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Research Article

An Evolution Framework for Evaluating Intelligent Spectrum Sensing Mechanisms in Cognitive Radio

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Abstract: Cognitive radio technology has advanced to address the challenge of limited spectrum availability by employing spectrum sensing techniques. This process is framed as a detection problem involving two core hypotheses: Hypo-0 and Hypo-1. Hypo-0 represents the scenario where only noise is present, and its modeling depends on parameters such as the number of observed samples, the timing of signal acquisition, and the presence of Gaussian white noise with a defined variance. In contrast, Hypo-1 accounts for the presence of a signal, incorporating a channel propagation factor that reflects the interference power received. Several techniques have been developed to address this challenge, with energy detection emerging as a widely adopted approach due to its ability to function without requiring prior knowledge of the signal. However, its effectiveness diminishes under low signal-to-noise ratio (SNR) conditions. This paper introduces an evaluation framework that formulates the spectrum sensing problem using two primary hypotheses, H0 and H1. It benchmarks conventional energy detection techniques and those specifically designed for low SNR environments through comprehensive statistical analysis. This work introduces a novel framework for benchmarking spectrum sensing methods, filling a gap not addressed in current literature. It evaluates the performance of ten cooperative spectrum sensing techniques, Maximum Eigenvalue Detection (MED), Generalized Likelihood Ratio (GLR), Maximum-Minimum Eigenvalue Detection (MMED), Energy Detection (ED), Arithmetic to Geometric Mean Ratio (AGM), Hadamard Ratio (HR), Volume-Based Detection (VD), Gershgorin Radii Centers Ratio (GRCR), Gini Index Detection (GID), and the newly proposed Rician Rice Factor-Based Detection (RFD). The analysis focuses on the probability of detection across varying signal-to-noise ratio (SNR) levels, from low to high, as well as different numbers of secondary or cognitive users. Among all methods evaluated, the proposed RFD technique consistently achieves higher detection accuracy, maintaining strong performance under both challenging noise conditions and with an increasing number of cognitive users.

Keywords: Security Spectrum Sensing, Cognitive Radio, Cooperative Sensing, Energy Detection Method, Statistical Analysis

Introduction

A rapid development has taken place in the evolution of wireless communication technology over the last decade. The evolving generation of wireless communication standards is 2G, 3G, 4G, 4 G-LTE, 4 G-LTE-Adv, and now 5G (Mshvidobadze, 2012; Albreem, 2015). There are various applications and services being offered and also conceptualized to be offered in the future over these evolving wireless communication and network platforms (Wang *et al.* 2020). The future generation application and services utilize both licensed and unlicensed radio frequency bands (Khan *et al.*, 2020). The traditional mechanism adopts a static way of spectrum allocation to the devices irrespective of the actual requirements, which is not a suitable method in the case when the spectrum is available in a limited aspect, as it offers either under-provisioning or over-provisioning of the spectrum (Hu *et al.* 2018). The rapid growth of the Internet of Things, or a communication system of anything to anything, demands a dynamic allocation of the spectrum. In other words, it can be said

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that the rapid growth in the demand for wireless communication-based applications leads to evolve various technologies and open up new market dimensions. One of the applications, where the IEEE 802.22 detects the unused bands of the spectrums in digital TV channel and make it to be utilized into the rural broadband connectivity. There are restrictions on transmission through the air, and the allocation is generally handled by the regulatory bodies, and the spectrum allocation is a quite difficult and challenging task. The allocation is a quasi-static process and the generally whenever a certain frequency band is assigned to a group of the users, they hesitate to release it, whereas the traditional technology becomes obsolete with the new kind of the use-case requirements (Saha, 2019). Therefore, an efficient method namely cognitive radio technology has evolved in order to provide a method to use the available spectrum in optimal way (Ahmad *et al.*, 2020).

In the radio frequency spectrum, there exist many unused or unoccupied frequency bands, popularly known as spectrum holes or white spaces. The cognitive radio technology allows to use of these white spaces, which increases the efficiency of the available radio frequency spectrum. The cognitive radio technology-based network is known as Cognitive Radio Network (CRN), which usually have both primary and secondary users as PU and SU respectively. The PUs are licensed user and rest all users are also known as Cognitive Radio Users (CRU). In CRN the primary task of each CRU is to detect or identify the PUs and also detect the available spectrum, this process is known as Spectrum Sensing (SS). Therefore, primarily the CRU shall identify the white spaces and utilize it to maximize their throughput and Quality of Service (QoS) without switching or inducing any kind of interference to PUs. Thus, the problem of spectrum sensing is termed as a problem of detection which is critical and important for performance balance for both PUs and CRUs.

There is always possibility of multipath fading, receiver uncertainty problem and shadowing in a real-time scenario which causes challenges on method for the detection of white spaces and presence of primary user. These challenges can be minimized if the CRUs work co-operatively by sharing the information of their sensing to the other CRUs and this approach is called as cooperative sensing, which is an efficient approach to mitigate these challenges (Mishra *et al.*, 2006). Therefore, the problem of optimization of detection performance is an open research problem. The goal of optimization is to maximize the probability detection within the maximum threshold of probability of false alarm. A typical architecture of the scenario of the collaborative use of the spectrum by both the PUs and CRUs is illustrated in the Figure 1.

The evolution framework is a structured approach for assessing the development of intelligent spectrum sensing mechanisms in cognitive radio systems. It focuses on utilizing AI and machine learning to enhance the detection and utilization of available frequency bands. Cognitive radios dynamically adjust their operating parameters based on the environment, and the framework evaluates their effectiveness through methods and metrics that measure detection accuracy, speed, and adaptability. It also considers how these radios adapt to changing environments through learning, using simulations to test various algorithms and optimize performance through algorithm refinement and resource allocation.

