A Blind Detection Algorithm Utilizing Statistical Covariance in Cognitive Radio

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Abstract

As the expression of performance parameters are obtained using asymptotic method in most blind covariance detection algorithm, the paper presented a new blind detection algorithm using cholesky factorization. Utilizing random matrix theory, we derived the performance parameters using non-asymptotic method. The proposed method overcomes the noise uncertainty problem and performs well without any information about the channel, primary user and noise. Numerical simulation results demonstrate that the performance parameters expressions are correct and the new detector outperforms the other blind covariance detectors.

Keywords: *Covariance, Cognitive Radio, Cholesky Decomposition, Blind Detection.*

1 Introduction

Recently cognitive radio technology has become a important way to solve the shortage of spectrum resources and improve the efficiency of spectrum use. Spectrum detection is the one of the key technology in cognitive radio[1-3]. Covariance detection algorithm in cognitive radio utilizes statistics characteristic of the received signal covariance matrix to detect PU signal. This detection algorithm, relative to the ED (Energy Detector) and cycle stationary detector, doesn't need any priori information include PU users and sensing channels, and is robust to the uncertain noise of the sensing channel. [4] exploits the element difference of covariance matrix and proposes CAV(Covariance Absolute Value) algorithm. MME (Maximum to Minimum Eigenvalue) algorithm proposed by [5] and MET (Maximum Eigenvalue Trace) algorithm proposed by [6] takes advantage of the PU largest eigenvalue of the covariance. [7] proposed a new parameters optimization algorithm to obtain better performance. [8] derives GLR (Generalized Likelihood Ratio) blind detection algorithm based on GLRT(Generalized Likelihood Ratio Test) algorithm. [9] exploits eigenvector correlation of continual covariance matrices to help detection. BOC[10] algorithm introduces the cholesky decomposition into detection step only to figure out the asymptotic performance parameters expressions.

In this paper, we improve BOC detection algorithm proposed by [10], and present a blind detection algorithm with good performance based on cholesky decomposition of covariance matrix. After performance analysis, we derived the performance's parameters using non-asymptotic method. Theoretical analysis and simulation results show that the performance parameters expressions are correct and the proposed algorithm outperforms BOC algorithm and the other covariance blind detection algorithm when the algorithm detection performance at low SNR.

2 Signal Model

The frequency spectrum sensing problem can be modeled as two hypothesis model in Cognitive radio[11]. After sampling and A/D conversion, received signal $y(l)$ is expressed as

$$\begin{aligned} &H_0 : y(l) = v(l) \\ &H_1 : y(l) = x(l) + v(l) \qquad l = 0,1,2,\cdots \end{aligned} \tag{1}$$

where H_0 represents the absence of the primary signal $x(l)$, and H_1 represents the presence of a primary signal in the band. Received signal $y(l)$ contains only additional white Gaussian noise (AWGN) $v(l)$ when H_0, where $v(l) \sim CN(0,\sigma_v^2)$. $y(l)$ contains the primary signal $x(l)$ corrupted by noise $v(l)$, where $\mathbf{x} \sim CN(0,\mathbf{\Sigma}_N)$. $N(\cdot)$ represents Gaussian distribution function. σ_v^2 represents the noise variance whose components are independent of each other. We also assume that the PU signal and the noise are independent of each other. $\mathbf{\Sigma}_N$ represents symmetry covariance matrix of full rank, with diagonal elements of 1. r represents correlation strength of adjacent samples of the received signal, whereas correlation strength of non-adjacent element is zero.

$\mathbf{\Sigma}_N$ can be defined as

$$\begin{bmatrix} 1 & r & 0 & \cdots & 0 \\ r & 1 & r & 0 & \vdots \\ 0 & r & \ddots & r & 0 \\ \vdots & 0 & r & 1 & r \\ 0 & \dots & 0 & r & 1 \end{bmatrix}_{N\times N}$$

Considering a sensing interval of n samples, we can represent the received signal and the primary transmitted signal in vector form as follows: $\mathbf{x}=[x(0),x(1),\cdots,x(N-1)]^T$ and $\mathbf{y}=[y(0),y(1),\cdots,y(N-1)]^T$. Considering the multipath and other interference factors, (1) is equivalent to a binary hypothesis model of N-dimensional vector space:

$$\begin{aligned} &H_0:\mathbf{y}\sim CN(0,\sigma_v^2\mathbf{I}_N) \\ &H_1:\mathbf{y}\sim CN(0,\mathbf{R}_y) \end{aligned} \tag{2}$$

where $\mathbf{R}_y=\mathbf{\Sigma}_N+\sigma_v^2\mathbf{I}_N$, $\mathbf{\Sigma}_N=\mathbf{E}(\mathbf{x}\mathbf{x}^T)$, $\mathbf{R}_y=\mathbf{E}(\mathbf{y}\mathbf{y}^T)$ and $(\cdot)^T$ denotes complex conjugate, $\mathbf{E}(\cdot)$ denotes taking the expectation.

