Eigen Value Detection: A Novel Approach for Spectrum Sensing in Cognitive Radio Network

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ABSTRACT: The growth rate of mobile users is increasing at very high speed. This rapid increase in wireless technologies has resulted in over-flooded data traffic and created a surplus radio spectrum requirement. This growing demand led to the invention of Cognitive Radio (CR) to providea reliablesolution for spectrum congestion. CR is a special type of radio which operates on Software Define Radio (SDR). It can sense the external environment and decide on dynamic resource allocation. The most significant role of CR is to manage the spectrum efficiently and provide maximum allocation in a short period of time. Spectrum sensing is one key technique that can help reduce frequency congestion in wireless communication networks. An imbalance between the amount of actual spectrum resources in a certain frequency band and the demand for available spectrum is known as spectrum congestion. One way to lessen congestion is to use spectrum sensing techniques effectively. This paper discusses the technique called eigen value detection and energy detection to reduce spectrum congestion becausechannel and signal information are not required by this approach as prior knowledge.CR can also be combined with Artificial intelligence and Machine learning for real-time processing and for efficient results. The advances in Artificial intelligence enable many software tools to require less human intervention.

Keywords: Cognitive radio, Spectrum sensing, Energy Detection, Eigen value detection

1. INTRODUCTION

According to Cisco Visual Networking Index, 66% of the global population is using the Internet which was 51% in 2018. Every year, many new devices with modern capabilities and intelligence are

implemented and adopted in the industry. One of them is Cognitive Radio, introduced in 1991 by JosephMitolla[kaabouch et al., 14]. CR is very different from normal radio in terms of features and operations as it worked only on Software Define Radio (SDR) which is responsible for all the transmissions. The most significant goal of the CR is to give access of certifiedspectrum to unlicensed users which is also called Secondary User (SU). SU can switch the spectrum continuously without disturbing the transmission of the Primary User (PU) and this technique is called Dynamic Spectrum Access (DSA). There aremany techniques in the literature that help in finding the PU such as Covariance detection, Matched filter detection, Eigen value detector etc. However, many factors in the environment limit the performance of these techniques, for e.g.,low computation power, noise uncertainty, and multipath fading. All these issues can be solved by incorporating coordination in CR.
Spectrum Sensing: It is the first and most important task in which SU sense the channel first and identifies the most suitable channel according to its requirement and then detects spectrum holes or white space. The key features of spectrum sensing are the detection of PU, capture of the information, control and start monitoring. The SU may know the status of the channel and other information to give the assistance n the next stages.
Spectrum decision: After completing the sensing phase, it’s time to decide whether to move on a particular channel or not, and this process is called spectrum decision[kaabouch et al., 14] [Salahdine et al.,17]. The CR determines data rate, spectrum selection, spectrum characterization and mode of transmissionthen the appropriate channel is selected according to user requirements. Proper selection of spectrum plays an important task in spectrum management due to the coupling of source and destination. In order to get an optimal decision, the transmission parameters and routing protocol need to be reconfigured again and again. Different routing protocols are [Lu et al., 12] [Salahdine et al., 17].
Spectrum Sharing: It is responsible for sharing vacant bands when not in use to avoid any kind of collision. It includes three main aspects spectrum allocation, spectrum access and selection of spectrum.
Spectrum mobility: When the spectrum moves to another frequency band in order to fulfil the transmission rate it is called spectrum mobility. It is usually done in such a manner that PU does not have to wait for transmission. There are various handoff strategies in the literature to avoid any kind of collision [Risheek kumar, 14]. In [Lu et al., 12] author discusses the comprehensive survey on spectrum handoff techniques and their limitations.