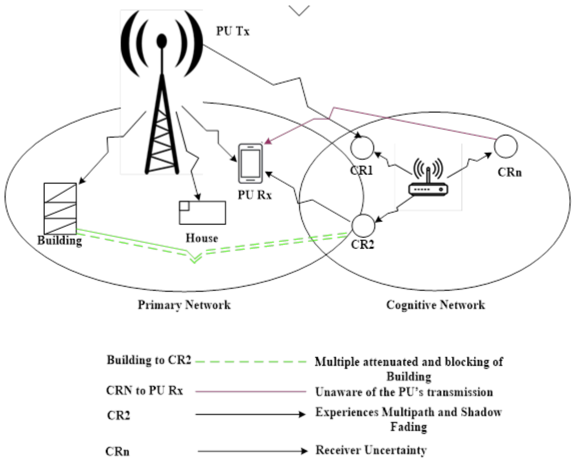

Fig. 1: Architecture of the scenario of the collaborative spectrum sharing between Pus and CRUs

There are various methods for the spectrum sensing including Energy detection, cyclostationary features detection, matched filter detection, covariance based-detection and now a day's machine learning-based sensing schemes are gaining popularity. The trade-off between the probability of the detection and the probability of false alarm is the core objective of the evolution of the solution strategies The higher probability detection ensures lower interferences to the PUs, whereas if the sensing takes less time, then it provides better opportunity to the SUs or the CRUs to avail the white space spectrums to maximize their network performance Many of the traditional methods lacks these possibilities, therefore this paper aims to optimize the traditional Energy Detection Method (EDM) which works well in the presence of high SNR and then further evaluate the methods which works well in lower SNR.

Secondary Users (SUs) are those who do not have licensed access to specific spectrum bands but can use them temporarily when the Primary User (PU) is not active. They rely on spectrum sensing to detect and use these gaps without causing interference to the PUs. Cognitive Radio Users (CRUs) are a more advanced type of SU, equipped with cognitive radio technology that allows them to adapt their operating parameters based on real-time spectrum conditions. CRUs can learn from past

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experiences, improve their spectrum usage strategies, and make intelligent decisions on spectrum access. While all CRUs are SUs, not all SUs have the advanced capabilities of CRUs.

Related Works

The broader classification of the spectrum sensing technique includes analysis of either one frequency or many frequencies channel at a given time instance, which are known as Narrowband and wide-band sensing respectively.

Narrowband Sensing Techniques

In the narrowband sensing algorithms, the methods like, energy detection (Ranjan *et al.*, 2016; Arjoune & Kaabouch, 2019), cyclostationary features detection (Jang, 2020; Reyes *et al.*, 2016), matched filter detection (Salahdine *et al.*, 2016; Lv & Gao, 2015), covariance based-detection (Chen *et al.*, 2019; Zeng & Liang, 2009), and now a day's machine learning-based sensing (Tian *et al.*, 2019; Lu *et al.*, 2016) is gaining popularity. The software defined capability of the cognitive radio allows to operate on the various parameters including, power, spectrum band and type of the modulation by the software itself. It is observed by Ranjan *et al.* (2016) that the probability of the detection generally increases with the probability of false alarm, when an Energy Detection Algorithm (EDA) is coded in sequential programming, whereas the method adopted by (Ranjan *et al.*m 2016) uses a fixed threshold of noise. In contrast, in the work of (Srisomboon *et al.*, 2015) , a double constraint is considered which is an adaptive energy detection method where the threshold are decided on the correlation of the probability detection and the false alarm. The higher detection rate of (Srisomboon *et al.*, 2015) comparatively ensure that the interference to the PU is less as well as the minimal time of sensing ensure higher opportunity to the SU or CRUs to avail the spectrum allocated for the PUs. Though the EDA does not depend of the heuristic details of the PUs but it fails to classify between the noise with the signal and due to this it provides lower detection and higher false alarm in lower SNR. In this direction, in the work of (Arjoune *et al.*, 2018b), using a blind technique, the threshold is selected dynamically depending upon the power of the noise and found that in this way the detection probability and the false alarm is optimizes as compared to the static threshold-based method. The future generation applications require higher data transfer speed and spectrum utilization, with the minimal interferences with overcoming the adverse effect of channel fading. The model proposed by the (Eslami & Karamzadeh, 2016), uses double thresholding for the spectrum sensing to improvise the reliability of the conventional energy detection methods and analyses the effect in low SRN in a specific fading channel. One more work carried out by Muralidharan *et al.* (2015) adopts the dynamic threshold where the system trains themselves for the heuristic decision and exhibits better performance as compared to the conventional-EDA. In the extensive study by Arjoune & Kaabouch (2019), highlights that the double-thresholding or adaptive thresholding does not provide acceptable probability of detection in the lower SNR conditions as well as it is highly sensitive in the noise variations. The false alarm is also higher in comparison of single thresholding.

On the other hand, if the signal which is received is known as cyclo-stationary if the value of its mean and the auto-correlation are periodic. These cyclo-stationary signal features are exploited in the cyclo-stationary based detection method in order to classify the signal from the noises by means of the spectrum correlation analysis (Jang, 2020). In the work of (Yawada & Wei, 2016), a non-cooperative spectrum sensing based on the cyclo-stationary signals are proposed whose performance is analyzed using Receiver Operating Curve (ROC) which provides better result in comparatively lower SNR as well as comparatively less sensitive to the unclear noises. For the wideband signals in cognitive radio it is essential to achieve very reliable as well as efficient spectrum sensing but the traditional Nyquist methods which are used to adjust the lower sampling suffers from a limitations of lower SNR, therefore, in order to achieve the robustness along with the efficiency, in the work of (Cohen & Eldar, 2017), a cyclo-stationary detection is proposed where the periodic spectrums are recovered from a low rate samples. In the work of (Reyes *et al.*, 2016), an experimental approach of an auto-correlation based spectrum sensing is proposed where the evaluation of the both the performance metrics probability of detection and false alarm is evaluated at different Gaussian noises using USRP device and GNU radio software and it gives better results as compared to the energy detection.

