Development of Novel Spectrum Sensing Algorithm for 5G Cognitive Radio

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ABSTRACT

With the fast and unremitting growing of cellular services and users throughout the world, development of the next generation cellular mobile networks are inevitable. A common spectrum resource is included in the envisaged next generation cellular architecture using the dynamic spectrum sharing (DSS) technology. This resource is shared by a wide range of different network systems and entities. While this proposed method would significantly increase overall spectrum efficiency, it also suggests the experiment of optimizing cohabitation between the entities constituting the overall network by reducing their mutual interference. The cognitive radio (CR) paradigm's unique spectrum sensing (SS) function is currently being introduced in this context as one of the key enablers for successful DSS with minimal interference. This paper presents the novel spectrum sensing algorithm utilizing power techniques to determine the dominating eigenvalue of the signal's covariance matrix received at the unlicensed user. Compared to other algorithms, the presented algorithm greatly reduces system overheads and also has lower computational complexity. Proposed algorithm gives better detection performance compared other existing algorithms.

KEYWORDS

Primary User, Secondary User, Cognitive Radio, Dynamic Spectrum Access, Spectrum Sensing

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1. iNTRODUCTION

Presently, the 5G is widely acknowledged to represent both hypothesized necessities and prospective substitutes when compared to prior generations as the rapid expansion of mobile cellular gadgets and services necessitates the progression in the upcoming generation of the cellular mobile network. The 5G demands are given by three primary pillars: (i) very high broadcast rates, (ii) extremely low delay, (iii) worldwide coverage [1]. As a response, feasible elucidations are identified by the three categories: (i) increased energy efficiency massive and heterogeneous network densification, (ii) improved efficiency in terms of bandwidth and spectrum, and (iii) significant and diverse networks densification [2]. Overall, 5G framework will consists a large number of unique network elements that will primarily share common spectrum resource in terms of frequency. Dynamic spectrum sharing (DSS) technology is utilized on contrary to static band assignment, as it is more efficient and can be obtained by using frequencies that comes under licensed and unlicensed bands.

This method vitally boosts overall efficiency of spectrum and also aims in improving several components which consists of technologies systems and devices to co-exist. As a result, cognitive radio (CR) presented in [3], is now considered as main enabler for efficient DSS for several system components. In order to achieve this, a variety of CR enabled spectrum resource organizing strategies have lately been proposed. For effective DSS with restricted interference, the afore named methods have been set at different phases of 5G architecture. Taking the advantage of CR capability of gathering data related to occupying the spectrum and to apply best possible method is the fundamental concept of these mechanisms. Spectrum sensing (SS) is typically referred as the task of gathering information about spectrum resource and these sensing outcomes are then used in improving spectrum distribution amongst various system components. A range of spectrum sensing methods have put forward in the literature [4] and [5].

Among the detectors with less complexity in computations, energy detection (ED) sensing algorithm gives a remarkable outcome without requiring a prior awareness of user signals which are licensed [6]. Nonetheless, it needs the awareness of noise power and performance quickly falls at a fast rate with uncertainty in noise power [7]. To mitigate the noise power, detection methods with noise power estimation have been investigated in [7]. In [8], the noise power is initially anticipated by turning off RF terminals, and later modified to noise samples that are obtained from past sensing periods. Two categories of common spectrum sensing methods with numerous antennas are detection based on (i) eigenvalues [9] and (ii) covariance of received signals [10].

The Fundamental idea behind the sensing algorithm which uses eigenvalues is to ascertain whether or not the covariance matrix of the received signals is a scaled identity matrix. The noise variances are implicitly assumed to be congruent at various antennas. Nevertheless, this presumption is not justifiable in certain situations like noise variances, diverse neighboring environments or receivers that are not correctly calibrated, may not be totally alike at various antennas. Regardless of noise variances at different antennas are identical or not, the covariance matrix-based detectors operate well by adequately considering high spatial correlation. It is worth noting that detection based on eigenvalues often performs marginally better compared to detection based on covariance. But, due to eigenvalue decomposition, the former is substantially more complicated than the later [11]. the investigation for the decision threshold of the detection based on eigenvalue technique has been carried out by using random matrix theory.

