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A Three Phase Explorative Sensing and Power Allocation Scheme for Non-Cooperative Cognitive Radio Networks

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Abstract: The spectrum sensing is an essential problem in cognitive radio Networks, where secondary users (SUs) need to detect the presence of primary users (PUs) before they use their spectrum. In this paper, we consider three phase sensing and power allocation in hybrid overlay/underlay non-cooperative cognitive radio networks. In the first stage, the well-known Energy Detector(ED) provides fast sensing under high signal to noise ratio(SNR), the sensing goes to second stage for more accurate sensing using Maximum Eigen Detection(MED) when a signal is not detected due to lower SNR, finally the true source of signal is detected by source localization. The proposed scheme also allocates transmit power (overlay/underlay) based on the channel sensing outcome (channel idle or busy). The sensing switches between two-stage or three-stage based on the decision statistics of ED and MED. In our proposed technique, the sensing time does not effectively increase alongside the number of stages, as these stages are Pipelined. Further due to three level detection the probability of detection is considerably increased. The proposed three-stage sensing and power allocation algorithm are analyzed theoretically. The performance of the proposed scheme is verified by simulation results.

Keywords: Cognitive Radio; Energy Detector; Power Allocation; Spectrum Sensing.

I. INTRODUCTION

The radio spectrum is getting to be distinctly scarcer with the rising number of users on one side, and the opposite side, the report from the Federal Communications Commission uncovered that the vast majority of the authorized spectrum are critically underutilized [1]. Cognitive radio (CR) [2], [3] is therefore proposed, to deal with the dilemma between spectrum scarcity and spectrum underutilization. CR allows opportunistic use of licensed user's or primary user's (PU's) spectrum by unlicensed users or secondary users (SUs) such that the induced interference to the licensed users is within the tolerable level. CR system can alter the frequency of operation, modify transmission parameters and tweak the output power for efficient spectrum utilization. Spectrum sensing is a crucial phase in CR that detects a spectrum hole and protects PU from the interference of SU.

A. Literature survey

There are two main categories of spectrum sensing. They are non-cooperative spectrum sensing methods and cooperative spectrum sensing methods. Some of the most common non-cooperative techniques proposed in the literature are energy detection (ED), Cyclo-stationary based methods, matched-filter detection, and maximum eigenvalue detection(MED) etc. ED is the simplest most frequently used technique with the least implementation complexity. ED does not require any prior information of the incumbent signal [4]. The authors in [5] have studied Spectrum sensing with known and unknown noise levels. Matched filtering technique, however, is a function of prior knowledge of the PU transmission characteristics such as the bandwidth, modulation type, pulse shaping, carrier frequency and frame format etc. It is also faster and optimum sensing technique [6]. Cyclo-stationarity based technique uses the periodicity of the received signal with increased computational complexity and hardware cost [7]. MED technique has turned out to be a prominent technique in recent research topics as it offers a decent performance and it is robust to noise [8], [9]. Spectrum access can be Overlay or Underlay. In overlay schemes, SUs perform spectrum sensing and transmit with full power if the channel state is found to be idle. The drawback with Overlay access is that SUs are restricted to transmit when PUs are operational on the channel. In underlay access, on the other hand, SUs coexist with PUs under low power transmission such that SU-PU interference remains within the tolerable limit. Hybrid spectrum approach combines the benefits of both overlay spectrum access and underlay spectrum access to attain improved spectrum utilization. In a hybrid method of spectrum access, SUs function in Overlay fashion with full transmission power if the channel is empty; otherwise, SUs function in underlay fashion with reduced transmission power

Sensor arrays are used to precisely carryout source localization to estimate various signal parameters. Source localization [21] can be carried out for near-field or far-field. In both Near-field and far-field source localization signal parameters that can be estimated involves amplitude, frequency, DOA. MUSIC [23] and ESPRIT [26] are conventional source localization algorithms. Detection of far-field PUs beside the assessment of their frequencies, amplitudes, and DOAs is proposed In [25]. CR has the potential to accommodate fifth-generation (5G) communication systems, since it can fully utilize all available noncontiguous spectrums flexibly and efficiently in 5G wireless networks [27].