Another technique, in the line of evolution is the Matched Filter Sensing Techniques (MFST), where the comparison takes place between the pre-allocated and the signal received. The samples signals are obtained from the same transmitter are used to compute the trial or assessment statistics for the comparison with the threshold and finally if the signal is higher than this threshold it is considered to be present. In the paper by Salahdine *et al.* (2015), in oppose to the static threshold, a dynamic threshold is considered with the matched filter technique and compared its performance with previously discussed techniques. The model suggested by Lv & Gao (2015) considers a PU with single and SU with multi antennas and assumed that PU works at varied power levels. They assume that a cooperation exists among the PU and SU. In this method not only, the PUs is detected rather it also identify the transmit power of the PUs. The model is mapped with the problem space of MFST and introduces new performance metrics.

Since, the signals of the PUs are correlated, which can be classified differently from the noise, therefore, the Covariance Detection Algorithm (CDA) manipulate the covariance matrix of the signal and the Singular Value Decomposition (SVD) to detect the PUs. In the work of (Chen *et al.*, 2019), the spectrum sensing problem is being studied that is correlated with multi antennas in the context of the fading channel for the cognitive radio network. In the model they assumed that all the antennas having similar or rather same variance of noise and designed a covariance-based detection by taking a theoretical threshold for the computation of the false alarm. The probability of detection and the RoC is considered as a benchmarking parameter and if analyzed provides better results scenario as compared to the works of Kumar *et al.* (2013) and Zeng & Liang (2009).

In the recent days, the machine learning based approaches are gaining momentum to solve various complex task. The schemes or algorithms proposed in the cognitive radio network aims to formulate a classification problem for detecting the white spaces in the spectrum using feature vectors like probability vector and the energy statistic (Tian *et al.*, 2019). In the study by Balaji *et al.* (2015), a co-operative sensing of spectrum is devised. In Khalfi *et al.* (2017), a supervised learning model is used to estimate the occupation of the spectrum and claims to achieve higher accuracy in lower overheads. Another approach of using machine learning for spectrum sensing CRN is found by Lu *et al.* (2016), where a probability vector is introduces as a feature set for the training the classifier in place the energy vector as a feature which makes it to perform faster in less training period.

Wide-Band Sensing

In this type of spectrum sensing method, the division of the spectrum takes place as multiple sub-bands and these bands are sensed. The sensing process takes place in both concurrently as well as sequentially by using the above discussed narrow-band techniques. Both the sequential and concurrent sensing method suffers the challenges of the higher energy consumption and computational complexities respectively (Lu *et al.*, 2017). An extensive survey is conducted by Sun *et al.* (2013) on Wide-Band Spectrum Sensing (WBSS) , and the use of the sub-Nyquist is found more frequent for the sampling process. Under the Nyquist WBSS, various methods using wavelet detection is found relevant. In reality the while spectrum sensing the prior knowledge are not available, Zhao *et al.* (2014) introduced a novel WBSS using wavelet transformation with an assumption that the PUs signal carries a sparse information whereas noise contains higher degrees of information, and the domain transformation distinguishes the signals more effectively. The computational complexity reduces from degree 2 to degree one in comparison to the ED and CS methods. In the line of evolution, Kumar *et al.* (2016) proposed an improved wavelet transformation where non-linear scaling of the coefficients ensure better accuracy. The study by Capriglione *et al.* (2016) highlights the fact the wavelet-based methods are comparatively better but works well only in the high SNR scenarios or context. Therefore, a further evolution or optimization is required to work with the dynamic and challenging SRN conditions. The multiband joint detection is an approach towards that.

Zhi Quan *et al.* (2009) introduced an optimal WBSS as multiband joint detection where detection of the signal from the PUs takes place on multiple frequency bands in a given instant of time. The performance metric of the method considerably improvises and establishes a milestone for the distributed WBSS algorithm in CRN. Alijani & Osman (2020) discussed that methods like cooperative sensing and multi-band joint detection are proposed to improve the performance as compared to the energy detection methods.

Further, Filter based, Compressive Sensing-based WBSS are proposed in a literature. The purpose of the multicarrier data transmission takes place by means of the use of the OFDM as it is found to be suitable for the SS in CR but due to its cyclic nature of prefix the efficiency of the spectrum gets reduce, where multicarrier filter banks replaces the OFDM. Muralidharan *et al.* (2015) using cosine modulated filter a two-step SS in CRN is proposed using FIR filter and FRM filter. Another work by Lin *et al.* (2011), introduces a new filter namely Multi-Stage Coefficient Filter (MSCF) for WBSS in CR to minimize the overheads. An extensive survey on the application which uses compressed sensing in CRC is done by Sharma *et al.* (2016). Arjoune *et al.* (2017) reveals that the occupancy of the spectrum is not optimal in the domains of the time, frequency and space where compressed sensing theory is useful. There are important processes like sparse recovery or non-linear decoding, measurement collection and sparse representation of the signal in compressed sensing. Arjoune *et al.* (2018a) analyses various measurement metrices in compressed sensing.

Background

Management Modeling Spectrum Sensing Problem

In a cooperative spectrum sensing scenario, Cognitive Users (CUs) or Secondary Users (SUs) work together to gather signal samples within a defined sensing period. When the total number of such users is denoted as 'M', where each user contributes 'K' signal samples, the objective is to determine the presence or absence of a Primary User (PU). This setup can either represent a single CU or SU equipped with 'M' receiving antennas, or 'M' individual users each equipped with one antenna. The resulting collection yields a total of $M \times K$ signal samples, which are then forwarded to a centralized unit for signal fusion. However, this assumption is only feasible if one node is capable of capturing all $M \times K$ samples independently, which is generally unrealistic. On the other hand, having M distributed users each transmitting K samples to a fusion center introduces several implementation complexities. Due to these

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constraints, the cognitive detection process is better modeled using two fundamental hypotheses: Hypo-0 and Hypo-1. The Hypo-0 scenario incorporates parameters such as the time instance (t) during which the sampling occurs, the number of contributing samples (M), and the presence of Gaussian white noise with a specific variance (σ^2), forming the foundation for detection analysis.