It is presented in [12] and [13] that the supreme and smallest eigenvalues of Wishart matrices are assessed to predicted values. With many samples of the received signal, the highest eigenvalue follows the Tracy-Widom distribution. The asymptotic decision threshold is given in [14] on the basis of some theorems. The exact decision threshold is derived in [15] by utilizing the expressions of the joint distributions of a random subset of ordered eigenvalues in Wishart matrices [16]. This study presents a novel spectrum sensing approach for computing the dominating eigenvalue of the covariance matrix of signals received at the secondary user. The algorithm is based on power methods.

Rest of the paper is organized as follows for ease of reading and comprehension. Section 2 introduces the system model and reviews the eigenvalue-based detection. Detailed description on novel detection technique is given in section 3. Section 4, presents simulation results to verify the analysis. Finally, conclusions are discussed in section 5.

2. SYSTEM MODEL

Spectrum sensing is commonly viewed as an issue of binary hypothesis testing, where a choice must be made on the presence or absence of primary signals. The null hypothesis (no primary signals present) and the alternative hypothesis (primary signals present), respectively, are denoted by 0 and 1, respectively. Figure 1 shows the considered scenario for dynamic spectrum access where multiple primary users (PUs) and secondary users (SUs) are coexisting. The SU network's unscrupulous access to PU bands the interference to PUs is minimal. The aforementioned operating networks may be homogeneous or heterogeneous. The assumption here is that one primary user operates in a authorized band and a secondary user is fortified with N_t antennas.

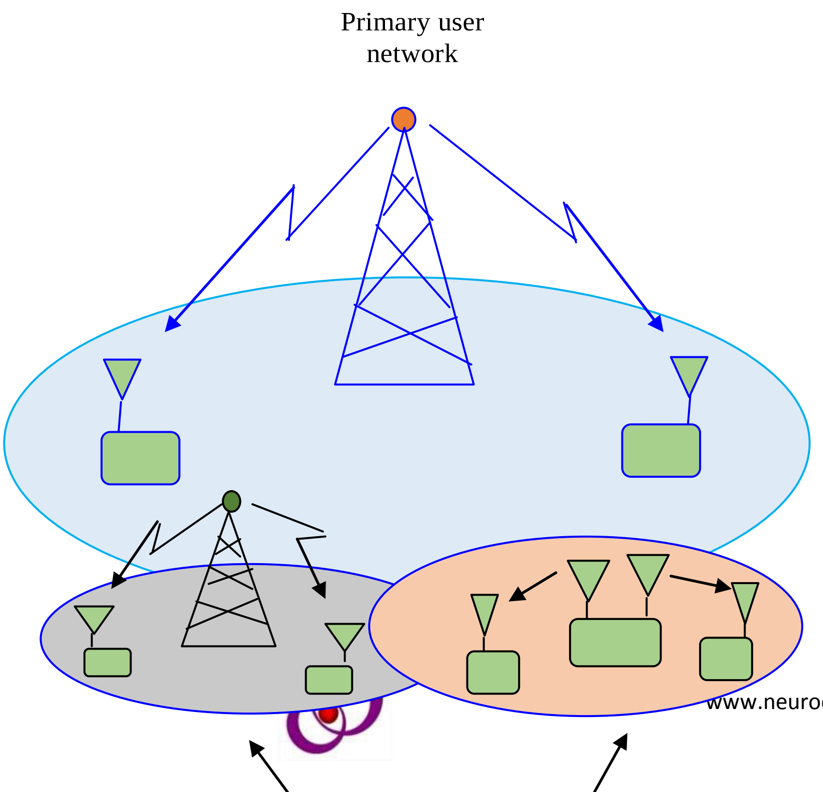

FIGURE 1 Coexistence of multiple primary and secondary user networks

Now consider cognitive radio terminal performing spectrum sensing based on K discrete time vector observations y[k], k = 0,1,…,K-1, to determine whether primary user is there or not. The i^{th} element of y[k], denoted as $y_i[k]$, i = 0,1,…,N_t-1, is the output of i^{th} antenna, in which N_t is number of antennas at the CR terminal. For notational convenience an aggregate observation matrix is defined as

$$Y = (y[0], y[1], y[2]\ldots.., y[K-1]) \quad (1)$$

Assume that, y[k] denotes the k^{th} sample of the received signal, which comprises of a noise and signal.