B. Our Contribution

Our proposed scheme is a three-phase spectrum sensing with power allocation for Non-Cooperative Cognitive Radio networks. We implement the sensing and power allocation in three phases, fast sensing using ED, accurate sensing using MED and explore sensing using source localization.

The key contributions of this study are (1) three-stage spectrum sensing scheme that provides fast and accurate and explore sensing. (2) Fast sensing at high SNR, and accurate sensing at low SNR with an increased probability of detection. (3) Malicious user detection using source localization. (4) Overlay/Underlay power allocation. The significance of our work can be seen in the simuation results which clearly shows that the proposed method out performs the existing methods.

The rest of the paper is organized as follows. In section II, we present the system model and describe the prominent spectrum sensing techniques: ED, MED and source localization technique the MUSIC algorithm. In section III, we present the proposed method of three-phase sensing and power allocation. Section IV gives simulation results and conclusions are drawn in section V.

II. SYSTEM MODEL AND BASIC SPECTRUM SENSING.

A. System model

The cognitive radio system assumed (Fig.1) consists one or more Primary users and a secondary user with relay having multiple sensors. The SU has K sensors $d=\lambda_m/2$ distance apart where λ_m is the minimum wavelength of the detected signal. A channel is either free (H_0), which is a spectrum hole or occupied by a user (H_1). The detected signal $y_i(n)$ at the nth sampling result, i=1,2, . . . , K, n=1,2, . . . , N, where N denotes the number of samples given by

$$y_i(n) = \begin{cases} v_i(n), & H_0: channel\ free \\ a_i s_i(n) + v_i(n), & H_1: channel\ occupied \end{cases} \quad (1)$$

In the following subsections, we will review the single stage spectrum sensing methods.

B. Energy Detection

ED is computationally simplest and fastest method for spectrum sensing. However, ED is unreliable, when the received signal has low SNR or when the noise power is highly uncertain. The average energy of the detected signal that is used to define the decision statistics can be given as follows.

$$T_{ED} = \frac{1}{N}\sum_{n=0}^{N} |y_i(n)|^2 \quad (2)$$

Where T_{ED} represents the test statistics and N denotes sampling interval.

The detection probability $p_{d,ED}$ and false alarm probability $p_{f,ED}$ can be mathematically modeled as follow:

$$p_{d,ED} = Q\left[\frac{\lambda_{ED} - (\sigma_v^2 + \sigma_s^2)}{(\sigma_v^2 + \sigma_s^2)/\sqrt{N/2}}\right] \quad (3)$$

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$$p_{f,ED} = Q\left[\frac{\lambda_{ED} - \sigma_v^2}{\sigma_v^2 / \sqrt{N/2}}\right] \qquad (4)$$

Where λ denotes decision threshold, σ_v^2 and σ_s^2 denotes noise and signal variances respectively, and Q(.) represents Gaussian complementary cumulative distribution function. From equation (4), the decision threshold of Energy Detection can be written as,

$$\lambda_{ED} = \left(Q^{-1}(p_{f,ED})\sqrt{2/N} + 1\right)\sigma_v^2 \qquad (5)$$

C. *Maximum eigenvalue detection*

The false alarm probability and the detection probability are essential statistics to calculate the throughput. Thus, allocation of the decision statistics in the absence and in the presence of the primary user has to be known. The allocation of decision statistics for sensing techniques based on eigenvalue can be computed using the results from random matrix theory. Recently, threshold interpretations of MME and MED based on test statistics distributions are formulated in some studies [20], [22] and [24]. It is shown that the proposed exact thresholds achieve better performances however, the computation of exact threshold turn out to be complex as the number of samples increase. So, unconventional asymptotic thresholds for MME and MED methods are derived for a fixed number of antennas with large number of samples in some studies. A realistic cognitive radio can only have small number of antennas however large number of samples can be used for sensing.