$$A(t) = \begin{bmatrix} A_1(t) \\ A_2(t) \\ \vdots \\ A_M(t) \end{bmatrix}$$

Where, A(t) is an M x 1 column vector that represents *M* signal samples as a complex time series signal at the time instant *t*, in other side, the complex Gaussian white space/noise formed at the random variance of σ^2 for B, is represented by B(t) $\{B(t) \mid B(t)\, \forall, t = \{1, 2, \ldots M\}\}$. The system adopts a Hypo-0 such that, *A(t) = B(t)*. In the formulation of Hypo-1, it takes a parameter propagation channel that evaluates the power arrival as an interference. The propagational channel at time instance *t* is $p_c(t) \in P_c^{M\times 1}$, evaluates the interference between the Primary User (PU) and *M* collaborative CUs | SUs. If D(t) is a denotation of circular complex Gaussian (CCG) to sample set as *t* = 1,2,…M, which detects the source of the signal which having mean value of 0 and the variance = 1, it means that the condition below is satisfied:

$$E\left[D^2(t)\right] = \sigma_D^2 \neq 0$$

Therefore, the data staking of the observe sensing is:

$$Z = \begin{bmatrix} A_1(1)\, A_1(2) \ldots A_1(K) \\ A_2(1)\, A_2(2) \ldots A_2(K) \\ A_M(1)\, A_M(2) \ldots A_M(K) \end{bmatrix}_{M\times K}$$

In a case, where if the signal samples $K \to \infty$, then,

$$Q = \frac{1}{K} Z Z^H$$

Where, Q is the signal sample Co-variance matrix which converge as $Q \to E\left[A.A^H\right]$, s.t A←M sample by M, CU_S | SU_S, Therefore, Eigen vector of (Q) → Primary signal. Finally, the system adopts a Hypo-1 such that: A(t) = $p_c(t)$ x D(t) + B(t).

Spectrum Sharing Using Energy Detection Technique

There are various variants of determining the PUs energy detection for spectrum sensing. Most the model assume that a specific bandwidth is allocated to the PUs. Whereas, the SUs or CRUs are one who uses these bandwidths opportunistically. The algorithms aim to minimize the false positive so that it balances the interests of PUs, CRUs and the service providers. If *E* is the energy detected and E_p is the energy of the PUs. The signal generates takes *N* as noise, the problem of energy detection is formulated as a signal generation: E = E_p + N, if the Primary user is present, else, E = N. In the evaluation model, the signal *E* is generated and a random input test for each method including Classical Energy Detection (CED), General Energy Detection (GED) and Modified Energy Detection (MED) and the performance evaluation takes place between the detection probability versus false alarm. The algorithm for the Classical Energy Detection (CED) is given as below:

Input: Ns, SNR, α

Output: $(d), Pb(fa)$

Start

Initialize: Ns, SNR, α

for each power factor $P \in 1, 2, 3, 4, 5$ **do**

  $Pb(fa) = \sum[(fa)_i, (n-1)\Delta d]$, where $(fa)_i$ is the initial value of fa, $n = 100$, Δd = increment

end for

for each $Pb(fa)_n$ **do**

  for each α **do**

    $N = f_1(Ns)$ // generate noise

    $Ep = SNR \times f_{rand}(Ns)$ // primary user signal

    $E = Ep + N$ // PU present with added noise

    Compute: $\mu_0, \mu_1, \sigma_0, \sigma_1$

    $Th(P) = \mu_0(P) \times Q_f(Pb(fa)n) + \mu_1(P)$

    $E = |E|_P$

    $[E] = (1/N_s) \times \sum E$

    if $[E] \geq Th(P)$ **then**

      Update $\vec{E}$

    end if

  end for

end for

$Pb(d) = \vec{E}/\alpha$

End

The algorithm initializes the number of the samples (Ns), signal to noise ratio (SNR) and, the observation in a unit probability of a false alarm (fa) value(α). The values of the probability of the detection: Pa(d) and the probability of the false alarm: Pb(fa) is computed for each of the power factor P ∈ {1,2,3,4,5} with 1% of continuous incremental of the Pb(fa) and unit incremental till the α.

Further, the (MED) is improvised as improved energy detection (IED) and finally, the dynamic evolution takes place as variable or changing threshold-based energy detection (VTED). In the CED, a predefined threshold (Th) is considered to compare the signal (E), if E>Th then it defines the presence of the PU else it is assumed that the PU is absent, whereas the GED works on the same principal of the CED except that unlike considering the $|E|^2$, i.e, square of the value of the amplitude of the E, it raises a power P, as $|E|^P$, where $P \in \{1,2,3,4,5\}$. Figure 2 shows the performance graph of the probability of detection Pb(d) versus the probability of the false alarm Pb(fa).

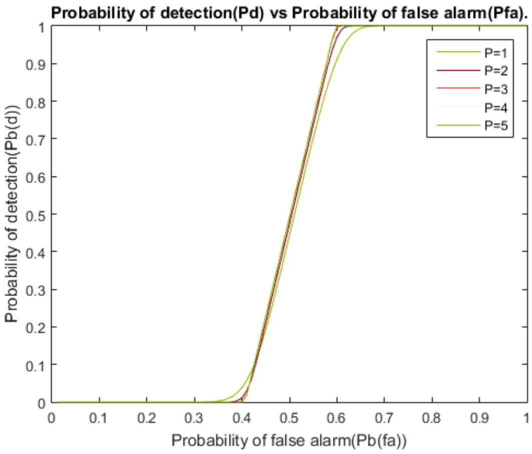

Fig. 2: Probability of Detection Vs Probability of the false alarm

In order to minimize the false negative (fn) a modified energy detection (MED) is designed, as whenever there exist some short of the impulsive dynamic changes due to various conditions of the environment, in those cases the computed *E* drops below the Th, therefore this technique adjust the value or the amplitude of the *E* as it maintains the heuristic recodes of the mean values of the previously detected energy. The process works as if E>Th, then the PU is considered to be present even if E_{mean} > Th it considers PU is present otherwise PU is considered to be absent. Further, the to minimize the false alarm (fa) of the MED, the improved energy detection (IED) is proposed, which considers the mean value of the previously measured value of E as well checks the last but one value to take the decision for existence of PUs.