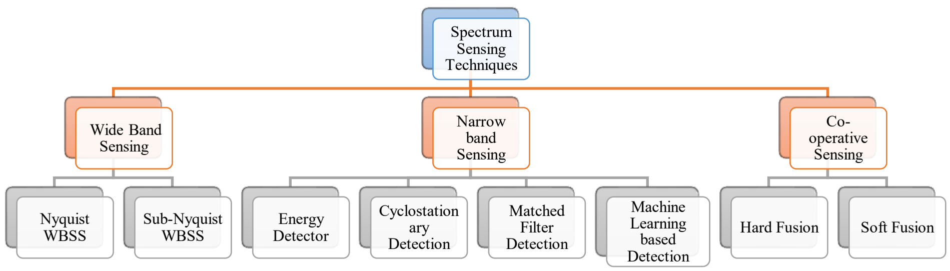

Figure 1 Different techniques of spectrum sensing

1.1 Spectrum Sensing techniques

The key objective of spectrum sensing is to sense the spectrum at the base station and continuously check whether the PU is present on the channel or not. While continuously sensing, there are a few issues that arise like determining the spectrum characteristic, and channel statistics. In order to get optimal performance, there should be prior knowledge about the presence of PU and noise. In traditional sensing methods like energy detection, cyclo stationary, the hidden terminal problem arises due to the shadowing effect at Cognitive Radio. Designing a less complex, and highly robust sensing scheme is a really challenging task. There is a trade-off between optimal sensing and its requirement. So to solve these problems,prior knowledge of signal and a high computational intelligence algorithm is needed for efficient sensing. One common method used for spectrum sensing is energy detection, which is widely used due to its simplicity and lack of prior knowledge about the signal. However, energy detection is ideal only for Independent and Identically Distributed (I.I.D) signals[Anaand et al., 2016] and falls short when dealing with correlated signals. In this article, we will explore an alternative approach to spectrum sensing using eigenvalue detection, specifically focusing on the maximum eigenvalue. By leveraging the power of eigenvalue-based algorithms, we can overcome the limitations of energy detection and improve the detection performance in the presence of correlated signals.

1.2 Blind signal Detection

It is also a part of blind Signal Processing where the presence of signal can only be estimated based on the received signal and this approach can help in minimizing the error vector.It require no prior knowledge of signal and power.

(a) Energy Detection: An Energy Detector (ED) is the most commonly used detectorto sense the presence/absence of PU by measuring the received signal power. It is also a blind detector because both noise and signal are unknown. It calculates the energy (T_e) of PU signal by comparing the received signal power with a predefined threshold(λ_e) [Srisomboon et al., 15].ED has gained much attention as it is the first approach to come tomind when applying a detection algorithm due to its low complexity and the need for prior knowledge of the signal [Gunichety et al., 15]. The accessibility of ED allows many sensing techniques to operate in different environmental conditions. Due to these advantages, ED proves to be capable of extensive research and offers researchers to study it in different channel conditions. Researchers investigate the performanceof ED in real-time applications and inference is made on its low computation power. ED cannot differentiate between noise and signal. It can only operate in the time and frequency domain. The test statistics are given below

$$T_e = \frac{1}{N_e} \sum_{n=0}^{N-1} |X(n)^2| \quad (1)$$

Average SNR is calculated by equation (2)

$$\mathrm{SNR} = \frac{P}{\sigma_n^2} \quad (2)$$

Where received signal power is defined as

$$P = \lim_{n\to\infty} \frac{1}{N} \sum_{n=0}^{N-1} |X(n)^2| \quad (3)$$

Where X(n) is the received signal. N is the number of samples which is calculated as N_e= 2TW,$\sigma_n^2$is the noise variance. The noise is Additive White Gaussian Noise (AWGN) with zero mean[kaabouch et al., 14] [Anaand et al., 2016].

(b) Cyclo Stationary feature Detection (CFD):In CFD signals having periodicity confirm the presence of PU. Generally, periodicity is defined in the form of a sinusoidal wave, spreading and hamming code of primary signal. This kind of periodicity is not found in noise and interference that's why it is robust to noise and performs better than energy detection even in low SNR.

(c) Eigen value-based Detection: It is based on eigenvalues of the covariance matrix of received signals. It has comparatively high robustness against noise.

Eigenvalues are scalar values called lambda (λ) of a square matrix A [Ali et al., 19]. By determining the correlation between samples, eigenvalues are used in signal identification to identify noise in signal samples as noise samples are uncorrelated with each other. When a signal is absent, the received signal in the covariance matrix is converted into an identity matrix and multiplied by the noise power (σ^2I)[8], with the result that all of this matrix's eigenvalues are equal to the noise power.

