COOPERATIVE SPECTRUM SENSING USING RMT FOR COGNITIVE RADIO IN PRESENCE OF NOISE CORRELATION

[1]K VENKATESH, [2]RAJOO PANDEY

[1,2]Department of Electronics and Communication Engineering, National Institute of Technology, Kurukshetra
E-mail: [1]venky2045@gmail.com, [2]rajoo_pandey@nitkkr.ac.in

Abstract— This paper presents an eigen-value based cooperative spectrum sensing (SS) technique in the presence of noise correlation for Cognitive Radio (CR). In this work, a new Standard Condition Number (SCN) based decision statistics is defined using asymptotic random matrix theory (RMT) for the decision making process. First, the effect of noise correlation under both noise only and signal plus noise hypothesis is defined. Then the new bounds for the correlated noise scenario are defined and a the new SCN based threshold is derived for SS in CR. Simulation results show that sensing with the proposed threshold gives better performance in the presence of noise correlation.

Index Terms—Random Matrix Theory (RMT), Noise Correlation, Standard Condition Number (SCN), Spectrum Sensing (SS).

I. INTRODUCTION

Cognitive Radio (CR) senses the overall spectrum over the wide frequency bands and uses temporally the unoccupied bands for wireless transmission. The CR acts as a Secondary User (SU) and it will not have any primary rights to pre-assign any frequency bands. So, it has to dynamically sense the spectrum to detect the presence of primary user (PU). It is known that the Federal Communications Commission (FCC) has given rights for the opportunistic Spectrum Sharing [1], which led to the formation of IEEE 802.22 working group for developing the standard Wireless Regional Area Network (WRAN) based on the CR technology. WRAN will operate on the unused bands of Very High Frequency (VHF)/ Ultra High Frequency (UHF) (TV broadcasting bands and other wireless microphone bands, which are PUs. WRAN system needs to periodically detect the presence or absence of PU to avoid interference [2].

From the above discussion, it is clear that spectrum sensing (SS) is the fundamental component for a CR system. There are many facts which make spectrum sensing difficult. One of these the important factors is the PU's Signal to Noise Ratio (SNR) received by the secondary receiver, which may be very low. The targeted detection SNR level given by WRAN at worst case is -20dB [2]. Next is the time dispersion and fading of the wireless channel, which complicates the sensing problem. Third is the noise uncertainty, which is caused by the noise/interference level changing with time [3].

In order to address these difficulties, several SS algorithms including energy based detection, matched filter based detection Feature detection, Autocorrelation based detection, Eigen-value based detection, beacon based detection have been investigated [3]. Matched filter based detection, Feature based detection, Beacon based detection are non-blind SS techniques i.e., they requires some specific information about the parameters of the PU signal/system. Energy detection, Autocorrelation Based detection, covariance based detection etc., are blind SS techniques, which do not require any information about the parameters of the PU signal/system. Of all these techniques, energy detection is robust to unknown dispersive channel, but its detection depends on the knowledge of the accurate noise power and its inaccuracy leads to SNR wall and high probability of false alarm [4]-[5]. Thus, it is vulnerable to detect a signal in the presence of noise uncertainty and also it cannot detect the correlated signal. To improve the SS performance, different diversity techniques like cooperative, multi-antenna and oversampling techniques have been introduced. All these techniques use the properties of the received signal. Recent results of the Random Matrix Theory (RMT) [6] are also used. The main advantage of eigen-value based detection is that it requires no prior knowledge of the PU signal and it is better than energy detection technique [4].

In this paper, the problem of Cooperative SS in the presence of noise uncertainty [3] is considered. Here the Standard Condition Number (SCN) of the noise covariance matrix is used to examine and resolve the effect of the noise correlation on the eigen-value based SS. The SCN of a matrix is the ratio of maximum to minimum eigen-value and it is a metric to characterize the asymptotic eigen-value probability detection function (aepdf) support of a random matrix. Then the SCN of the received signal's covariance matrix is used for the decision process. The PU is present, if the calculated SCN is greater than the noise only SCN. In this model, the presence of noise correlation is assumed, which affects the SCN of the noise covariance matrix and as a result the decision metric is affected. To overcome over problem of SS in the presence of noise correlation we employ a method taken from [7]-[8].