In all the methods, of CED, GED, MED, IED methods considers a fixed or a constant value of the Th, whereas in contrast, the Variable Threshold Energy Detection (VTED), considers a varying threshold (Th) based on the noise variance factor of $\hat{o}$ which changes in correlation with the previous observation of E. Though the method of the energy detection is popular one as it does not require the priori heuristic about the signals of the PU but it has its own limitations such as higher time complexity to compute the Pb(d), performance is dependent on the noise power uncertainty. It cannot differentiate the primary signals of the CRUs as well it is not suitable to identify the spread spectrum signals. However, this method remains popular in cooperative signal. Further, this performance issue gets mitigated by the additional gains by optimal cooperation.

Materials

This study uses a MATLAB-based simulation environment to evaluate ten cooperative spectrum sensing techniques under varying Signal-to-Noise Ratios (SNR) from -20 dB to 10 dB. The cognitive radio network model includes multiple secondary users observing a shared spectrum, with each user collecting between 128 and 1024 samples per sensing interval. Signals are modeled under two hypotheses: noise-only (H0) and signal-plus-noise (H1), with AWGN and Rayleigh or Rician fading channels. Detection performance is assessed using probability of detection and false alarm across 10,000 Monte Carlo simulations. The newly proposed Rician Rice Factor-Based Detection (RFD) is compared against conventional methods using an OR-rule for cooperative sensing. All algorithm implementations were developed and tested using MATLAB R2023a.

Methods

The improvement into the sensing capacity is achieved by means of cooperative approach among the SUs or CRUs (Akyildiz *et al.*, 2011). Whereas, the Cooperative Spectrum Sensing (CSS) poses overhead of the bandwidth due to higher number of the node's participation in the process of the transmission of the data. In the method of CSS, all the sensing information collected by the SUs or CRUs is reported to the special computer unit namely, Fusion Centre (FC), where the final decision is taken on the basis of the statistical analysis. This implementation is a performance evaluation towards model validation of various Data Fusion Cooperative Spectrum Sensing Techniques (DF-CSST) in Low SNR condition for cognitive radio applications under the conditions of : Uniform noise and Non-uniform noise. There are two different modes for DF-CSST namely centralized and decentralized, in the centralized- DF-CSST a Fusion Centre (FC) exist to aggregate or fuse the sensing information from Sus or CRUs in order to detect the white space for SUs/CRUs, whereas in the De-centralized mode of the DF-CSST such FC does not exist, In the decentralized mode of the DF-CSST, each SUs or CRUs exchanges their sensed information to their respective neighbour SUs/CRUs and anyone of the SUs/CRUs takes the final decision.

The system model is built of the various parameters including the number of Primary User (PU) transmitters, the number of Secondary Users (SU) / (CRuS) receivers, the average signal-to-noise ratio (SNR) across all SUs, the number of samples collected by each SU, and the type of PU signal (Gaussian or QPSK), along with the length of the QPSK transmitted symbols, the average noise variance across all SUs. Other parameters like the fractions of noise power and received signal variations about their means, the type of PU-SU channel according to the configurable sensing channel Rice factor K (mean and std deviation), the reference probability of false

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alarm (Pfa) at which the probability of detection (Pd) is computed by varying several of the system parameters (K, m, s, n, SNR, rhoN = rhoP). Based on the these parameters, the test statistics of several spectrum sensing techniques are generated for all Monte Carlo runs, and the performance of the techniques are plotted in terms of Pd versus the respective parameters of the variations.

Signal Generation

The evaluation of the models is performed on the basis of the varying parameters of secondary users where the number of SU, m ∈ {2,4,6,8,10,12} and the SNR ∈ Range of {-20:2.5:0}. For each value of SU, m ∈ {2,4,6,8,10,12} and SNR ∈ Range of {-20:2.5:0}, the fraction of the noise power variations with respect to the mean (FracN) is assumed to be equal to the fraction of the receiver power (PRxavg) power variation with respect to the mean is computed using Eq. 1:

$$\mathrm{PRxavg} = \mathrm{Sigma2avg} \times 10^{\frac{\mathrm{SNR}}{10}} \quad (1)$$

Where, Sigma2avg is the average noise power, whereas the value of the source power or the power of the transmitter (PTx) is given by Eq. 2:

$$\mathrm{PTx} = \frac{\mathrm{PRxavg}}{s} \quad (2)$$

Where, s is the number of primary user transmitter. Theoretically the function CDF () of a random variable for each number of events for computing the empirical CDFs, is a function f(X) s.t FX(x) =Probability of (X≤x) ∀ x ∈ R. On the basis of the generation of the random number from the normal distribution function the PUs signal (PxN) is computed where in the condition where PUSignal =0, then the computation of the signal(S) follows the initial computation of S using Eq. 3:

$$\mathrm{S} = \mathrm{R}f\left(\mu, \sigma, s, n\right) + \mathrm{I}f\left(\mu, \sigma, s, n\right) \quad (3)$$

Where, μ is a mean parameter, σ is a standard deviation parameter, s is the number of primary users and finally n is the number of samples per secondary users. The $\mathrm{R}f$ () and $\mathrm{I}f$ () are the real and imaginary part of the random generator from a normal distribution of { μ, σ, s, n }, where, $= 1/\sqrt{2}$, then the vector S is further normalized and approximated as per Eq. 4:

$$S = \Rsh S \times D\left(\sqrt{PTx}\right) \quad (4)$$

Where, $\Rsh$ is the transpose operation of a vector and D is the diagonal matrix. Figure 3 shows the generated signal in both the frequency and time domains.

Further, for the computation of the Noise variance across ($\sigma 2$) all the iterations of the sensing, the initial value is computed with Eq. 5 and finally approximated using Eq. 6.

$$\sigma 2 = \sum\left[\left(NR \times 2 \times FracN\right), \left(1 - FracN\right)\right] \quad (5)$$

$$\sigma 2 = \left[\frac{\sigma 2}{\frac{1}{2\sum_{i=1}^{m}(\sigma 2_i)}}\right] \times Sigmaavg \quad (6)$$

Where N_R is several random values, equal to the number of the secondary receiver (m). The received power (PRx) vector in all the sensing iterations is PRx f(m, FracP, PRxavg). The channel matrix (Mxp), Gaussian noise matrix, the signal and the noise power measured are PRx (Measured) & Pnoise (Measured), the received signal vector(Xh0 / Xh1)) for both hypotheses: Hypo-0 and Hypo-1, are the construct of the evaluation model. Another variable is the covariance of the received signal, and the eigenvalues are RH_0 and λ H_0 respectively.