$$y[k] = p[k]+q[k] \quad (2)$$

Where p[k] is the k^{th} sample of the primary signal seen at the receiver, and q[k] is the additive noise at the CR receiver, modeled as an independent and identically distributed zero-mean circularly symmetric complex Gaussian noise that is independent of p[k] with unknown noise variance σ_q^2, i.e., $q(k) \sim \mathcal{CN}\left(0,\sigma_q^2 I\right)$, where I denotes the identity matrix.

The main objective is to determine if there is a presence of signal. The spectrum sensing problem can therefore be formulated by discriminating between the following binary hypotheses:

H_0: y[k] = q[k], k = 0,1,2,…,K-1 (3)

H_1: y[k] = p[k] + q[k], k = 0,1,2,...,K-1 (4)

Two significant constraints related with the estimation of the spectrum sensing performance are the probability of detection, P_D, and the probability of false alarm, P_{FA}, which are defined according to, probability of detection

$P_D = \Pr\{decision = H_1/H_1\} = \Pr\{ TS >\Gamma/ /H_1\}$ (5)

Probability of false alarm

$$P_{FA} = \Pr\{decision = H_1/H_0\} = \Pr\{ TS <\Gamma/ /H_0\} \quad (6)$$

In which Pr{·} is the likelihood of certain occurrence event, TS is the test statistic that depends on detection, and Γ is the threshold decision. The decision threshold values is selected in accordance with specifications for performance of spectrum sensing. This can be assessed using receiver operating characteristic (ROC) curves that depicts variation of Γ with respect to P_{FA} versus P_D. The Neyman Pearson (NP) theorem states that the binary hypothesis test that maximizes the probability of detection (defined as the probability of deciding H_1 when H_1 is true) for a given probability of false alarm (the probability of deciding H_1 when H_0 is true) uses the likelihood ratio

$$TS=\frac{\Pr\left(y/H_1\right)}{\Pr\left(y/H_0\right)} \quad (7)$$

The ideal Neyman-Pearson assessment is to compare the log-likelihood ratio to a threshold.

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$$TS=\log\left(\frac{\Pr(y/H_1)}{\Pr(y/H_0)}\right) \quad (8)$$

Evidently, the distribution of the signal to be detected affects the above ratio.

3.NOVEL DETECTION TECHNIQUE

The main parts of proposed method is illustrated in Figure 2. The covariance matrix is obtained using sampled signals that are provided by radio network terminals. The matrix eigenvalues are then calculated with a specific algorithm to form a maximum-minimum ratio; with user's threshold settings defined and detection of signal existence is carried out by comparing with eigenvalues ratio.

3.1 Eigenvalue analysis of covariance matrix

To elucidate the detection algorithm, the covariance matrix must be subjected to eigenvalue analysis. The observed sequence is x[k] = y[k] + q[k], where q[k] is complex additive white Gaussian noise with power spectral density σ^2, the $N_t \times N_t$ covariance matrix of x[k] can be expressed as

$$R_{xx}=R_{yy}+\sigma_q^2 I_{N_t} \quad (9)$$

Where R_{yy} is the covariance matrix for the signal y[k], $\sigma_q^2 I_{N_t}$ is the covariance matrix for the noise and N_t size of the covariance matrix. By performing eigenvalue decomposition of matrix R_{xx}, the eigenvalues be ordered in decreasing value with $\lambda_1>\lambda_2>\ldots>\lambda_{Nt}$ and the correlating eigenvectors be represented as $\{\nu_i, i = 1,2..N_t\}$. It is considered that eigenvectors to be standardized, such that $\nu_i^H.\nu_j=\delta_{ij}$ (where H is complex conjugate transpose). When noise is not present, the eigenvalues λ_i ,i = 1,2,…n_t are non-zero while $\lambda_{n_t+1}=\lambda_{n_t+2}=\ldots=\lambda_{N_t}=0$. Thus, the eigen vectors ν_i, i=1,2,..n_t span the signal subspace.