Given the receiver matrix $\{\mathbf{y}_1,\mathbf{y}_2,\cdots,\mathbf{y}_{N_s}\}$, we have

$$\hat{\mathbf{R}}_y=\frac{1}{N_s}\sum_{i=1}^{Ns}\mathbf{y}_i\mathbf{y}_i{}^T \tag{3}$$

where N_s denotes the number of sample vector. We have the cholesky factorization

$$\hat{\mathbf{R}}_y=\mathbf{Q}^T\mathbf{Q} \tag{4}$$

$\mathbf{Q}$ is an upper-triangular matrix with non-negative diagonal elements. If there is no primary signal, then we have $\mathbf{Q}=\sigma_v\mathbf{I}_N$ due to $\mathbf{R}_y=\sigma_v^2\mathbf{I}_N$, which means that the non-diagonal elements of $\mathbf{Q}$ are all zero. If the primary signal is present, the non-diagonal elements of $\mathbf{Q}$ should be nonzero due to the correlation of the primary signal.

3 Blind Detection Algorithm Based on Choleskey Decomposition

3.1 Algorithm Description

After cholesky factorization in the signal model, the BOC algorithm is described as follow[12]:

$$\frac{\sum_{1\le i<j\le N}\hat{q}_{ij}^2}{\sum_{1\le i\le N}\hat{q}_{ii}^2}\ \overset{H_1}{\underset{H_0}{\gtrless}}\ \varepsilon \tag{5}$$

where ε is the threshold, and $\hat{q}_{ij}$ is the (i,j)-th element of $\mathbf{Q}$.

Previous studies of signal detection show that the detection performance of BOC algorithm is not optimal when the detection algorithm bases on the element value of the statistical covariance matrix. For example CAV algorithm has been proved to be better than other detection algorithms of the same kind which work on the element value of covariance matrix [4] [12], so we propose a new detection algorithm to outperform the BOC algorithm in the next section.

A. Algorithm description

Based on the algorithm of [7] and the CAV algorithm, we propose a new spectrum detection algorithm described as follow:

Step.1) Use (3) to get the maximum likelihood estimator $\hat{\mathbf{R}}_y$ of the receive signal's covariance matrix. $\hat{\mathbf{R}}_y$ obeys the distribution in (5).

$$\hat{\mathbf{R}}_y\sim\begin{cases}\frac{1}{N_s}W_N(N_s,\mathbf{R}_y) & |H_1 \\ \frac{1}{N_s}W_N(N_s,\sigma_v^2\mathbf{I}_N) & |H_0\end{cases} \tag{6}$$

where $W(\cdot)$ represents the wishart distribution.

Step.2) Take cholesky decomposition of $\hat{\mathbf{R}}_y$, then $\hat{\mathbf{R}}_y=\hat{\mathbf{Q}}^T\hat{\mathbf{Q}}$, where $\hat{\mathbf{Q}}$ is a upper-triangular matrix. Also its diagonal elements is nonzero.

Step 3) Determine the presence of the primary signal based (6) as follow.

$$L(y)=\frac{\left|\sum_{1\le i<j\le N}\hat{q}_{ij}\right|}{\left|\sum_{1\le i\le N}\hat{q}_{ii}\right|}\ \overset{H_1}{\underset{H_0}{\gtrless}}\ \gamma \tag{7}$$

where $\hat{q}_{ij}$ is the i-th row j-th column element in $\hat{\mathbf{Q}}$, γ is the threshold.

3.2 Performance Analysis

P_f and P_m is the main performance parameters of the spectrum detection algorithm, and the decision threshold of the proposed detector can be determined by P_f. For a good detection algorithm, both P_f and P_m should be low, and P_d should be high. Lower value of P_f means that CU has more opportunity to occupy the channel, and higher value of P_m means that CU has less opportunity to detect PU.