Here we consider the asymptotically large matrices where the eigen-values are said to follow Marchenko-Pastur (MP) law, which provides the convergence of largest and smallest eigen-values of the matrices. Using MP law, a binary hypothesis test under white noise condition is performed in [9], which provides a SCN for the Wishart matrices. But the sample covariance matrix cannot be a Wishart matrix in the presence of correlated noise [4]. In this paper, the noise correlation due to imperfection and oversampling in filtering is considered. Due to the presence of noise correlation, the eigen-value distribution may not follow the MP law and the threshold from [9] will degrade the PU sensing performance. In our paper, a new threshold to carryout the SS in the presence of noise correlation is defined.

The paper is organized as follows. Section II describes the problem. Section III describes the signal model for both white as well as colored noise. Section IV describes the setting of threshold for our problem. Section V provides the Simulation results. Section VI concludes the paper.

Notations: Throughout the paper, boldface lower and upper case letters denotes vectors and matrices, respectively; $\mathbf{E}[.]$ Denotes expectation; $(.)^T$ denotes the transpose of a matrix; $(.)^H$ denotes the conjugate transpose of a matrix; $(.)^*$ denotes the complex conjugate; $\mathbf{I}$ is identity matrix; $(x)^+$denotes $\max(0,x)$; $\boldsymbol{R_X}$ denotes the statistical covariance of $\boldsymbol{X}$; $\hat{\boldsymbol{R}}_{\boldsymbol{X}}$ denotes the sample covariance matrix of $\boldsymbol{X}$.

II. PROBLEM DESCRIPTION

Using RMT, many eigen-value based SS techniques have been investigated. But most of the works assume that the noise is white at the CR terminal. Practically, the noise may not be white all the time because the received signal must be passed through a pulse-shaping filter, where a correlation is introduced in the signal. The noise correlation in the CR sensing is due to following two reasons [4].

A. Filtering

CR is a dynamic system and when a white noise is passed through a dynamic system, it is converted to a colored noise, typically a LPF (low pass filter), which is also known as shaping filter. The received signal when passed through shaping filter, which is at the input of the receiver, the noise that is added to the signal before filtering will also pass through the same filter. The noise covariance matrix will depend on the TF (Transfer Function) of the pulse-shape filtering used at the Radio Frequency (RF) front-end of the CR. As a result, the output signal of the filter contains the colored noise and the color of the noise can be tuned by adjusting the shaping filter's parameters.

B. Oversampling

Consider that the bandwidth of the shaping filter is B, which is equal to the bandwidth of the signal. But the sampling rate of the signal is higher than 2B, which leads to the correlation at the sampled output even though the input noise process is white.

Coherent receivers like matched filters are not suitable for the application of SS because no prior knowledge about the PU signal and channel is known. So, for the application of SS in CR, active RC filter with tunable cutoff frequency are proposed. A white noise signal with a power spectral density of $N_0/2$ is given as input to an RC filter having a time constant RC, the noise will be colored after filtering. We assume that the noise correlation effect is dominating the overall effects. We also assume that the RC filter transforms the input autocorrelation function (white noise) into a output autocorrelation function given in [10] $R_y(s) = (N_0/4)RC\exp(-|s|/RC)$ i.e., a exponential correlation model is considered in our paper.

An important research challenge, cooperatively sensing the signal in the presence of the noise correlation, is considered in this paper. A new SCN based decision statistics like other eigen-value based SS techniques [4] is defined. The new SCN based decision to improve the SS performance in the presence of noise correlation is taken from [7]. Also note that, one sided noise correlation model is considered and also an exponential correlation model matrix to define the correlation matrix components is used.

III. SYSTEM MODEL

In the present system model, the main focus is on the cooperative SS in which we have K cooperative SUs and let N be the number of samples that a cognitive user analyzes for making the decision about the presence or absence of a signal. We assume that each SU samples the received signal at the same rate, same instant and during the same interval (neglecting the delay in receiving the PU signal). For detecting the presence or absence of the PU signal, two hypothesis H_0 and H_1 are defined. where H_1 represents the hypothesis for presence of PU signal and H_0 represents the hypothesis for absence of PU signal. It can be shown as follows:

$$\mathsf{H}_0 : y_k(i) = \hat{z}_k(i) \text{ PU absent}$$
$$\mathsf{H}_1 : y_k(i) = h_k(i)s(i) + \hat{z}_k(i) \text{ PUpresent} \quad (1)$$

where $y_k(i)$ represents the received signal by the k^{th} cooperative SU at i^{th} instant, i=1,2,3,………N. $s(i)$ represents the PU signal at i^{th} instant, which has to be detected; $h_k(i)$ represents the channel amplitude gain for the k^{th} cooperative SU at the i^{th} instant and $\hat{z}_k(i)$ gives the colored noise for the k^{th} cooperative SU at the i^{th} instant. Assume, the transmitted PU symbols are independent and identical distributed (i.i.d) Gausssian symbols.

As there are K cooperative SUs and each SU analyzes N samples, we can form a *KxN* received signal matrix $\mathbf{Y}$. Let $\mathbf{H}$ denotes the *KxN* channel matrix whose entries consist of i.i.d coefficients and $\mathbf{H}$ can be represented in matrix form as, $\mathbf{H} \triangleq [\mathbf{h}_1^T \ \ \mathbf{h}_2^T \ \ \mathbf{h}_3^T \ldots\ldots \ \ \mathbf{h}_K^T]^T$, where $\mathbf{h}_k$ is the column matrix given by, $\mathbf{h}_k \triangleq [h_k(1) \ \ h_k(2) \ \ h_k(3) \ldots\ldots \ \ h_k(N)]$ with k =1, 2,……..K and also assume that the coherence time of the channel is small so that channel is not correlated.

Let us consider τ as the sensing duration and T_s as the symbol interval. During the sensing process in a cognitive receiver τ and T_s may not be same and will depend on the bandwidth of the signal and the sampling rate at the receiver. So, for the present model, under the hypothesis H_1, the transmitted symbol will remains constant during the sensing period. This case may occur when the rate of sampling at the receiver is much higher than the symbol rate of the transmitter. The received signal can be written as $\mathbf{Y} = \sqrt{p}\mathbf{H}s + \hat{\mathbf{Z}}$ where s is the constant transmitted symbol, p is the transmitted symbol power, and $\hat{\mathbf{Z}} \triangleq [\hat{\mathbf{z}}_1^T \ \ \hat{\mathbf{z}}_2^T \ \ \hat{\mathbf{z}}_3^T \ldots\ldots \ \ \hat{\mathbf{z}}_K^T]^T$ with $\hat{z}_k$ a column matrix $\hat{\mathbf{z}}_k \triangleq [\hat{z}_k(1) \ \ \hat{z}_k(2) \ \ \hat{z}_k(3) \ldots\ldots \ \ \hat{z}_k(N)]$. Assume the noise variance is normalized to unit value i.e., SNR= p . Therefore, the transmitted signal's sample covariance is $R_s = \mathbf{E}[s^2] = 1$.

Therefore, the received signal can be written as,

$$Y = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_K \end{bmatrix} = \begin{bmatrix} y_1(1) & y_1(2) & \cdots & y_1(N) \\ y_2(1) & y_2(2) & \cdots & y_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ y_K(1) & y_K(2) & \cdots & y_K(N) \end{bmatrix} \qquad (2)$$

Assume that the source signal and noise are independent. Therefore, the covariance matrix of the received signal is given as,

$$\begin{aligned} \mathbf{R_Y} &= \mathbf{E}[\mathbf{YY}^H] = \mathbf{E}[(\sqrt{p}\mathbf{HS})(\sqrt{p}\mathbf{HS})^H] + \mathbf{E}[\hat{\mathbf{Z}}\hat{\mathbf{Z}}^H] \\ &= p\mathbf{E}[\mathbf{HH}^H] + \mathbf{R}_{\hat{\mathbf{Z}}} \end{aligned} \qquad (3)$$

Where $\mathbf{R}_{\hat{\mathbf{Z}}} = \mathbf{E}[\hat{\mathbf{Z}}\hat{\mathbf{Z}}^H]$. The sample covariance matrix of noise and received signal are $\hat{\mathbf{R}}_{\hat{\mathbf{Z}}}(N) = (1/N)\hat{\mathbf{Z}}\hat{\mathbf{Z}}^H$ and $\hat{\mathbf{R}}_{\mathbf{Y}}(N) = (1/N)\mathbf{YY}^H$ respectively. The received signal is,

$$\mathbf{Y} = \sqrt{p}\mathbf{H}s + \hat{\mathbf{Z}} \qquad (4)$$

where $\hat{\mathbf{Z}} \sim \mathrm{CN}\,(0.\,\hat{\mathbf{R}}_{\hat{\mathbf{Z}}}(N))$is the colored noise. The SCN of noise's sample covariance $\hat{\mathbf{R}}_{\hat{\mathbf{Z}}}(N)$ will depends on the amount of noise correlation among noise samples.