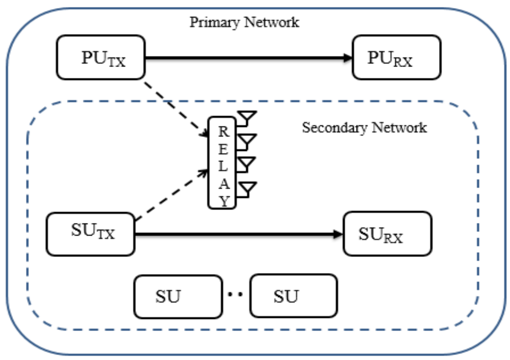

Fig.1 System model

Here Maximum eigenvalue detection method is chosen as the method provides accurate result at lower SNR and is robust to noise. From (1) for H_1 we have

$$Y_i(n) = a_i S_i(n) + V_i(n) \qquad (6)$$

Where

$$Y_i(n) = [y_i(n)\ \ y_i(n-1)\ \ldots\ \ y_i(n-N+1)] \qquad (7)$$

$$S_i(n) = [s_i(n)\ \ s_i(n-1)\ \ldots\ \ s_i(n-N+1)] \qquad (8)$$

$$V_i(n) = [v_i(n)\ \ v_i(n-1)\ \ldots\ \ v_i(n-N+1)] \qquad (9)$$

The matrices of statistical covariance of signal and noise can be given as

$$R_y = E[Y_i(n)Y_i^T(n)] \qquad (10)$$

$$R_s = E[S_i(n)S_i^T(n)] \qquad (11)$$

$$R_w = E[V_i(n)V_i^T(n)] = \sigma_w^2 I_N \qquad (12)$$

The above equations are related as

$$R_y = R_s + \sigma_w^2 I_N \qquad (13)$$

For a given threshold λ_{MED}, the detection and false alarm probabilities $p_{d,MED}$, $p_{f,MED}$ for MED [10], [14] are

$$p_{d,MED} = 1 - W_M^m\left(\sqrt{N}(\beta\lambda_{MED} - 1)\right) \qquad (14)$$

$$p_{f,MED} = 1 - F_M^m\left(\sqrt{N}(\lambda_{MED} - 1)\right) \qquad (15)$$

The F_M^m(x) and W_M^m(x) represents the distribution of the corresponding regulated test statistics of $\sqrt{N}(T_j(y) - 1$ and $\sqrt{N}(\beta T_j(y) - 1$ respectively under H0 and H1.

III. THREE-STAGE SENSING AND POWER ALLOCATION

Here we consider three-stage sensing and power allocation in hybrid overlay/underlay non-cooperative cognitive radio networks. In the first stage the well-known Energy Detector(ED) provides fast sensing under high signal to noise ratio(SNR), the sensing goes to second stage for optimal sensing when a signal is not detected due to lower SNR. This stage provides accurate sensing using Maximum Eigen Detection(MED) method finally, the third phase localizes the source and allocates transmit power (overlay/underlay) based on the outcome (channel idle or busy) in sensing phases. Fig.3 depicts the block diagram of the proposed three stage spectrum sensing scheme.

A. *With decision statistics ED:H_0, -Two stage ED-MED sensing.*

The probability of detection can be obtained as

$$p_d = 1 - (1 - p_{d,ED})(1 - p_{d,MED}) \qquad (16)$$

Substituting (3), (14) in (16)

$$p_d = 1 - \left(1 - Q\left[\frac{\lambda_{ED} - (\sigma_v^2 + \sigma_s^2)}{(\sigma_v^2 + \sigma_s^2)/\sqrt{N/2}}\right]\right)\left(W_M^m\left(\sqrt{N}(\beta\lambda_{MED} - 1)\right)\right) \qquad (17)$$

Which can be written as

$$p_d = 1 - W_M^m\left(\sqrt{N}(\beta\lambda_{MED} - 1)\right) + Q\left[\frac{\lambda_{ED} - (\sigma_v^2 + \sigma_s^2)}{(\sigma_v^2 + \sigma_s^2)/\sqrt{N/2}}\right] W_M^m\left(\sqrt{N}(\beta\lambda_{MED} - 1)\right) \qquad (18)$$

Similarly, the false alarm probability is given as

$$p_f = 1 - (1 - p_{f,ED})(1 - p_{f,MED}) \qquad (19)$$

Substituting (4), (15) in (19)

$$p_f = 1 - \left(1 - Q\left[\frac{\lambda_{ED} - \sigma_v^2}{\sigma_v^2/\sqrt{N/2}}\right]\right)\left(F_M^m\left(\sqrt{N}(\lambda_{MED} - 1)\right)\right) \qquad (20)$$

The algorithm 1 in fig.2. depicts two-state sensing and power allocation.