In order to analyze the performance of the proposed algorithm, we set $\hat{\mathbf{R}}_y^{'}=\frac{N_s\hat{\mathbf{R}}_y}{\sigma_v^2}$, according to the nature of wishart distribution, (5) is transformed into

$$\hat{\mathbf{R}}_y^{'}\sim\begin{cases}W_N(N_s,\frac{N_s\mathbf{R}_y}{\sigma_v^2}) & |H_1 \\ W_N(N_s,\mathbf{I}_N) & |H_0\end{cases} \tag{8}$$

Take cholesky decomposition of $\hat{\mathbf{R}}_y$ to get the upper-triangle matrix $\mathbf{D}$

$$\hat{\mathbf{R}}_y^{'}=\mathbf{D}^T\mathbf{D} \tag{9}$$

According to the nature of the wishart distribution and (5)(6),we have

$$\frac{\left|\sum_{1\le i<j\le N}\hat{q}_{ij}\right|}{\left|\sum_{1\le i\le N}\hat{q}_{ii}\right|}=\frac{\left|\sum_{1\le i<j\le N}d_{ij}\right|}{\left|\sum_{1\le i\le N}d_{ii}\right|} \tag{10}$$

Where d_{ij} is the(i,j)-th of $\mathbf{D}$, so we rewrite (7) as

$$L(y)=\frac{\left|\sum_{1\le i<j\le N}d_{ij}\right|}{\left|\sum_{1\le i\le N}d_{ii}\right|}\mathop{\gtrless}_{H_0}^{H_1}\gamma \tag{11}$$

3.3 The Calculation of P_f and P_m

When PU signal does not exist, we can get $\hat{\mathbf{R}}_y^{'}\sim W_N(N_s,\mathbf{I}_N)$ from formula (3) due to CU only detecting the noise signal. After setting $\mathbf{D}=\mathbf{U}|H_0$, all the elements u_{ij} of $\mathbf{U}$ are independent with

$$\begin{array}{ll} u_{ii}^2\sim\chi^2_{N_s-i+1} & 1\le i\le N \\ u_{ij}\sim N(0,1) & 1\le i<j\le N\end{array} \tag{12}$$

It is no hard to verify that u_{ii} follows Chi distribution[13] with N_s-i+1 degrees of freedom from (12).

$$u_{ii}\sim\chi_{N_s-i+1}\quad 1\le i\le N \tag{13}$$

According to the nature of Chi distribution[13], we have

$$\lim_{N_s\to\infty}\frac{\chi_{N_s-i+1}-\mu_i}{\sigma_i}\to N(0,1) \tag{14}$$

where μ_i,σ_i^2 are the expectation and variance of u_{ii} respectively. When the value of N_s is big, we have

$$u_{ii}\sim N(\mu_i,\sigma_i^2)\quad 1\le i\le N \tag{15}$$

where $\mu_i=\sqrt{2}\frac{\Gamma((N_s-i+2)/2)}{\Gamma(N_s-i+1/2)}$, $\sigma_i^2=(N_s-i+1)-\mu_i^2$, $\Gamma(\cdot)$ denotes as gamma function. Due to the independence of every u_{ij}, we get

$$\sum_{1\le i\le N}u_{ii}\sim N\left(\sum_1^N\mu_i,\sum_1^N\sigma_i^2\right) \tag{16}$$

where $\sum_1^N\mu_i=\sum_1^N\sqrt{2}\frac{\Gamma((N_s-i+2)/2)}{\Gamma(N_s-i+1/2)}$, $\sum_1^N\sigma_i^2=\sum_1^N(N_s-i+1)-\mu_i^2$.

According to the formula (7), the distribution of sum of non-diagonal elements u_{ij} is deduced to obey Gaussian distribution.

$$\sum_{1\le i<j\le N}u_{ij}\sim N\left(0,\frac{N(N-1)}{2}\right) \tag{17}$$

According to the nature of the Gaussian distribution [11], using (11)(12), PDF of $L(y)=\frac{\left|\sum_{1\le i<j\le N}u_{ij}\right|}{\left|\sum_{1\le i\le N}u_{ii}\right|}$ can is derived as