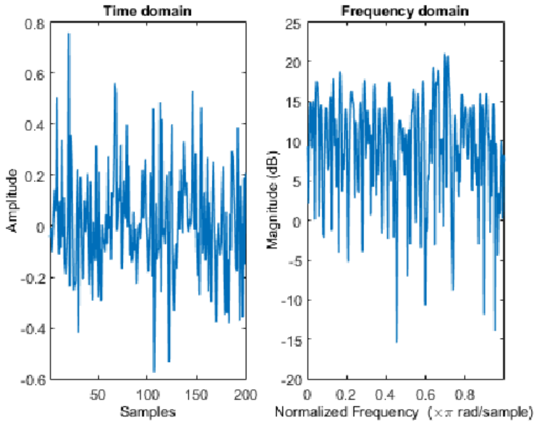

Fig. 3: Generated signal represented in both the frequency and time domains

Statistical Test Parameterization

The evaluated methods include Hadamard Ratio (HR) (Sedighi *et al.*, 2015), Volume-Based Detection (VD) (Huang *et al.*, 2015), Gershgorin Radii Centers Ratio (GRCR) (Guimarães, 2018), Gini Index Detection (GID) (Guimarães, 2019), Generalized Likelihood Ratio (GLR) (Lim *et al.*, 2008), Maximum-Minimum Eigenvalue Detection (MMED) (Zi-li *et al.*, 2019), and Energy Detection (ED) (Liang, 2020). The Arithmetic to Geometric Mean Ratio (AGM) is referenced by both Shakir *et al.* (2013) and Torad *et al.* (2015), highlighting its relevance across multiple studies.

Maximum Eigen Value Detection (MED)

This approach relies on evaluating the eigenvalues of the covariance matrix derived from the primary user's signal and is grounded in the principles of Random Matrix Theory (RMT). It emphasizes identifying the largest eigenvalue for detection purposes. The analysis of the two hypotheses, H0 and H1, is carried out using Eqs. 7 and 8.

$$\text{Hypo-0 (MED)} = \frac{\lambda_{h0}}{\sigma_2} \quad (7)$$

$$\text{Hypo-1 (MED)} = \frac{\lambda_{h1}}{\sigma_2} \quad (8)$$

In this method, the Pr(D) reduces with the increment of correlation level, therefore, thresholding is used to compensate for the deviation in the detection accuracy

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and becomes a suitable sensing mechanism in the correlated context or scenarios of the noise.

Generalized Likelihood Ratio (GLR)

This method also utilizes the covariance matrix's eigenvector from the sample signal, it exploits the fact that the signals of PUs in CR occupy a subspace of the dimensionality much smaller than the observed one, which indicates the spectrum is a non-white space. It takes various parameters like noise variance dimension of the signal space, which provides better results as compared to the traditional ED. It performs the computation of the Hypo-0 and Hypo-1 using Eqs. 9 and 10.

$$\text{Hypo-0 (GLRT)} = \frac{\lambda_{h0}}{\sum_{i=2}^{m}(\lambda_{h0})i} \quad (9)$$

$$\text{Hypo-1 (GLRT)} = \frac{\lambda_{h1}}{\sum_{i=2}^{m}(\lambda_{h1})i} \quad (10)$$

The basic limitation of the generalized likelihood ratio test (GLRT) for SS is that it poses higher computational complexities because of computational resource requirements for the estimation of the signal covariance matrix and decomposition of the eigen matrix. Whereas it is quite useful for the opportunistic access mechanism of the spectrum because in the shorter interval of the sensing, the desired Pr(D) and Pr(Fa) are achieved.

Maximum-Minimum Eigenvalue Detection (MMED)

The Eigenvalue detection-based SS methods can be customized to perform better even in low SNR, if the maximum and minimum ratios of the eigenvalues value ratio is exploited and this fundamental is used in the SS methods based on the MMED. It performs the computation of the Hypo-0 and Hypo-1 using Eqs. 11 and 12.

$$\text{Hypo-0 (MMED)} = \frac{\lambda_{h0}}{\lambda_{h0}\forall m} \quad (11)$$

$$\text{Hypo-1 (MMED)} = \frac{\lambda_{h1}}{\lambda_{h1}\forall m} \quad (12)$$

In the context of the uncertainty of the variance in the noise say at the 0dB noise or low noise conditions, the Pr(D) of the methods based on MMED performs better as compared to the ED and MED

Energy Detection (ED)

This method is implemented and described in detail, whereas the generalized computation of the Hypo-0 and Hypo-1 using Eqs. 13 and 14.

$$\text{Hypo-0 (ED)} = \frac{\sum|\lambda_{h0}|^2\forall m}{(\sigma_2)\forall m} \quad (13)$$

$$\text{Hypo-1 (ED)} = \frac{\sum|\lambda_{h1}|^2\forall m}{(\sigma_2)\forall m} \quad (14)$$

In general, the ED is an optimal method for the detection of the PUs with a constraint s of single antenna use and the distribution of noise and signal takes place as Gaussian random variable (GRV) in very identical and independent manner as well as the power or the noise variance is known.

Arithmetic to Geometric Mean Ratio (AGM)

There are methods for SS based on the consideration of the ratio of the higher eigen and smaller eigen values. Whereas in AGM a average or the arithmetic mean of the eigen value or sometime largest eigen value is considered. The generalized computation of the Hypo-0 and Hypo-1 takes place using Eqs. 15 and 16.

$$\text{Hypo-0 (AGM)} = \sum \frac{\lambda_{h0}}{\varphi(\lambda_{h0})^{\frac{1}{m}}} \quad (15)$$

$$\text{Hypo-1 (AGM)} = \sum \frac{\lambda_{h1}}{\varphi(\lambda_{h1})^{\frac{1}{m}}} \quad (16)$$

This method considers an approximation of the probability density function (PDF) for gamma matching method. Here, $\varphi()$ is a array element product function. This method is feasible in the highly faded context with the expectation of the low Pr(D) and Pr(F).