2. System Model

Consider a model where a signal processing unit is connected to a receiver/detector with an antenna for signal processing. Additionally, take note of the antenna's ability to transmit the signal it receives to its processing unit.

Hypothesis testing is used for signal detection. Using the hypothesis testing procedure, we assert the existence of a signal. H_0, the null hypothesis, and H_1, the alternate hypothesis, are the two hypotheses. H_0 is a representation of the absence of a signal or the presence of noise, while H_1 is a representation of the simultaneous presence of a signal and noise. The antenna's received signal is provided by

H_0 : x(n) = ŋ(n)   (4)

H_1: x(n)= t(n) + ŋ(n)   (5)

Where n =1,2,3….N

Where t(n) is the received signal that passes through a wireless channel consisting of multipath fading, path loss and time dispersion effects at the antenna/receiver and η(n) is the received noise at the antenna/receiver. The received source signal can also be written as

$$T(n) = \sum_{K=1}^{N_P} \sum_{l=0}^{\mathrm{qk}} C_k \ (l) S_k(\text{n-l}) \quad (6)$$

Where Np is the number of primary signals, S_k(n) transmitted primary signal from the primary user or antenna C_K(l) denotes the propagation channel coefficient from the k^{th} primary user or antenna to the receiver/antenna and q_k is the channel order for C_k.

For channel sensing, two probabilities are primarily utilized: the probability of false alarm and the probability of detection [15]. The existence of PUs when they are truly absent is determined by the probability of a false alarm, or P_{fa}. A low probability of false alarm should constantly be the goal in order to increase the likelihood that the Secondary users (SU) will employ the sensed spectrum when it becomes available. The amount of time that the sensing algorithm takes to accurately determine whether the PU (licensed) is present is known as the probability of detection[16].

Probability of false alarm is given by

$$P_{fa} = Q\left(\frac{\lambda-\sigma_n^2}{\sqrt{\frac{2\sigma_n^2}{N}}}\right) (7)$$

The probability of detection is given by

$$P_d = Q\left[\frac{[\lambda-(P+\sigma_n^2)]}{\frac{\sqrt{2(P+\sigma_n^2)}}{N}}\right] \quad (8)$$

The equations of threshold can be calculated as

$\lambda = Q^{-1}(P_{fa}).\frac{\sqrt{2\sigma_n^4}}{N} + \sigma_n^2$ (9)

$\lambda = Q^{-1}(P_d).\sqrt{\frac{2(P+\sigma_n^2)^2}{N}} + P + \sigma_n^2$ (10)

From equation (7) (8) & (9) we can find the relationship between N, SNR, P_{fa} , P_d

$P_d = Q\frac{\left[Q^{-1}P_{fa}\sqrt{\frac{2}{N}} - SNR\right]}{\sqrt{\frac{2}{N}}(SNR+1)}$ (11)

Probability of miss detection can be calculated by

$P_{miss\text{-}detection} = 1 - P_d$ (12)

There are several methods based on eigenvalues to detect the presence of PU's signal, such as Maximum to Minimum Eigenvalue detection (MME), Maximum Eigenvalue Detection (MED), Minimum Eigenvalue Detection, and Generalized Likelihood Ratio Test (GLRT) [10].

2.1 Maximum Eigen value Detection

In this detection, we use the maximum eigen value of the covariance matrix as the test statistic to detect the presence of PU [Ali et al., 19] It can be written as:

$T_{MED} = \lambda_{max}$ (13)$P_{fa} = P(\lambda_{max}(R_w(N) > \eta_{MED}\sigma_w^2) \cong 1 - F_1\left[\frac{[\eta_{MED}\ N - \mu]}{v}\right]$ (14)

Where $\mu = (\sqrt{(N-1)} + \sqrt{ML})^2$

$V = \left(\sqrt{N-1+ML}\right)\left[\frac{1}{\sqrt{N-1}} + \frac{1}{\sqrt{ML}}\right]^{1/3}$ (15)

F_1 is the Cumulative Distribution Function (CDF) of the Tracy wisdom distribution of order 1.