Algorithm 1: two-phase sensing and power allocation

1: Received signal at CR $y \Leftarrow hs + n$
2: Signal energy , E=$|y|^2$
3: If E>λ_{ED} then
4: underlay transmission with power P_1 from (24)
5: elseif T>λ_{MED}
7: underlay transmission with power P_1 from (24)
7:else
6: overlay transmission with power P_0 from (21)
7:endif

Fig.2 sensing and power allocation

B. power allocation in underlay/overlay hybrid cognitive radio

The Hybrid mechanism uses sensing outcomes for power allocation. If the channel detected is idle, SU-TX transmits with a higher power P_0 (overlay); otherwise, SU-TX transmits with a lower power P_1 (underlay). To prevent PUs from harmful interference due to errors caused by miss detection, P_M the probability of miss detection is typically kept under control in the overlay, and in underlay access, the transmit power P1 is regulated to fulfil certain standard interference check, called 'interference temperature' [3], [15].

The transmit power P_0 and P_1 in overlay and underlay access is shown to be [11], [12]

$$P_0 = \left[\frac{-(B_0/A_0) + \sqrt{(B_0/A_0)^2 - 4(C_0/A_0)}}{2}\right]^+ \quad (21)$$

Where

$$\frac{B_0}{A_0} = \frac{2\sigma_0^2 + P_P g_{psr}}{g_{ss}} - \frac{\rho_0}{\lambda\varepsilon g_{sp} + \mu\rho_0} \quad (22)$$

$$\frac{C_0}{A_0} = \frac{1}{g_{ss}}\left[\frac{\sigma_0^4 + \sigma_0^2 P_P g_{psr}}{g_{ss}} - \frac{\sigma_0^2\rho_0 + \alpha_0 P_P g_{psr}}{\lambda\varepsilon g_{sp} + \mu\rho_0}\right] \quad (23)$$

$$P_1 = \left[\frac{-(B_1/A_1) + \sqrt{(B_1/A_1)^2 - 4(C_1/A_1)}}{2}\right]^+ \quad (24)$$

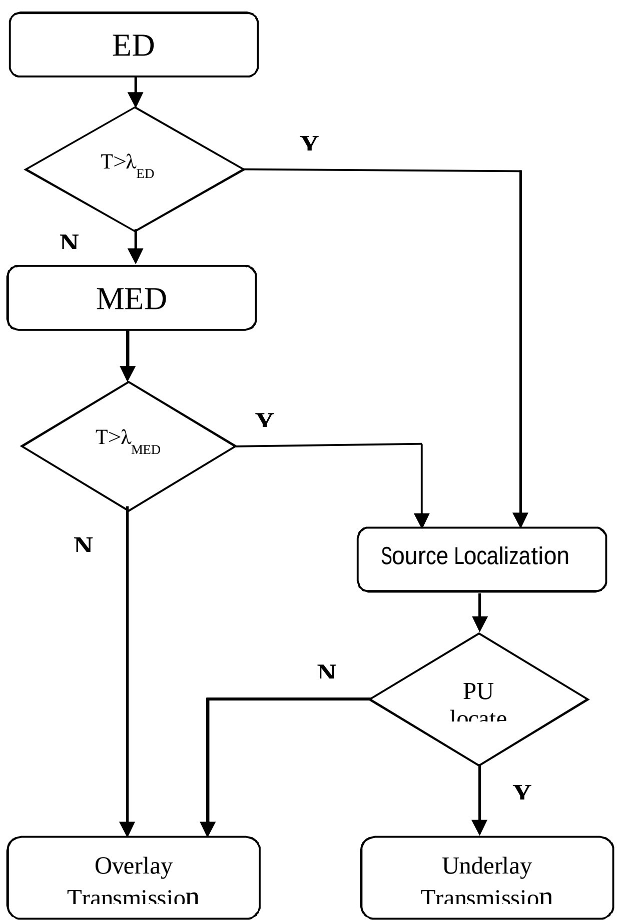

Fig.3 Block diagram of the proposed three stage spectrum sensing scheme.