A. Modeling of Noise Correlation:

In this paper, a single-sided noise correlation model is considered as given in [8]. This model relates colored noise with white noise as shown:

$$\hat{\mathbf{Z}} = \mathbf{\Gamma}^{1/2}\mathbf{Z} \qquad (5)$$

where $\mathbf{Z}$ is a *KxN* matrix with i.i.d Gaussian entries with zero mean and unit variance and represents white noise, and $\mathbf{\Gamma}$ is a *KxK* Hermitian matrix, where it entries corresponds to correlation among the noise samples. In (5) $\mathbf{\Gamma}^{1/2}$ is the square root of $\mathbf{\Gamma}$. $\mathbf{\Gamma}$ is normalized by considering $(1/K)\mathrm{trace}\{\mathbf{\Gamma}\} = 1$, so that it does not affect noise power. The entries of exponential correlation model are taken as described in [11].

$$\phi_{ij} = \begin{cases} \rho^{(j-i)}, & i \le j \\ (\rho^{(i-j)})^*, & i > j \end{cases} \qquad (6)$$

where ϕ_{ij} is the (i,j)th element of $\mathbf{\Gamma}$ and $|\rho| \le 1$.

B. Under H_0 Hypothesis:

Under the H_0hypothesis and for correlated noise scenario, $\hat{\mathbf{R}}_{\mathbf{Y}}(N)$ is equal to $\hat{\mathbf{R}}_{\hat{\mathbf{Z}}}(N)$ and is written as,

$$\hat{\mathbf{R}}_{\mathbf{Y}}(N) = \hat{\mathbf{R}}_{\hat{\mathbf{Z}}}(N) = \mathbf{\Gamma}^{1/2}\mathbf{ZZ}^H\mathbf{\Gamma}^{1/2} \qquad (7)$$

In the case of white noise, $\hat{\mathbf{R}}_{\mathbf{Y}}(N) = \mathbf{ZZ}^H$.

C. Under H_1 Hypothesis:

Under the assumption that the signal and the noise are independent and for large values of N, the approximate received signal sample covariance matrix for the white noise case [4] is,

$$\lim_{N\to\infty} \hat{\mathbf{R}}_{\mathbf{Y}}(N) \approx p\mathbf{HH}^H + \hat{\mathbf{R}}_{\mathbf{Z}}. \qquad (8)$$

In this case, $\hat{\mathbf{R}}_{\mathbf{Y}}(N)$ is the sum of two Wishart matrices i.e., $p\hat{\mathbf{R}}_{\mathbf{H}} = p\mathbf{HH}^H$ and $\hat{\mathbf{R}}_{\mathbf{Z}}$ with the same degree of freedom and having different covariance structures. In this case, MP law holds for both matrices.

Using the same conditions as above, the approximation under correlated noise case is,

$$\lim_{N\to\infty} \hat{\mathbf{R}}_{\mathbf{Y}}(N) \approx p\mathbf{HH}^H + \hat{\mathbf{R}}_{\hat{\mathbf{Z}}}. \qquad (9)$$

where $\hat{\mathbf{R}}_{\mathbf{Y}}(N)$ is the sum of one Wishart matrix $p\hat{\mathbf{R}}_{\mathbf{H}}$ and a correlated Wishart matrix $\hat{\mathbf{R}}_{\hat{\mathbf{Z}}}$. In this case, MP law can be applied for only $p\hat{\mathbf{R}}_{\mathbf{H}}$ and the analysis is carried out for $\mathbf{H_0}$ hypothesis in (7) is applied for $\hat{\mathbf{R}}_{\hat{\mathbf{Z}}}$.