$$\begin{aligned} f_u(\gamma)=&\frac{\sqrt{(N(N-1)/2)\sum_1^N\sigma_i^2}}{\pi\left(\gamma^2\sum_1^N\sigma_i^2+N(N-1)/2\right)}\exp\left(-\frac{\left(\sum_1^N\mu_i\right)^2}{2\sum_1^N\sigma_i^2}\right)\\ &+\frac{N(N-1)/2\sum_1^N\mu_i}{\sqrt{2\pi}\left(\gamma^2\sum_1^N\sigma_i^2+N(N-1)/2\right)^{3/2}}\\ &\times\exp\left(-\frac{\gamma^2\left(\sum_1^N\mu_i\right)^2}{2\left(\gamma^2\sum_1^N\sigma_i^2+N(N-1)/2\right)}\right)\\ &\times\left[1-2Q\left(\frac{N(N-1)/2\sum_1^N\mu_i}{\sqrt{(N(N-1)/2)\sum_1^N\sigma_i^2\left(\gamma^2\sum_1^N\sigma_i^2+N(N-1)/2\right)}}\right)\right]\end{aligned} \tag{18}$$

We get P_f using the calculation of the PDF of $L(y)$, The brief calculation process and the results are as follows

$$\begin{aligned} P_f=&F_u(\gamma)=P\left(L(y)=l>\gamma|H_0\right)=\int_\gamma^\infty f_u(l)dl\\ =&\frac{1}{\pi}\tan^{-1}\left(\frac{\sqrt{N(N-1)/2}}{\gamma\sqrt{\sum_1^N\sigma_i^2}}\right)\\ &+2V\left(\frac{\gamma\sum_1^N\mu_i}{\sqrt{\gamma^2\sum_1^N\sigma_i^2+N(N-1)/2}},\frac{\left(\sqrt{N(N-1)\Big/\left(2\sum_1^N\sigma_i^2\right)}\right)\sum_1^N\mu_i}{\sqrt{\gamma^2\sum_1^N\sigma_i^2+N(N-1)/2}}\right)\end{aligned} \tag{19}$$

where $V(u,v)=\frac{1}{2\pi}\int_0^u\int_0^{vx/u}\exp\left(-\frac{x^2+y^2}{2}\right)dydx$, $\sum_1^N\mu_i=\sum_1^N\sqrt{2}\frac{\Gamma((N_s-i+2)/2)}{\Gamma(N_s-i+1/2)}$, $\sum_1^N\sigma_i^2=\sum_1^N((N_s-i+1)-\mu_i^2)$.

It can be seen that formula (18) is complex, but we also can use the computing software on the computer to get the value of γ if we input the value of P_f. The expression can be obtained as follow:

$$\gamma = F_u^{-1}\left(P_f\right) \tag{19}$$

Detection probability of detection algorithm represents spectrum signal detection ability of PU. When PU signal exists, the covariance matrix of receiving signals $\mathbf{R}_y$ is the sum of the signal matrix and noise matrix. After transforming and cholesky decomposition, we can get $\frac{N_s \mathbf{R}_y}{\sigma_v^2} = \mathbf{G}^T\mathbf{G}$. As $\mathbf{R}_y$ is a positive definite symmetric matrix and $\mathbf{G}$ is a N-dimensional upper-triangle matrix, according to formula (3), $\hat{\mathbf{R}}_y^{'} \sim W_N(N_s, \frac{N_s \mathbf{R}_y}{\sigma_v^2})$ when PU signal exists.

We set the upper-triangle matrix $\mathbf{D} = \mathbf{C}\left|H_1\right.$, where c_{ij} is the (i,j)-th element, $d_{ij} = c_{ij}\left|H_1\right.$.

Because of $\mathbf{U}^T\mathbf{U} \sim W_N(N_s, \mathbf{I}_N)$, according to [14], we can get

$$\begin{aligned} \mathbf{G}^T\mathbf{U}^T\mathbf{U}\mathbf{G} &= (\mathbf{U}\mathbf{G})^T\mathbf{U}\mathbf{G} \sim W_N(N_s, \mathbf{G}^T\mathbf{I}_N\mathbf{G}) \\ &= W_N(N_s, \frac{N_s\mathbf{R}_y}{\sigma_v^2}) \end{aligned} \tag{20}$$

For the reason that $\mathbf{U}$ and $\mathbf{G}$ are upper-triangular matrix similarly, it can be seen that $\mathbf{C}$ and $\mathbf{UG}$ follow the same distribution from the uniqueness theory of cholesky decomposition. In other words, after setting $\mathbf{L} = \mathbf{UG}$, we obtain that c_{ij} and l_{ij} have the same distribution, and l_{ij} in $\mathbf{L}$ can be expressed as

$$l_{ij} = \begin{cases} \sum_{x=i}^{j} u_{ix} g_{xj} & j \ge i \\ 0 & j < i \end{cases} \tag{21}$$

According to the formula (7) (9) (10) (11), we derive

$$\begin{aligned} l_{ij} &\sim N(\sum_1^N g_{ii}\mu_i, \sum_1^N g_{ii}^2\sigma_i^2) \\ c_{ij} &\sim N(\sum_1^N g_{ii}\mu_i, \sum_1^N g_{ii}^2\sigma_i^2) \end{aligned} \tag{22}$$

where $\mu_i = \sqrt{2}\frac{\Gamma((N_s - i + 2)/2)}{\Gamma(N_s - i + 1/2)}$, $\sigma_i^2 = (N_s - i + 1) - \mu_i^2$.