where

$$\frac{B_1}{A_1} = \frac{2\sigma_0^2 + P_P g_{ps}}{g_{ss}} - \frac{\rho_1}{\lambda(1-\varepsilon)g_{sp} + \mu\rho_1} \quad (25)$$

$$\frac{C_1}{A_1} = \frac{1}{g_{ss}}\left[\frac{\sigma_0^4 + \sigma_0^2 P_P g_{ps}}{g_{ss}} - \frac{\sigma_0^2\beta_1 + \alpha_1(P_P g_{ps} + \sigma_0^2)}{\lambda(1-\varepsilon)g_{sp} + \mu\rho_1}\right] \quad (26)$$

Where $\{g_{psr}, g_{gst}, g_{sp}, g_{ss}\}$ are the channel gain from PU_{TX} to SU_{RX}, PU_{TX} to SU_{TX}, SU_{TX} to PU_{RX}, and SU_{TX} to SU_{RX} respectively.

C. power allocation for hybrid underlay/overlay cognitive radio

Hybrid transmission mechanism is based on sensing outcomes. If the detection outcome is idle, SU-TX transmits with a higher power P_0 (overlay); otherwise, SU-TX transmits with a lower power P_1 (underlay). The algorithm is depicted in fig.4.

With K sensors and N samples from each sensor we have K X N samples. The normal distribution of largest eigen value of the covariance matrix is given by [19]

$$\lambda_1 \sim N\left((\sigma_s^2 + \sigma_n^2) + \frac{(K-1)(\sigma_s^2 + \sigma_n^2)\sigma_n^2}{N\sigma_s^2}, \frac{(\sigma_s^2 + \sigma_n^2)^2}{N\sigma_n^2}\right) (2)$$

With signal to noise ratio = $\frac{\sigma_s^2}{\sigma_n^2}$, we have

$$\lambda_1 \sim N\left((\gamma\sigma_n^2 + \sigma_n^2) + \frac{(K-1)(\gamma\sigma_n^2 + \sigma_n^2)\sigma_n^2}{N\gamma\sigma_n^2}, \quad \frac{(\gamma\sigma_n^2 + \sigma_n^2)^2}{N\sigma_n^2}\right) \quad (3)$$

$$\frac{\lambda_1}{\sigma_n^2} \sim N\left((\gamma + 1) + \frac{(K-1)(\gamma + 1)}{N\gamma}, \quad \frac{(\gamma+1)^2}{N}\right) \quad (4)$$

$$mean\left(\frac{\lambda_1}{\sigma_n^2}\right) = \left((\gamma + 1) + \frac{(K-1)(\gamma+1)}{N\gamma}\right) \quad (5)$$

$$var\left(\frac{\lambda_1}{\sigma_n^2}\right) = \left(\frac{(\gamma+1)^2}{N}\right) \qquad (6)$$

Algorithm 2: : three-phase sensing and power allocation

1:Received signal at CR $y \Leftarrow hs + n$
2:Signal energy ,$E = |y|^2$
3:If E< λ||T > λMED then
4: Overlay transmission P_1 from (10)
5: else //interference detected
6: Identify source by DOA detection
7: From MUSIC Algorithm find (θ_x)
8: if ($\theta_x == \theta_p$) then //compare with PU
9: PU active Underlay transmission P_0 from (11)
10: else
11: PU not active Interference is due
12: 1) miss detection from another user or
13: 2) malicious user active
14 endif
15: endif
16: Repeat from step 1 to step 9

Fig.4 Three phase sensing and power allocation

The miss detection probability P_M for known noise level under AWGN channel is given as

$$P_M = 1 - Pr\left(\frac{(\lambda_1/\sigma_n^2) - mean(\lambda_1/\sigma_n^2)}{\sqrt{var(\lambda_1/\sigma_n^2)}} > \frac{\zeta - mean(\lambda_1/\sigma_n^2)}{\sqrt{var(\lambda_1/\sigma_n^2)}} | H1\right) \quad (7)$$

$$P_M = 1 - Q\left(\frac{\zeta - mean(\lambda_1/\sigma_n^2)}{\sqrt{var(\lambda_1/\sigma_n^2)}}\right) \quad (8)$$

$$P_M = 1 - Q\left(\frac{\zeta - \left((\gamma+1) + \frac{(K-1)(\gamma+1)}{N\gamma}\right)}{\sqrt{\left(\frac{(\gamma+1)^2}{N}\right)}}\right) (9)$$

$$P_M = 1 - Q\left(\frac{\sqrt{N}\zeta}{1+\gamma} - \frac{N\gamma + K - 1}{\sqrt{N}\gamma}\right) \quad (10)$$