IV. DETERMINATION OF THRESHOLD

To determine the threshold for spectrum sensing under the condition of noise correlated, we use RMT. RMT has many applications in the wireless communications. In the present model, two theorems of RMT, which are useful in determining the threshold for the decision statistics are given below.

Theorem 4.1: [6] Consider an *KxN* matrix $\mathbf{G}$ whose entries are independent zero mean (real or) complex random variables with variance (1/N) and fourth moment of order $O(1/N^2)$. As $K,N\to\infty$ with N/K→ α $(0 < \alpha < \infty)$, the empirical distribution of eigen values of $(1/N)\mathbf{GG}^H$ converges almost surely to a non-random limiting distribution with density given by,

$$g_\alpha(\lambda) = (1-\alpha)^+\delta(\lambda) + \frac{\sqrt{(\lambda-a)^+(b-\lambda)^+}}{2\pi\alpha\lambda} \qquad (10)$$

where $a = (1-\sqrt{\alpha})^2$, $b = (1+\sqrt{\alpha})^2$, $\delta(.)$ is a Dirac delta function. (10) is a limiting distribution called as MP law with ratio index α. The parameters a and b in the above distribution defines the support of distribution and corresponds to $\lambda_{\min}$ and $\lambda_{\max}$ respectively. So that

the ratio (b/a) defines the SCN of $(1/N)\mathbf{GG}^H$.
The asymptotic eigen-value distribution is obtained from the theorem. But in practice we have only a finite number of samples and the sample covariance matrix $\hat{\mathbf{R}}_{\mathbf{Y}}(N)$ may deviate from that of covariance matrix $\mathbf{R_Y}$ in [4]. In this case, the choice of threshold is difficult to determine for the purpose of SS because the eigen-value distribution of $\hat{\mathbf{R}}_{\mathbf{Y}}(N)$ is complicated due to the consideration of finite parameters in the analysis and also the performance of spectrum sensing algorithms becomes sensitive at the low SNR values. In this paper, an asymptotic analysis is considered to analyze noise correlation effects on the sensing performance because it provides a less complex solution when compared with finite analysis [7]. Under the H_0hypothesis, $\hat{\mathbf{R}}_{\mathbf{Y}}(N)$ is equal to $\hat{\mathbf{R}}_{\tilde{\mathbf{Z}}}(N)$ and is given by (7).
As N→ ∞, $\hat{\mathbf{R}}_{\mathbf{Y}}(N)$ converges to $\mathbf{R_Y}$. For large values of N, the asymptotic analysis holds good. $\hat{\mathbf{R}}_{\mathbf{Z}}(N)$ is nearly a Wishart random matrix in the case of white noise, but it is no longer a Wishart random matrix under correlated noise case. The Wishart matrix is generated using the RMT concept in [12]. In [8], it is given that the asymptotic density of eigen-values of $\mathbf{\Gamma}$ can be described as a tilted semi-circular law, which can be a close approximation for the exponential model. The following theorem describes this density:

Theorem 4.2: [8] let $\mathbf{\Gamma}$ be a positive definite matrix, whichis normalized as $(1/K)\text{trace}\{\mathbf{\Gamma}\}=1$, and whose asymptotic spectrum has a pdf

$$g_{\Gamma}(\lambda)=\frac{1}{2\pi\mu\lambda^2}\sqrt{\left(\frac{\lambda}{\sigma_1}-1\right)\left(1-\frac{\lambda}{\sigma_2}\right)} \tag{11}$$

with $\sigma_1 \le \lambda \le \sigma_2$ and $\mu=(\sqrt{\sigma_1}-\sqrt{\sigma_2})/4\sigma_1\sigma_2$. If G is a *KxN* standard complex Gaussian matrix, as defined in Theorem 4.1, then *K,N*→ ∞ with N/K→ $\alpha(0<\alpha<\infty)$ the asymptotic eigen-value distribution of $\mathbf{W}=\mathbf{\Gamma}^{1/2}\mathbf{GG}^H\mathbf{\Gamma}^{1/2}$ has pdf,

$$g_{\mathbf{W}}(\lambda)=(1-\alpha)^+\delta(\lambda)+\frac{\sqrt{(\lambda-\tilde{a})^+(\tilde{b}-\lambda)^+}}{2\pi\lambda(1+\lambda\mu)} \tag{12}$$