The threshold is selected in such a way to ensure a maximum probability of detection and minimum probability of false alarm. It can be calculated by the following equat

$\eta_{MED} = \frac{(\sqrt{N} + \sqrt{ML})^2}{N}\left[1 + \frac{(\sqrt{N} + \sqrt{ML})^{-2/3}}{(NML)^{1/6}} F_1^{-1}(1 - P_{fa}^F)\right]$ (16)

2.2 Maximum to Minimum Eigen value Detection

In this detection, we use the ratio of maximum to minimum eigen value of the covariance matrix as the test statistic to detect the presence of PU. It can be written as

$$T_{MME}=\frac{\lambda_{max}}{\lambda_{min}} \quad (17) \qquad P_{fa}\cong 1- F_{-1}\left[\frac{\eta_{MME}\left(\sqrt{N-1}-\sqrt{ML}\right)^{2}-\mu}{v}\right] \quad (18)$$

$$\eta_{MME} = \frac{\left(\sqrt{N}+\sqrt{ML}\right)^{2}}{\left(\sqrt{N}-\sqrt{ML}\right)^{2}}\left[1+\frac{\left(\sqrt{N}+\sqrt{ML}\right)^{-2/3}}{NML^{1/6}}F_{1}^{-1}(1-P_{fa(MME)}^{F}\right] \quad (19)$$

ɜnsing scheme	eference	lerits	Demerit
Energy Detectioı	[Salahdine et al., 1 [Lu et al., 12] [Salahdine et al., 1	Not required any pı knowledge of PU	High probability of fa alarm
Covariance Base *Detection*	[Ayeh et al., 14] [Anaand et al., 201	Blindly Detectioı prior knowledge c Signal and noise is required	Computational complexity
Eigen value *Detection*	[Jing et al., 12] Srisomboon et al.,	Reliable at low SN	signal fluctuations minimum eigenvalı
Matched Filter *Detection*	[Salahdine et al., 1 [Anaand et al., 201	Optimal sensing	mpractical because p nowledge of the sign not always availab
lachine Learning b *Detection*	[Krishna kumar et 22] [Jacob et al., 20	Minimise the detect Delay Use complex algori in easy manner	Complex Techniqu High dataset is need

Table 1: Different sensing scheme with its merits and demerits

3. Simulation Results

All the simulations are performed on MATLAB 2016R to show the influence of different parameters like probability of false alarm, probability of detection, SNR and no. of samples. Simulated results are obtained using a random primary signal modulated by BPSK. Fig 2 depicts the Receiver operating characteristic (ROC)curve of effects of SNR on the probability of detection for energy detection. At SNR 6 dB, the probability of detection 1 is achieved when $P_{fa}$is 0.5. The probability of detection gradually increases with the improvement in SNR. Then we examine the detection performance of energy with minimum eigen value (EME) and maximum-minimum eigen value. Fig 3 clearly shows that MME outperforms ED as P_d =1 is achieved at SNR -14dB. Whereas EMEdoesn't show that much good results but better than ED. Fig 3 shows the result of eigen value detection as a function of no. of samples and SNR. Fig 4 shows that probability of a false alarm decreases with an increase in SNR because a clearer signal gives less chance of a false alarm. Fig 5 shows the number of samples versusthe probability of miss detection. The ROC curve depicts that when there is a decrease in SNR, chances of miss-detection also get low with an increased number of samples.