The average hybrid interference constraint is expressed as

$$\mathrm{Eg}'\left[\mathrm{gspP0PM}(\gamma,\tau,\zeta) + \mathrm{gspP1}\left(1 - \mathrm{PM}(\gamma,\tau,\zeta)\right)\right] \le \bar{\Gamma} \quad (11)$$

For the channel with Rayleigh fading

$$\mathrm{Eg}\ [\mathrm{gspP0}]\bar{\mathrm{P}}\mathrm{M}(\bar{\gamma},\tau,\zeta) + \mathrm{Eg}[\mathrm{gspP1}]\left(1 - \bar{\mathrm{P}}\mathrm{M}(\gamma,\tau,\zeta)\right) \le \bar{\Gamma} \quad (12)$$

The transmit power P0 and P1 in overlay and underlay access is shown to be

$$P_0 = \left[\frac{-(B_0/A_0) + \sqrt{(B_0/A_0)^2 - 4(C_0/A_0)}}{2}\right]^+ (13)$$

where

$$\frac{B_0}{A_0} = \frac{2\sigma_0^2 + P_P g_{psr}}{g_{ss}} - \frac{\rho_0}{\lambda\varepsilon g_{sp} + \mu\rho_0} \quad (14)$$

$$\frac{C_0}{A_0} = \frac{1}{g_{ss}}\left[\frac{\sigma_0^4 + \sigma_0^2 P_P g_{psr}}{g_{ss}} - \frac{\sigma_0^2\rho_0 + \alpha_0 P_P g_{psr}}{\lambda\varepsilon g_{sp} + \mu\rho_0}\right] \quad (15)$$

$$P_0 = \left[\frac{-(B_1/A_1) + \sqrt{(B_1/A_1)^2 - 4(C_1/A_1)}}{2}\right]^+ (16)$$

where

$$\frac{B_1}{A_1} = \frac{2\sigma_0^2 + P_P g_{ps}}{g_{ss}} - \frac{\rho_1}{\lambda(1-\varepsilon)g_{sp} + \mu\rho_1} \quad (17)$$

$$\frac{C_1}{A_1} = \frac{1}{g_{ss}}\left[\frac{\sigma_0^4 + \sigma_0^2 P_P g_{ps}}{g_{ss}} - \frac{\sigma_0^2\beta_1 + \alpha_1\left(P_P g_{ps} + \sigma_0^2\right)}{\lambda(1-\varepsilon)g_{sp} + \mu\rho_1}\right] \quad (18)$$

D. Transmission phase

In this phase the secondary User is assumed to be transmitting with full power P_0 while SU also senses the channel to check possible interference due to PU or other users. The first two levels of sensing detect the interference as discussed in section 2. If interference is detected, then third level of detection must be carried out to detect whether the interferer is PU in which case SU must immediately relive the channel or switch to underlay(P_1) mode.

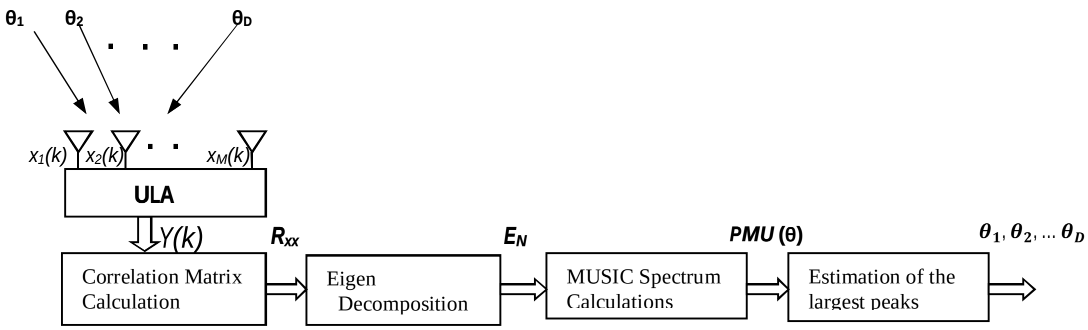

Fig.5. Model to estimate DOA(PMU(**θ**)

