets the signal beside with the pilot data sequence. The detection in Matched filter scheme is executed by extrapolating the pilot data xp, as given in the Figure 17 [16][17].

The test statistic is represented by:

$$T_{MFD} = \sum_N y(n)\ x^*{}_p(n) \tag{17}$$

in which x_p indicates the main user signal, y indicates the cognitive user signal, and T_{MFD} indicates the test metrics of the detector depending on the matched filter. The ultimate decision regarding the accessibility of the spectrum is taken by comparing the test metrics with the predetermined value.

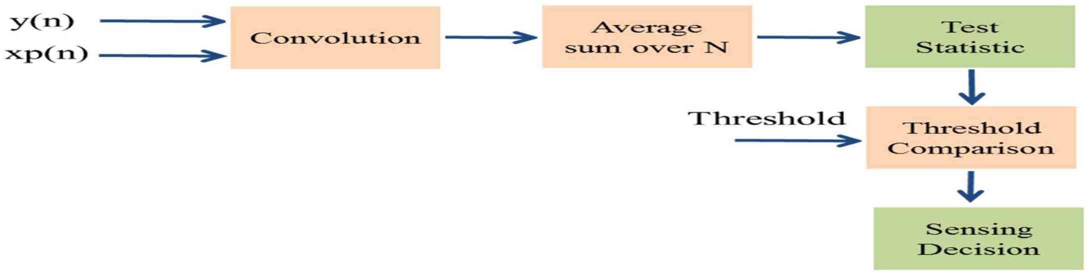

Figure 18: Matched Filter Detection

$$\begin{cases} \text{If } T_{MFD} \geq \lambda, & \text{PU signal present} \\ If\ T_{MFD} < \lambda, & \text{PU signal absent} \end{cases} \tag{18}$$

Depending on the criterion of Neyman-Pearson, the correlation among the probability of detection and the false alarm is expressed as.

$$Pd = Q(\frac{\lambda - E}{\sqrt{E\delta_w^2}}) \quad , \quad Pfd = Q(\frac{\lambda}{\sqrt{E\delta_w^2}}) \tag{19}$$

in which E represents the signal energy of PU, λ is the threshold value of sensing, Q(.) [18] denotes the Q- function, and $\delta^2{}_W$ represents the variance of the noise. The sensing predetermined value is written as function of the signal energy of the PU and the variance of the noise as [19].

$$\lambda = (Q^{-1}(Pfd)\ \sqrt{E\ \delta_w^2} \tag{20}$$

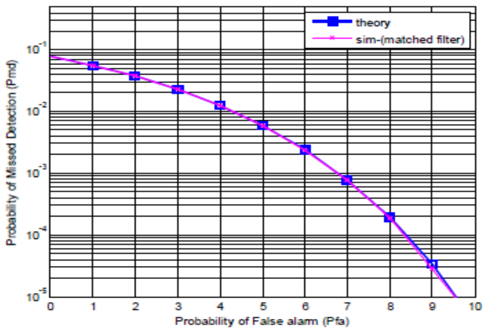

Figure 19: Simulation Result of Matched Filter Detection

The above Matlab simulated plot shows that for the proposed algorithm increase in the value of probability of false alarm results if the probability of detection increases in comparison with the theoretical value.

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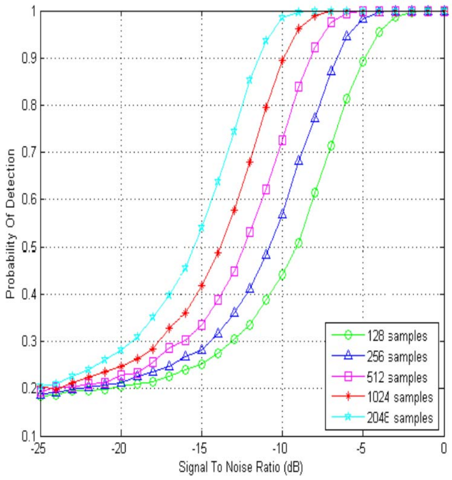

Figure 20: Simulation of Signal-to-Noise Ratio versus Probability of Detection with varying Sample

The above Matlab simulated result shows that the increase in probability of detection results as the SNR of the signal increases. The simulation also shows that the increase in the probability of detection is achieved by increasing the number of samples.