$\tilde{a}$ and $\tilde{b}$ are the parameters and corresponds to $\lambda_{\min}$ and $\lambda_{\max}$ respectively and the SCN of $\mathbf{W}$ is defined by the ratio $\tilde{b}/\tilde{a}$. where the values of $\tilde{a}$ and $\tilde{b}$ are given as,

$$\tilde{a}=1+\alpha+2\alpha\mu-2\sqrt{\alpha}\sqrt{(1+\mu)(1+\mu\alpha)}$$
$$\tilde{b}=1+\alpha+2\alpha\mu+2\sqrt{\alpha}\sqrt{(1+\mu)(1+\mu\alpha)} \tag{13}$$

In (12), the degree of noise correlation is controlled by the parameter μ and it varies the support of the distribution. $\mu$is related to ρ as $\mu=\rho^2/(1-\rho^2)$, given in [8].
In the case of white noise, the presence or absence of signal can be decided by using the deviation of the distribution of the eigen-values from its normal bounds (a,b). The presence of the PU signal can be decided if the eigen-values appear outside these bounds. If the eigen-values lie inside the bounds then the PU signal is absent [9]. In the same way, the presence or absence of PU signal under noise correlation scenario can be decided by sing the new bounds of the eigen-value distribution of the sample covariance matrix. The new bounds are $(\tilde{a},\tilde{b})$ and they depends on the noise correlation parameter μ.
Let us consider that both noise variance and noise distribution are unknown to the detector (practical scenario). Therefore the decision statistic for MP law under the white noise scenario is given as [8],

$$\text{decision}=\begin{cases} H_0, & \text{if } SCN \le \dfrac{b}{a} \\ H_1, & \text{otherwise} \end{cases} \tag{14}$$

The values of a and b can be determined from the expressions given in Theorem 4.1. Similarly the decision statistic for the correlated noise case can be determined from the Theorem 4.2. According to it, the decision statistic for the presence or absence of PU signal under noise correlation is given by,

$$\text{decision}=\begin{cases} H_0, & \text{if } SCN \le \dfrac{\tilde{b}}{\tilde{a}} \\ H_1, & \text{otherwise} \end{cases} \tag{15}$$

Using the decision statistics given in (14) and (15) we can decide the presence or absence of PU signal under white noise and correlates noise scenarios respectively.

V. SIMULATION AND RESULTS

To study the performance of eigen-value based SS in the presence of noise correlation with the given decision bounds, the probability of detection is used as the performance metric [13]. The channel is considered to be Rayleigh faded and its coefficients are generated from a complex random numbers whose real and imaginary parts are i.i.d Gaussian variables. As a result, $\mathbf{H} \sim CN\,(0.\mathbf{I})$.
It can be noted that under the white noise case, the eigen-value distribution of the received signal's covariance matrix follows MP law. Therefore, the decision rule given in (14) is used for sensing of the PU signal in white noise scenario. But under the correlated noise case, the decision rule in (15) is used to sense the presence or absence of PU signal.

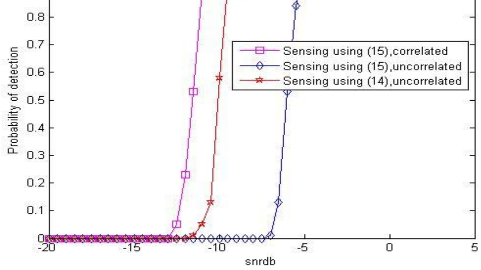

Fig. 1 Probability of detection versus SNR with (14) and (15) ($\alpha=2,\rho=0.5,N=100$ **)**

In the simulation results, the sensing performance is compared with MP–based threshold and the new proposed threshold. Fig.1 shows the probability of detection versus SNR for ρ=0.5, α=2 and N=100. From Fig.1, it can be observed that the performance of sensing using (15) out performs the sensing using (14) under correlated noise scenario. It can also be observed that the sensing of uncorrelated signal using (15) gives poor response. i.e., to decide the threshold correlation should be known. If correlation is zero go for (14), otherwise go for (15). The new threshold gives better response for the correlated noise scenario and if the same is used threshold for white noise case, its performance is poor for low values of SNR as shown in Fig.1.

Fig.2 shows the probability of detection versus the correlation coefficient (ρ) for SNR=-6dB and α=2. It can be observed that as the noise correlation is increasing the sensing performance is decreasing drastically.