Utilizing formula (7) (12)'s conclusion, we have CDF of $L(y) = \frac{\left|\sum_{1\le i<j\le N} c_{ij}\right|}{\left|\sum_{1\le i\le N} c_{ii}\right|}$ as

$$\begin{aligned} f_c(\gamma) = {} & \frac{\sqrt{(\sum_{1\le i<j\le N} g_{ij})^2 \left(N(N-1)/2\right)\sum_1^N g_{ii}^2\sigma_i^2}}{\pi\left(\gamma^2\sum_1^N g_{ii}^2\sigma_i^2 + (\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2\right)} \exp\left(-\frac{\left(\sum_1^N g_{ii}\mu_i\right)^2}{2\sum_1^N g_{ii}^2\sigma_i^2}\right) \\ & + \frac{(\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2\sum_1^N g_{ii}\mu_i}{\sqrt{2\pi}\left(\gamma^2\sum_1^N g_{ii}^2\sigma_i^2 + (\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2\right)^{3/2}} \times \exp\left(-\frac{\gamma^2\left(\sum_1^N g_{ii}\mu_i\right)^2}{2\left(\gamma^2\sum_1^N g_{ii}^2\sigma_i^2 + (\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2\right)}\right) \\ & \times\left[1 - 2Q\left(\frac{(\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2\sum_1^N g_{ii}\mu_i}{\sqrt{(\sum_{1\le i<j\le N} g_{ij})^2 (N(N-1)/2)\sum_1^N g_{ii}^2\sigma_i^2\left(\gamma^2\sum_1^N g_{ii}^2\sigma_i^2 + (\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2\right)}}\right)\right] \end{aligned} \tag{23}$$

We can calculate the probability of detection using PDF,

$$\begin{aligned} P_d &= F_c(\gamma) = P\left(L(y) = l > \gamma\left|H_1\right.\right) = \int_\gamma^\infty f_c(l)dl \\ &= \frac{1}{\pi}\tan^{-1}\left(\frac{\sqrt{(\sum_{1\le i<j\le N} g_{ij})^2\left(N(N-1)/2\right)}}{\gamma\sqrt{\sum_1^N g_{ii}^2\sigma_i^2}}\right) \\ & +2V\left(\frac{\gamma\sum_1^N g_{ii}\mu_i}{\sqrt{\gamma^2\sum_1^N g_{ii}^2\sigma_i^2 + (\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2}}, \frac{\left(\sqrt{(\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)\Big/\left(2\sum_1^N g_{ii}^2\sigma_i^2\right)}\right)\sum_1^N g_{ii}\mu_i}{\sqrt{\gamma^2\sum_1^N g_{ii}^2\sigma_i^2 + (\sum_{1\le i<j\le N} g_{ij})^2 N(N-1)/2}}\right) \end{aligned} \tag{24}$$

At last, we can derive the probability of missed detection using $P_m = 1 - P_d$.

4. Simulation results and analysis

In this section computer simulation validation and analysis is proposed in order to verify the correctness and effectiveness of the proposed algorithm. All PU and SU use single antenna in the simulation. The channel from PU to CU follows Gaussian distribution. PU signal covariance matrix uses normalized positive definite symmetric matrices whose diagonal elements and non-diagonal are about 1 and *r*. All the data is obtained using the Monte Carlo method with the simulation times of 10000 in the simulation.