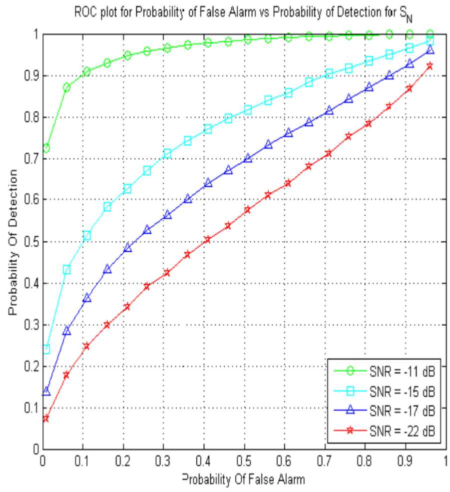

Figure 21: Simulation of ROC for various SNR's

The above Matlab simulated plot shows that as the SNR value reduces from -11 dB to -22 dB, the area under the curve is reduced. Consequently, larger the SNR better will be the probability of detection.

VI. SIMULATION RESULT ANALYSIS AND COMPARISON:

Metric	Energy Detector	Auto Correlation Based Detector	Euclidean Distance Based Detector	Wavelet Based Detector	Matched Filter Detector
Design Choices	Difficult to choose threshold for decision	Finding Auto correlation Function	Evaluating Euclidean Distance	Computing the Wavelet Transform of the signal	Transmission characteristics can be chosen to improve accuracy
Complexity	Low computational and implementation complexity	Moderately Complex	Less Complex	Moderately Complex	Highly Complex (Necessitates a devoted Rx for every primary signal)
Toughness	* Do not need the prior data of Tx signal * Needs awareness of noise power	Do not need any Tx data at the Rx	Do not need any Tx information at Rx	Do not need any Tx information at the Rx	Need near perfect Tx information at Rx
Accuracy of Detection	* Good results at large SNRs * meagre results at small SNRs	Good results at all SNRs	Good results at all SNRs	Good results at all SNRs	* Excellent performance at all SNRs * Poor performance in the absence of prior knowledge about the Tx

Table 2: Comparison of various Spectrum Sensing Schemes

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Energy Detector		Matched Filter Detector	
Probability of False Alarm	**Probability of Detection**	**Probability of False Alarm**	**Probability of Missed Detection**
0.1	0.87	0.1	10^{-1}
0.2	0.92	0.2	$10^{-1.5}$
0.3	0.93	0.3	10^{-2}
0.4	0.95	0.4	$10^{-2.5}$
0.5	0.96	0.5	10^{-3}
0.6	0.97	0.6	$10^{-3.5}$
0.7	0.98	0.7	10^{-4}
0.8	0.985	0.8	$10^{-4.5}$
0.9	0.99	0.9	$10^{-4.8}$
1	1	1	10^{-5}

Table 3: Result Comparison for SNR = -10 dB

VII. CONCLUSION AND FUTURE WORK:

This paper presents a detailed analysis of the working principle of different spectrum sensing techniques such as Energy Detection, Autocorrelation Detection, Euclidean Distance Detection, Wavelet Detection, Matched Filter Detection. It is concluded from the results that Energy Detection is simple and the Matched Filter Detection gives accurate result compared to other spectrum sensing schemes.

The above mentioned work can be extended with many other modulation schemes with OFDM, CDMA techniques which may give more efficient and accurate results for implementing in 5G applications.

REFERENCES

[1]. C. Liu, S. Zhang, W. Li, and S. Zhang, "Optimal power control with QoS constraint for OFDM-based cognitive radio network," in *6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM)*, 2010, pp. 1–4.

[2]. M. Kloc, S. Riess, J. Brendel, S. Linz, M. Gardill, R. Weigel, and G. Fischer, "Let's make them cognitive radio technology applied to professional wireless microphone systems," IEEE Microwave Magazine, vol. 17, no. 1, pp. 70–78, 2016.