From (15), it can be observed that a change in correlation coefficient results in a change in the ratio $(\tilde{b}/\tilde{a})$. Therefore, sensing using (15) for a correlated signal is better for large amount of correlation.

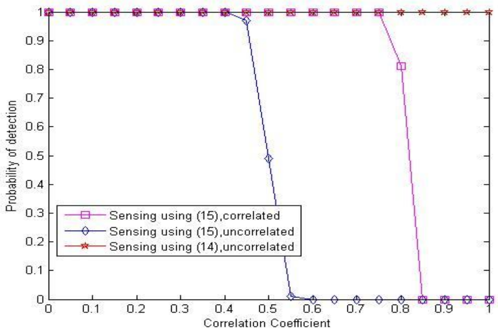

Fig. 2 Probability of detection versus correlation coefficient ($SNR = -6dB, \alpha = 2, N = 100$)

CONCLUSION

In this paper, the presence or absence of PU signal under the condition of noise correlated using eigen-value based cooperative spectrum sensing has been analyzed. A new threshold based on SCN has been used for the improvement of cooperative spectrum sensing performance for this scenario.

From the viewpoint of practical implementations of a CR, the spectrum sensing techniques should work effectively and efficiently where the channel and noise correlation are also present to certain extent. The present work can be extended by considering the presence of channel correlation in addition to the noise correlation and finding new sensing scheme suitable for the conditions.

REFERENCES

[1] FCC, "Facilitating opportunities for flexible, efficient and reliable spectrum use employing cognitive radio technologies, notice of proposed rule making and order," FCC 03-322, Dec-2003.

[2] Standard for wireless Regional Area Networks (WRAN) – Specific requirements – Part:22 Cognitive Wireless RAN Medium Access Control (MAC and Physical Layer (PHY) Specifications: Policies and procedures for operation in the TV Bands, The Institute of Electrical and Electronics Engineering, Inc. Std. IEEE 802.22.

[3] S. K. Sharma, T. E. Bogale, S. Chatzinotas, B. Ottersten, L. B. Le, and X. Wang, "Cognitive radio techniques under practical imperfections: A survey," IEEE Commun Surveys & Tutorials., vol. 17, no. 4, pp. 1858-1884, July 2015.

[4] Y. Zeng, and Y. C. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," IEEE Trans. On Commun., vol. 57, no. 6,pp-1784-1793, June 2009.

[5] A. Sonnenschein and P. M. Fishman, "Radiometric detection of spread spectrum signals in noise of uncertainty power," IEEE Trans. Aerospace Electronic Systems, vol. 28, no. 3, pp. 654-660, 1992.

[6] A. M. Tulino and S Verdu, "Random matrix theory and wireless communications," Found. Trends Commun. Inf. Theory, vol. 1, no. 1, pp. 1-182, June 2004.

[7] S. K. Sharma, S. Chatzinotas, and B. Ottersten, "Eigenvalue-based sensing and SNR estimation for cognitive radio in presence of noise correlation," IEEE Trans. On Vehicular Tech., vol. 62, no. 8, pp-3671-3684, Oct-2013.

[8] X. Mestre, J. R. Fonollosa, and A. P. Zamora, "Capacity of MIMO channels: Asymptotic evaluation under correlated fading," IEEE Journ. on Selected Areas in Commun., vol. 21, no. 5, June 2003.

[9] L. Cardoso, M. Debbah, P. Bianch,i and J. Najim, "Cooperative spectrum sensing using random matrix theory," in Proc. 3rd Int. Symp. Wireless Perv. Comput., pp-334-338, May-2008.

[10] S, Haykin, "Communication Systems," 4th ed. Hoboken, NJ, USA: Wiley 2010.

[11] S. Lokya, "Channel capacity of MIMO architecture using exponential correlation matrix," IEEE Commun. Lett., vol.5, no. 9, pp. 369-371, Sep. 2001.

[12] N. Raj Rao, and A. Edelman, "Random Matrix Theory," Cambridge University Press, pp. 1-65, 2005.

[13] S. M Kay, "Fundamentals of Statistical Signal Processing: Detection Theory. Englewood Cliffs, NJ, USA: Prentice Hall, 1998.

★★★