Hadamard Ratio (HR)

Many of the methods discussed above are quite sensitive to the non-uniformity factor of the noise variance of the antenna which occurs due to the faulty calibration. The faulty calibrated error is handled by the Hadamard Ratio based detection methods for the SS. The generalized computation of the Hypo-0 and Hypo-1 takes place using Eqs. 16 and 17.

$$\text{Hypo-0 (HR)} = \frac{\mathbb{R}|RH_0|}{\varphi(D(RH_0))} \quad (16)$$

$$\text{Hypo-1 (HR)} = \frac{\mathbb{R}|RH_1|}{\varphi(D(RH_1))} \quad (17)$$

An analytical modeling for the objective function of Pr(D) and the Pr (Fa) uses appropriate approximation.

Volume Based (VD)

Originally, the volume-based detector was developed for the purpose of It is worth pointing out that the volume-based detector is developed for the observations of the real value., where as its performance is not benchmarked broadly. The computation of the Hypo-0 and Hypo-1 takes place using Eqs. 18 and 19.

$$\text{Hypo-0 (VD1)} = \mathbb{R}\left(log\left(\left|\frac{1}{D(DH_0)} \times RH_0\right|\right)\right) \quad (18)$$

$$\text{Hypo-1 (VD1)} = \mathbb{R}\left(log\left(\left|\frac{1}{D(DH_1)} \times RH_1\right|\right)\right) \quad (19)$$

The volume-based detector exhibits better result as compared to the AGM and HR in terms of the identical and independent noise presence based Pr(Fa) and Pr(D)

Gershgorin Radii Centres Ratio (GRCR)

The detector Gerschgorin radii and centres ratio collectively popular with the name GRCR detector, where the covariance matrix for either one transmitter or for more than one transmitter is computed, for the Hype-0 and Hupo-1 using Eqs. 20 and 21.

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$$\text{Hypo-0 (GRCR)} = \frac{\sum(\sum(\text{↱}|\text{↱}(RH_0)|)-D(RH_0))}{\sum(D(RH_0))} \tag{20}$$

$$\text{Hypo-1 (GRCR)} = \frac{\sum(\sum(\text{↱}|\text{↱}(RH_1)|)-D(RH_1))}{\sum(D(RH_1))} \tag{21}$$

The statistical test analysis, does not exhibits a consistent Pr(Fa) as well as it is not very robust in the dynamic context of the non-uniform noise conditions and it is a cooperative and suitable method for the multiantenna SS.

Gini Index Detection (GID)

Though the Gini index is originally developed for the purpose of the introduction of a metric in economics as a statistical dispersion metric, whereas as many cooperative SS is proposed using Gini Index and those methods are known as gini index detector (GID). The normalized format for the computation of the Hype-0 and Hupo-1 using Eqs. 22 and 23.

$$\text{Hypo-0 (GID)} = \frac{\sum|RH_0|}{\sum_{i=1,j=1}^{m^2m^2}\left(\left|\left(RH_{0i}-RH_{0j}\right)\right|\right)} \tag{22}$$

$$\text{Hypo-1 (GID)} = \frac{\sum|RH_1|}{\sum_{i=1,j=1}^{m^2m^2}\left(\left|\left(RH_{1i}-RH_{1j}\right)\right|\right)} \tag{23}$$

Generally, GID exhibits robustness in dynamic noise conditions and unequal signal power which quite suitable for the Line Of Sight (LOS) channels and perform consistent Pr(Fa) in a simplest manner.

Prosed Rician, Rice Factor-Based Detection (RFD)

A method based on the Rician fading channel with different values of the K(Rice factor) for a multi-rate spectrum is proposed as Rice Factor Based Detection (RFD). The normalized approximated computation of the Hype-0 and Hupo-1 takes place using Eqs. 23 and 24.

$$\text{Hypo-0 (RFD)} = \frac{\sum|RH_0|}{\sum\left(|RH_0|-\frac{1}{2}\sum_{i=1}^{m}(RH_{0i})\right)} \tag{24}$$

$$\text{Hypo-1 (RFD)} = \frac{\sum|RH_1|}{\sum\left(|RH_1|-\frac{1}{2}\sum_{i=1}^{m}(RH_{1i})\right)} \tag{25}$$

Though the wideband SS using Nyquist sampling rates provides better performance in comparison of other SS, but the multi-rate SS like proposed RFD exhibits better Pr(D) and Pr(Fa) in lower computational complexity. The values of variance for both Hypo-o: Ho and Hypo-1H1 in average 2000 observations are tabulated in Table 1, to understand the consistency of the all SSDs discussed.

Table 1: Variance with 2000 observations

Method	MED	GLRT	MMED	ED	AGM
Hypo-H0	0.0977	0.0283	52.3458	1.0133×10^{3}	0.9973
Hypo-H1	3.8865	0.2765	239.4252	2.1822×10^{6}	2.0562
Method	HR	VD1	GRCR	GID	RFD
Hypo-H0	2.4172×10^{-4}	0.0042	0.0020	2.3392×10^{-6}	8.1796×10^{-4}

Results and Discussion

The iterative simulation of proposed RFD and six state of the art SS methods namely: AGM, MMED, GLRT, VD1, and HR is performed and the value of the probability of detection (Pr(D)) is tabulated in Table 2 from the lowest SNR value of -20 till 0.