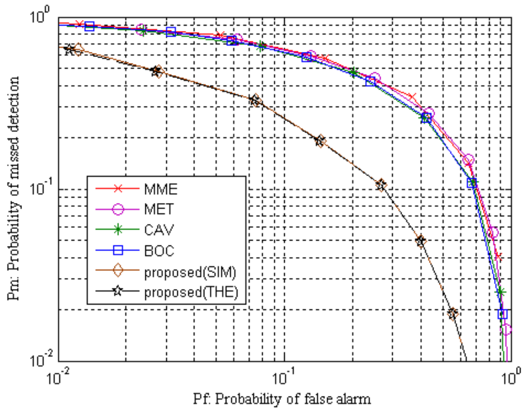

Fig1: ROC curve of the covariance blind detection algorithm under $SNR = -20dB$

With probability of false alarm on the horizontal axis and probability of missed detection on the vertical one, Figure 1 compares the proposed algorithm with other detection algorithm under low SNR. The simulation uses $r = 0.8$, $SNR = -20dB$, $N_s = 10000$. The theory curve (THE) in Figure 1 is obtained from formula (14) and (11). As can be seen, the Monte Carlo simulation curve of proposed algorithm and the theory curve overlap in the Figure 1, this indicates the correctness of the performance parameter formula (18) and (24). Also the detection probability of the proposed algorithm is bigger than 0.75 when the false alarm probability is equal to 0.1, meanwhile other detection algorithms are less than 0.4. This means that he proposed algorithm has better detection performance than MME, MET and CAV and BOC algorithm.

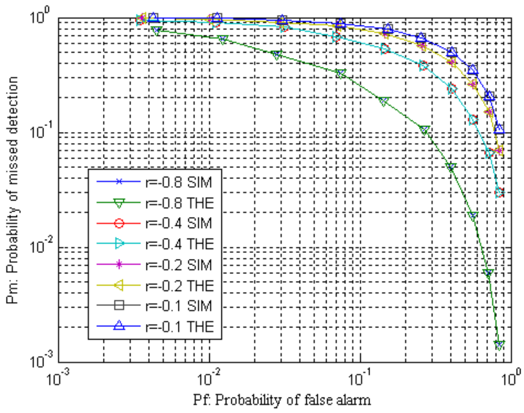

Fig2: the ROC curve of proposed algorithm with *r* changes

Figure 2 illustrates the performance of the proposed algorithm changes with the correlation coefficients. The simulation sets $SNR = -20dB$, $N_s = 10000$. As can be seen, Algorithm with the detection performance decreases with the decline of r .For $r = 0.1$ and $r = 0.2$, the algorithm almost has no ability to detect PU signal with extremely weak detection performance. The curve further shows that the correlation is the foundation of the proposed algorithm. meanwhile the Monte Carlo simulation curve of proposed algorithm and the theory curve overlap with *r* changes. The simulation results further prove that the derivation of performance parameters is correct in this paper.

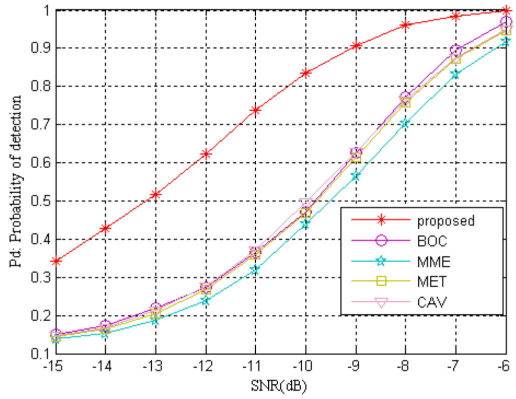

Fig3: Comparison of the detection performance for various detection algorithms ($2\ dB$ noise uncertainty)

Figure 3 shows that proposed algorithm's performance compare with other detection algorithm with the changing SNR under uncertainty noise. The simulation condition sets $N_s = 10000$, $N = 5$, $r = 0.8$. The scope of SNR is from $-15dB$ to $-6dB$. Noise uncertainty is set to $2\,dB$, and false alarm probability is fixed with $P_f = 0.1$. From the graph, it can be seen that BOC algorithm performance is equal to other detection algorithm meanwhile the proposed algorithm is better than other under noise uncertainty. For example, detection probability of proposed algorithm is equal to 0.35 meanwhile the other algorithm is lower than 0.15 when $SNR = -15dB$. In conclusion, The proposed algorithm is outperform the other algorithm with better detection performance in complicated channel environment.

5. Conclusion

Covariance blind detection algorithm is one of the important ways to improve the detection efficiency in cognitive radio. Taking advantage of cholesky decomposition, we propose a new covariance blind detection algorithm to decide whether there is PU or not in this paper and give the non-asymptotic expression of performance parameters. The simulation results show that the expression of performance parameters is correct and the proposed algorithm is better than MME, CAV, MET and BOC covariance blind detection algorithm with good performance.

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