In the presence of noise, the eigenvalue-decomposition separates into two groups of eigenvectors. The primary eigen vectors, group ν_i,i=1,2,..n_t, are comprises the signal subspace, whereas noise sub space includes group ν_i, i = n_t+1, n_t+2,…N_t, that are orthogonal to the primary eigenvectors. It follows that the signal y[k] is simply linear combinations of the principal eigenvectors. Lastly, eigenvalues of the covariance matrix and variances of the projections are identical. Therefore, in novel signal space, the main eigenvalues are considered to be power factors.

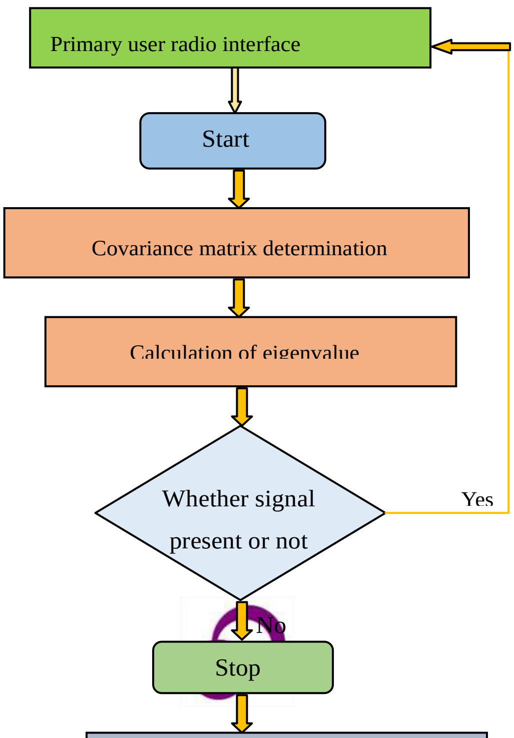

FIGURE 2 Flow chart of proposed method

3.2 Signal model

Assuming that the there is a central frequency (w_c) and a bandwidth (B) in the frequency range of interest. Single main user may utilize frequency band at a specified period. Cognitive radio network randomly distributes a number of secondary users. For signal detection, the binary hypothesis test can be formulated as

$$H_0 : y[k]=q[k] \quad (10)$$

and alternate hypothesis is given as

$$H_1 : y[k]=\sum_{k=0}^{N} h[k]p[n-k]+q[k] \quad (11)$$

Where y[k] indicates the secondary receiver's sampled signal, p[k] is the primary signal seen at the receiver, h[k] is the response of channel, channel order is represented with N, and noise samples are denoted with q[k]. By considering the sub samples of consecutive outputs, the entire signal model can be written as

$$\hat{y}[k]=H\hat{p}[k]+\hat{q}[k] \quad (12)$$

Where H is $N_t\times (N + N_t)$ matrix. The white noise and signal transmitted are assumed to be inter related. Also, considering the noise and signal transmitted statistical properties, received signal covariance matrix is represented by R, that is,

$$R=\frac{1}{N_s}\sum_{k=N_t}^{N_t-1+N_s} \hat{y}[k]\hat{y}^H[k] \quad (13)$$

In which, accumulated samples are denoted with N_s. If N_s is huge, depends on the assumptions made earlier, the covariance matrix is

$$R=E\left[\hat{y}[k]\hat{y}^H[k]\right]=HR_sH^H+\sigma_q^2 I_{N_t} \quad (14)$$

In which R_s is the input signal statistical covariance matrix, $R_s=E\left[\hat{p}[k]\hat{p}^H[k]\right]$, σ_q^2 is the variance of noise, I_{N_t} denotes $N_t\times N_t$ identity matrix. Let $\hat{\lambda}_{max}$ and $\hat{\lambda}_{min}$ be the maximum and minimum eigenvalues of R, $\hat{\varphi}_{max}$ and $\hat{\varphi}_{min}$ be maximum and minimum eigenvalues of HR_sH^H. Then

$$\hat{\lambda}_{max}=\hat{\varphi}_{max}+\sigma_q^2 \text{ and } \hat{\lambda}_{min}=\hat{\varphi}_{min}+\sigma_q^2 \quad (15)$$