Table 2: Probability of Detection (Pr(d)) versus Average SNT in (dB)

SNR	AGM	MMED	GLRT	VDI	HR	GID	Prop-RFD
-20	0.088	0.084	0.101	0.1265	0.325	0.18	0.1695
-17.5	0.0725	0.075	0.096	0.1475	0.2	0.233	0.2245
-15	0.073	0.065	0.096	0.2265	0.3325	0.3545	0.377
-12.5	0.0555	0.0485	0.0835	0.4415	0.6325	0.6155	0.669
-10	0.056	0.0515	0.093	0.7355	0.8785	0.853	0.9075
-7.5	0.0515	0.0575	0.112	0.951	0.979	0.9605	0.987
-5	0.0795	0.084	0.344	0.991	0.9955	0.988	0.996
-2.5	0.1945	0.1595	0.8095	1	1	0.995	1
0	0.5415	0.337	0.976	1	1	0.9985	1

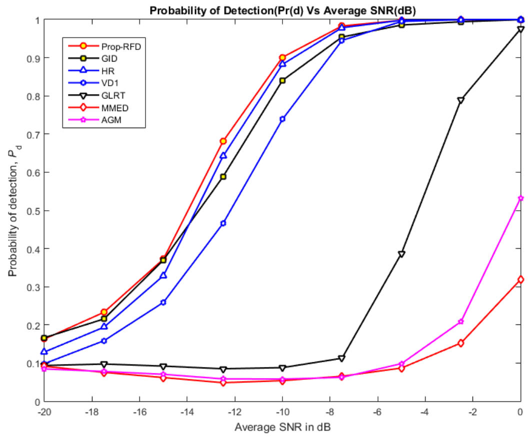

Fig. 4: Frequency and Time domain signal of Gaussian PU Signal when PUSignal = 0

Figure 4 plots these observations for Pr(D) Vs SNR. The graph shows that the Pr(D) for the MMED is lowest after AGM and the proposed RFD performs best after HR and closely to the VD1 in ranging low SNR of -20 till 0 The iterative simulation of proposed RFD and six state of the art SS methods namely: AGM, MMED, GLRT, VD1, and HR is performed and the value of the probability of detection (Pr(D)) is tabulated in Table 3 for the varying number of SUs or CRUs from lowest of 2 SUs to 12 in max at the incremental of two additional Sus.

Table 3: Probability of Detection (Pr(d)) versus Number of Secondary users(SUs/CRUs)

No of Sus/CRUs	AGM	MMED	GLRT	VDI	HR	GID	Prop-RFD
2	0.665	0.0665	0.0665	0.3515	0.392	0.313	0.398
4	0.0495	0.0465	0.07	0.6515	0.7925	0.7285	0.81
6	0.0595	0.044	0.0935	0.8255	0.9245	0.909	0.937
8	0.0685	0.055	0.129	0.9225	0.98	0.975	0.985
10	0.0765	0.0735	0.2025	0.9625	0.9945	0.995	0.9945
12	0.0795	0.0975	0.363	0.981	0.9995	0.9985	0.998

Figure 5 plots these observations for Pr(D) Vs SNR. The graph shows that the Pr(D) for the MMED is lowest after AGM and the proposed RFD performs best after HR and closely to the GID in ranging number of secondary or the cognitive radio users in the series of {2,4,6,8,10,12}.

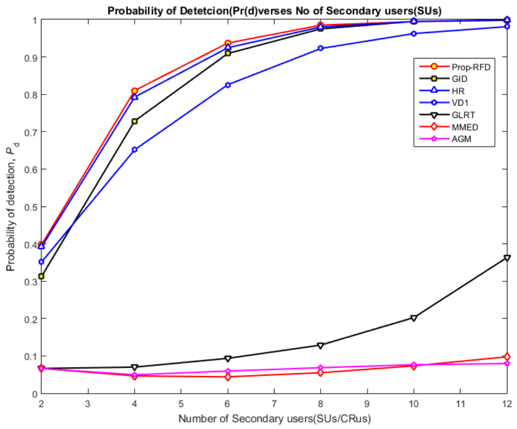

Fig. 5: Probability of Detection (Pr(d)) versus Number of Secondary Users (SUs / CRUSs)

Conclusion

Efficient spectrum sensing plays a critical role in enabling cognitive radio systems to support next-generation applications by facilitating optimal spectrum sharing between primary and secondary users, without causing interference to licensed transmissions. This work conducts a comprehensive statistical evaluation of various cooperative sensing approaches, analyzing their detection probability performance under both favorable and challenging SNR conditions. The Maximum Eigenvalue Detection (MED) technique employs a thresholding mechanism to mitigate errors, focusing on the analysis of the eigenvalues of the signal's covariance matrix. The Generalized Likelihood Ratio (GLR) method, on the other hand, incorporates eigenvectors along with parameters like noise variance, making it more complex and resource-intensive. The Maximum-Minimum Eigenvalue Detection (MMED) method demonstrates better accuracy than both ED and MED, particularly when fine-tuned for low SNR environments. Energy Detection (ED), despite its limitations, remains the most commonly adopted technique due to its simplicity, flexibility for standalone or cooperative use, and lack of dependency on prior signal knowledge. The Arithmetic to Geometric Mean (AGM) method evaluates different averages derived from the smallest and largest eigenvalues, incorporating a gamma distribution approximation for probability density function (PDF) matching. It proves to be effective in scenarios involving faded channels, especially when both the likelihood of detection and the false alarm rate are expected to be low. The proposed method, Rice Factor-Based Detection (RFD), utilizes the Rician fading channel with varying values of the Rice factor (K) for a multi-rate spectrum. This method, along with the Hadamard ratio, volume-based detection, Gershgorin Radii Centers Ratio (GRCR), and Gini Index Detection (GID), is thoroughly evaluated. The multi-rate Spectrum Sensing (SS), particularly the RFD approach, demonstrates improved detection probability (Pr(D)) and false alarm probability (Pr(Fa)) while maintaining lower computational complexity. While wideband spectrum sensing using Nyquist sampling rates delivers superior performance compared to other methods, the proposed RFD offers a practical trade-off.

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Author's Contributions

Archana Krishnamuthy: Development, implementation, and verification of methods.

Sudhindra Kumbhashi Rajgopal: Identification of the research problem and formulation of the manuscript.

Ethics

This study does not involve human participants or animal subjects. All data used are publicly available; hence, no ethical concerns are associated with this work.

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