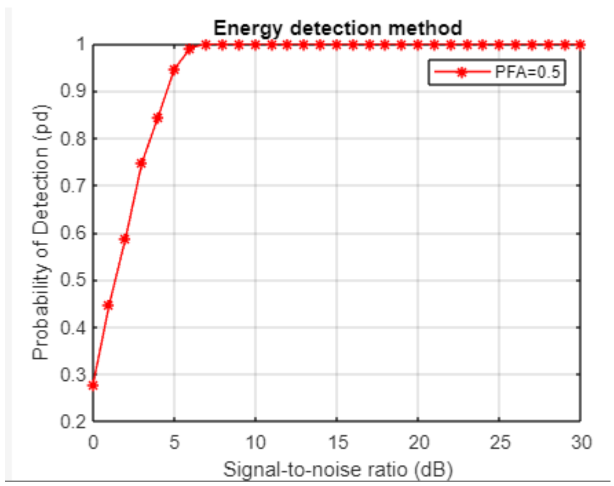

Figure 2: Probability of detection Verses different SNR for Energy detection

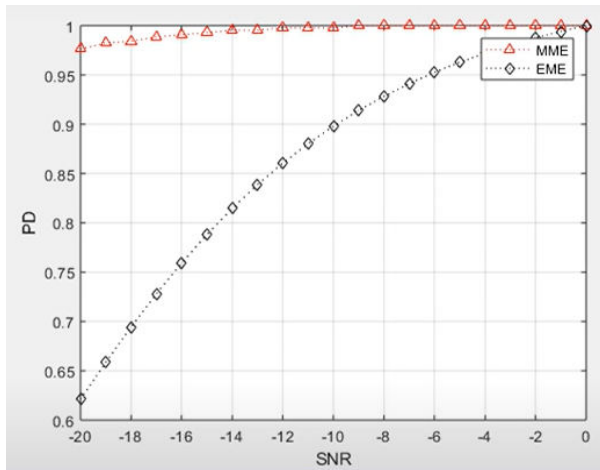

Figure 3: Probability of detection versus different SNR for MME and EME

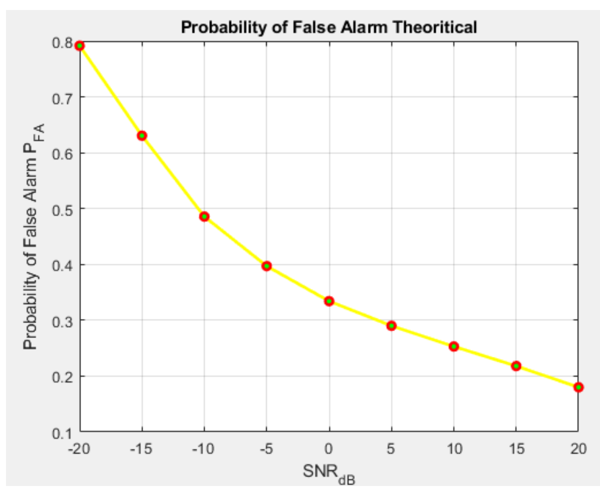

Figure 4: Probability of false alarm versus different SNR for energy detection

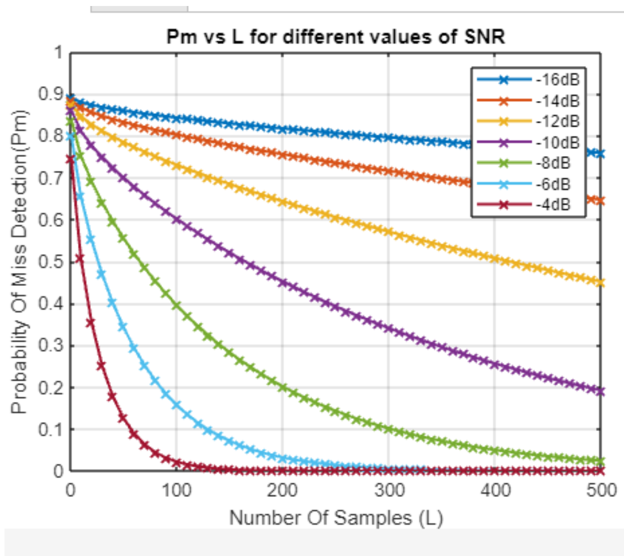

Figure 5: Probability of Miss Detection for different number of sample

3. Conclusion

conclusion, maximum eigenvalue detection offers a promising alternative to energy detection for spectrum sensing management in cognitive radio network. By leveraging the correlation information embedded in the eigenvalues, maximum eigenvalue detection can achieve higher detection performance, especially in the presence of correlated signals. The proposed semi-blind method, which utilizes the minimum eigenvalue as the test statistic, further enhances the detection performance by eliminating the need for prior knowledge about the channel or the signal. Future research in this area should focus on refining the proposed method and exploring its applicability in practical cognitive radio systems. By harnessing the power of maximum eigenvalue detection, we can unlock the full potential of spectrum sensing and pave the way for more efficient and reliable spectrum utilization in the era of cognitive radio.

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