$\hat{\varphi}_{max}$ = $\hat{\varphi}_{min}$ if and only if $HR_sH^H=\Theta I_{N_t}$, where Θ is positive number. When the primary signal is present, $\hat{\lambda}_{max}=\hat{\varphi}_{max}+\sigma_q^2$, $\hat{\lambda}_{min}=\sigma_q^2$ and when the primary signal is absent,

$\hat{\lambda}_{max}=\hat{\lambda}_{min}=\sigma_q^2$. Hence if there is no signal, the ratio of maximum to minimum eigenvalue is 1; otherwise, the ratio of maximum to minimum eigenvalue is greater than 1. The ratio of

$\hat{\lambda}_{max}/\hat{\lambda}_{min}$ can be used to detect the presence of the primary signal. However, $\hat{\lambda}_{max}$ and $\hat{\lambda}_{min}$ are estimated eigenvalues. In order to compute $\hat{\lambda}_{max}$ and detect the principal signal, power approach is utilized. This method uses simple algebraic operations to eigenvalues. This method reduces computational problems as processing of decomposition of eigenvalue can be avoided. The maximum eigenvalue λ_{max} of the covariance matrix R can be achieved using power approach. As single principal signal is involved, R has single largest eigenvalue, remaining $N_t - 1$ smallest eigenvalue. To obtain a much accurate outcome, compute the minimum eigenvalue λ_{max} of R as follows

$$\lambda_{min} = \frac{tr(R) - \lambda_{max}}{N_t - 1} \quad (16)$$

In which trace of R is indicated with tr(R). Lastly, test statistics of the novel detector is $\lambda_{max}/\lambda_{min}$.

3.3 Decision threshold

The threshold should be computed to analyze with respect to test statistic of the detecting measure in the general model of the spectrum sensing algorithm. This is done to detect the existence of licensed user. As a result, it is important to study the statistical distribution of the covariance matrix to ascertain the threshold for the statistical test. The eigenvalue distribution of R is very complicated.

Henceforth, the random matrix theory is exploited to closely match the random variable distribution and threshold is derived by using prior mentioned false alarm probability, PFA. In the absence of primary signal, R becomes Rq. The noise covariance matrix can be expressed as

$$R_q = \frac{1}{N_s} \sum_{k=Nt}^{Nt-1+Ns} \hat{q}[k]\hat{q}^H[k] \quad (17)$$

Rq is nearly a Wishart random matrix. The joint probability density function (PDF) of ordered eigenvalues of a Wishart random matrix has been recognized for long time. Nevertheless, as the PDF expression is very complex, the closed form expression for the marginal PDF of ordered eigenvalues have not been determined.

Let $F1$ and $F2$ be the cumulative distribution function (CDF) of Tracy-Widom of the first and the second order respectively. There is no closed form expression for the distribution functions. It is therefore generally difficult to evaluate them. Fortunately, there are tables for the functions, based on numerical computation. The decision threshold for the proposed detection technique can be derived by using the random matrix theory.

Let Γ represent the decision threshold for proposed detection technique, then the probability of false alarm is

$$P_{FA} = \Pr(\lambda_{max} > \Gamma\lambda_{min}) \quad (18)$$

The decision threshold for the proposed technique is

$$\Gamma = \frac{\left(\sqrt{Z}+\sqrt{G}\right)^2}{\left(\sqrt{Z}-\sqrt{G}\right)^2}\left(1 + \frac{\left(\sqrt{Z}+\sqrt{G}\right)^{-2/3}}{\left(ZN_t\right)^{1/6}} F_2^{-1}\left(1-P_{FA}\right)\right) \quad (19)$$

where Z= N_s-1, N_s is the number of collected samples and G=N_tL, L is number of receivers.