[3]. Meena M, Monisha M, Sharanya C, Dr. V Rajendran, Modeling of cognitive radio system for the improvement of spectrum utilization, International Journal of Engineering & Technology, 7 (2.33) (2018) 231-234.

[4]. Thangalakshmi, B. & Bharathy, G.T.. (2015). Review of Cognitive Radio Network. International Journal of MC Square Scientific Research. 7. 9-15. 10.20894/IJMSR.117.007.001.002.

[5]. B Thangalakshmi, GT Bharathy, MATCHED FILTER DETECTION BASED SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS, International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)ISSN: 0976-1353

[6]. N. Kaabouch and W.-C. Hu, "Handbook of Research on Software-Defined and Cognitive Radio Technologies for Dynamic Spectrum Management," IGI Glob. J., 2014.

[7]. T. Yucek and H. Arslam, "A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications," Proc. IEEE, vol. 97, no. 5, pp. 805–823, 2009.

[8]. F. Salahdine, N. Kaabouch, and H. El Ghazi, "A Bayesian Recovery with Toeplitz Matrix for Compressive Spectrum Sensing in Cognitive Radio Networks," pp. 1–13, 2017.

[9]. P. Avinash, R. Gandhiraj, and K. P. Soman, "Spectrum Sensing using Compressed Sensing Techniques for Sparse Multiband Signals," Int. J. Sci. Eng. Res., vol. 3, no. 5, pp. 1–5, 2012.

[10]. Q. Zhi, C. Shuguang, A. H. Sayed, and H. V. Poor, "Wideband Spectrum Sensing in Cognitive Radio Networks," in IEEE Int. Conf, pp. 901–906, 2008.

[11]. F. Salahdine, H. El Ghazi, N. Kaabouch, and W. F. Fihri, "Matched Filter Detection with Dynamic Threshold for Cognitive Radio Networks," Int. Conf. Wirel. Networks Mob. Commun., 2015.

[12]. A. A. Khan, M. H. Rehmani, and M. Reisslein, "Cognitive radio for smart grids: Survey of architectures, spectrum sensing mechanisms, and networking protocols," IEEE Commun. Surv. Tutorials, vol. 18, no. 1, pp. 860–898, 2016.

[13]. M. R. Manesh, A. Quadri, S. Subramanian, and N. Kaabouch, "An Optimized SNR Estimation Technique Using Particle Swarm Optimization Algorithm," The IEEE Ann. Computing and Commun. Workshop and Conf., pp. 1-7, 2017.

[14]. A. Elrharras, R. Saadane, M. El Aroussi, M. Wahbi, and A. Hamdoun, "Spectrum sensing with an improved Energy detection," Multimedia Computing and Systems Int. Conf., pp. 1–6, 2014.

[15]. W. C. Reyes, H., Subramaniam, S., Kaabouch, N., Hu, "A Bayesian inference method for estimating the channel occupancy," Ubiquitous Computing, Electronics & Mobile Commun. Conf. IEEE Ann., pp. 1–6, 2016.

[16]. M. R. Manesh , S. Subramania, H. Reyes, and N. Kaabouch, "Real-time Spectrum Occupancy Monitoring Using a Probabilistic Model," Computer Networks, Elsevier, 2017.

[17]. P. Avinash, R. Gandhiraj, and K. P. Soman, "Spectrum Sensing using Compressed Sensing Techniques for Sparse Multiband Signals," Int. J. Sci. Eng. Res., vol. 3, no. 5, pp. 1–5, 2012.

[18]. D. Cabric, A. Tkachenko, and R. W. Brodersen, "Spectrum sensing measurements of pilot, energy, and collaborative detection," Proc. IEEE Mil. Commun. Conf., pp. 1–7, 2007.

[19]. W. Jinlong, F. Shuo, W. U. Qihui, Z. Xueqiang, and X. U. Yuhua, "Hierarchical Cognition Cycle for Cognitive Radio Networks," in Communications, China, 2015, pp. 108–121.

[20]. B.Thangalakshmi, G.T.Bharathy, Review of Cognitive Radio Network, International Journal of MC Square Scientific Research 7(1), 10-17,2015.

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