4 RESULTS

Few simulation results are provided using randomly generated signals to illustrate the performance of the proposed sensing technique. A licensed frequency band with only one active primary user is taken into consideration. The primary signal employs Binary Phase Shift Keying (BPSK) modulation and frequency of the carrier is 10 MHz. BPSK is preferred here over other modulation schemes since it is the most robust modulation scheme for long distance wireless communication. The sampling frequency is fixed at 40 MHz. and N_s is the number of collected samples. The results are averaged over 10000 tests using Monte-Carlo realizations written in Matlab version R2021b.

The signal to noise ratio of a cognitive radio network across frequency band that is licensed is expressed as the mean power of the signal to be received to that of mean power noise.

$$SNR = \frac{E\left(\|y[k]-q[k]\|^2\right)}{E\left(\|q[k]\|^2\right)} \qquad (20)$$

The desired false alarm probability should be less than 0.15. The decision threshold is determined based on (19). Along with noise uncertainty, the energy detection of same system is simulated for comparison. The threshold for energy detection is given in [6]. On the basis of estimated noise power the threshold at noise uncertainty is always determined.

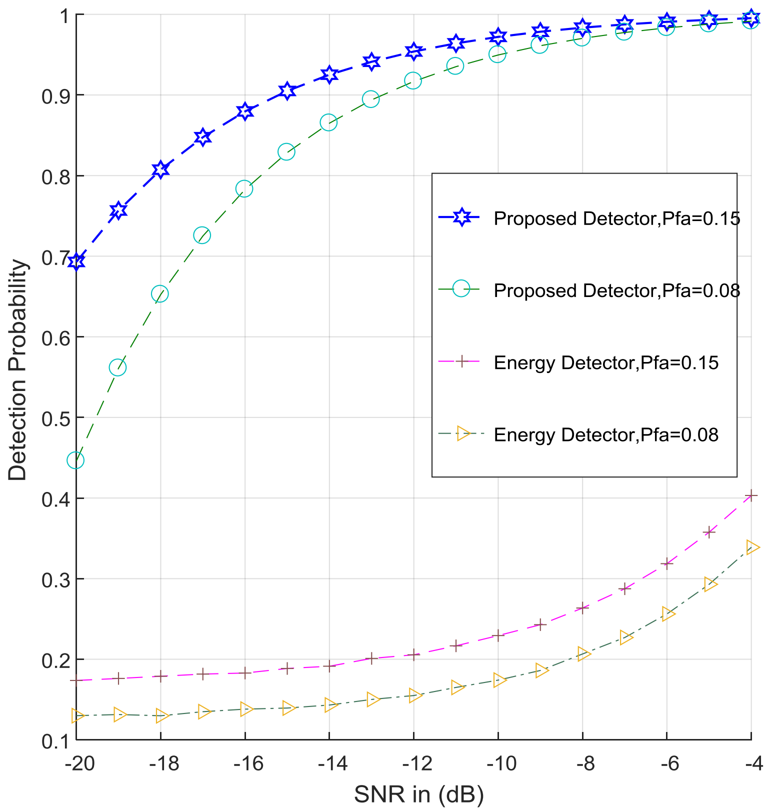

FIGURE 3 SNR versus probability of detection curve

Figure 3 shows plot between SNR and detection probability of proposed detection technique and energy detection technique. Number of samples Ns = 104 and SNR ranging from -20dB to -4dB considered for testing the performance of detector. As shown in the figure, the proposed detection technique can achieve satisfactory prediction outcome in situation with weak SNR. The probability of identifying the main user with proposed detector is 0.9539 at SNR = -12dB and P_{FA} = 0.15, whereas with energy detector detection probability is 0.2055 at same

SNR and PFA. Figure indicates that for the same SNR, increasing the false alarm probability enhances the detection probability. This shows that there is trade-off between probability of detection and probability of false alarm.

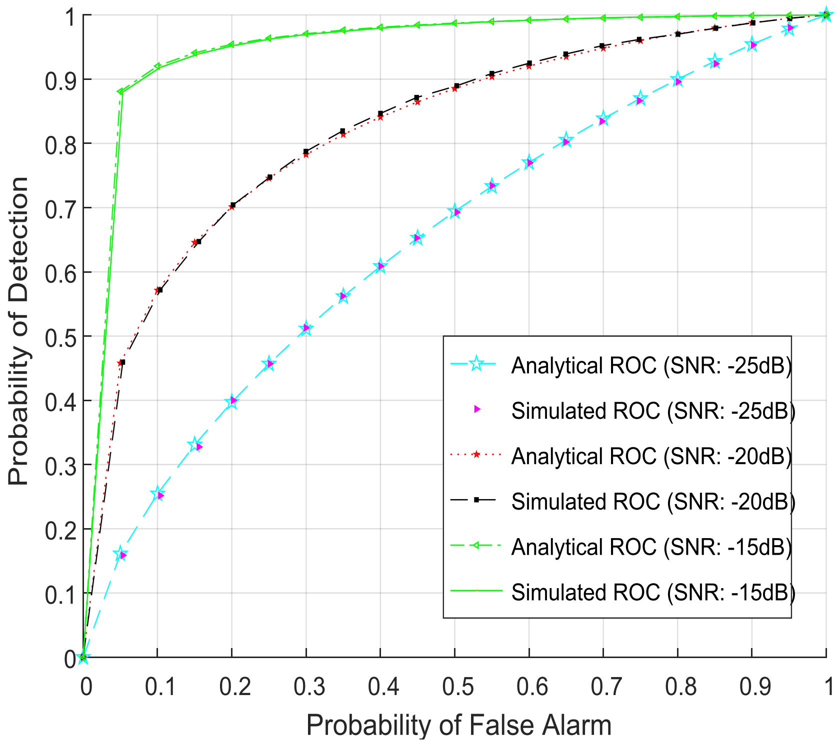

FIGURE 4 Receiver operating characteristics of proposed detector

Figure 4 represents the ROC curves of the proposed detector. From the figure it can be observed that simulated ROC is coincides with theanalytical ROC curves. Figure 4 clearly illustrates thetradeoff between detection probability and false alarm probability. When PFA increases, there is a high likelihood of detecting a signal even when there is no signal present. Obviously, for a good detection algorithm, the probability of detection should be high and the probability of false alarm should be low. The requirements of P_d and P_{FA} depend on the application. At SNR = -15dB, P_{FA} = 0.1, the detection probability is observed to be 0.9184. At SNR = -20dB, P_{FA} = 0.1, the detection probability is observed to be 0.5719. At SNR = -25dB, P_{FA} = 0.1, the detection probability is observed to be 0.2517. Finally, all the simulation results shows that the developed technique performs better without utilizing the knowledge of the channel, signal and noise power. The proposed method of detection outperforms the energy detection method.

Henceforth, energy detection method is unreliable in the presence of noise uncertainty because it has a less detection probability and more false alarm probability. It is evident that primary challenge in sensing of spectrum is ability to identify noise samples from samples that include very faint signal masked by noise. Very faint principal signals must be able to be identified by CR. Nonetheless, important restrictions appear when detection occurs at less SNR. For instance, it is necessary to be have knowledge of noise variance in order to obtain the energy detector's decision threshold. If the estimation of noise variance is incorrect, the threshold will be erroneous; this for obvious reasons, the energy detector performance quickly deteriorates. However, the proposed detector uses latest random matrix theories to set the decision thresholds and to obtain the probability of detection for attaining a better detection outcome. The proposed detection technique is universal in the sense that it can identify any kind of signal, and also not necessitate any prior awareness of signal to be determined same as the energy detector. Further, it does not utilize any significantly accessible signal awareness.

5CONCLUSIONS

A technique that is formed on the basis of eigenvalues of received signal sample covariance matrix has been suggested for cognitive radio networks. The suggested method makes use of the power technique to determine the supreme and smallest eigenvalues of the covariance matrix formed by the MIMO antenna construction. The outcomes of suggested detection approach is demonstrated through simulations utilizing arbitrarily produced signals. It has been depicted that the proposed detection performs better under low SNR conditions when using several antennas. Without having awareness of channel, noise and signal power, and the method can be applied to a several detection applications. Moreover, the technique exploits power approach to avoid processing of eigenvalue decomposition and lessen system overhead.

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