If the interferer is not PU, then there must be miss detection from other SU or malicious user in which case SU need not relieve channel. The transmission phase sensing and power allocation is depicted in algorithm 2 (fig.4). To identify the interferer, we must detect other parameters such as range, DOA (direction-of-arrival) etc. Angle of arrival (AOA) or DOA (direction-of-arrival) estimation is the process of determining the direction of incoming radio signal source (PUs or SUs).

Here we determine the phase difference of signals at individual different elements of the antenna. These delays in turn give angle or direction (θ). The estimation is done via a function which is known pseudo spectrum PMU (θ). There are several methods used to estimate pseudo spectrum PMU(θ) such as beam-forming, eigen analysis, linear prediction array correlation matrix, MUSIC, root-MUSIC, maximum likelihood, minimum variance and many other approaches. In this study MUSIC algorithm [11] is considered. Fig.6. shows the model for estimation of PMU (θ)

The elements of ULA (Fig.5) receives the signals form a remote source, *i*.

$$x_m(t) = S_i(t)\sum_{i=1}^{d} e^{j(m-1)\mu_i} + n_m(t) \qquad (19)$$

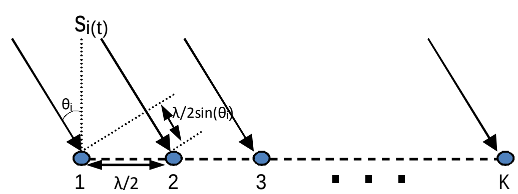

Fig.6 Uniform linear array antenna.

The elements spacing is kept half the wavelength of received signals. Considering that a narrowband signal plane wave signal caused by the source *i* impacts on the array at an angle θi is $s(t)$. This wave moves at a speed of ***c*** and reaches the first leftmost elements. If we assume all the signals generated by all the *d* sources, *Si, 1≤i≤ d*, ***the*** total signal and noises received by the mth array element at time *t* can be expressed as [17] which can be written as

$$x(t) = [a(\theta_1), a(\theta_2) \ldots\ a(\theta_d)]\begin{bmatrix} S_1(t) \\ S_2(t) \\ \vdots \\ S_d(t) \end{bmatrix} + n(t) \qquad (20)$$

$$x(t) = AS(t) + n(t) \qquad (21)$$

where

$$x(t) = [x_1(t)\ x_2(t) \ldots x_k(t)]^T \qquad (22)$$

$$S(t) = [S_1(t)\ S_2(t) \dots S_K(t)]^T \qquad (23)$$

$$n(t) = [n_1(t)\, n_2(t) \dots n_K(t)]^T \qquad (24)$$

is a zero mean spatially uncorrelated additive noises with covariance matrix. A represents steering matrix $K \times D$

$$A = [\vec{a}(\theta_1)\ \vec{a}(\theta_2) \dots \vec{a}(\theta_D)] \qquad (25)$$

where

$$\vec{a}(\theta_i) = \left[1\ e^{j\varphi_i}\ \ e^{2j\varphi_i} \dots\ \ e^{(K-1)j\varphi_i}\right]^T \qquad (26)$$

is the steering vector.

$$\varphi_i = \frac{2\pi}{\lambda}\frac{\lambda}{2}\sin(\theta_i) \qquad (27)$$

$\frac{2\pi}{\lambda}$ is wave number and $\frac{\lambda}{2}$ is element spacing.

$$\varphi_i = \pi \sin(\theta_i) \qquad (28)$$

Where φ_i is called special frequency.

The notion is to 'steer' the array in one path at a time and quantify the output power. The steering direction which matches with the DOA of a signal and result in a maximum output power yields the DOA estimates. The array can be steered electronically or mechanically. A weight vector ***w*** is used to linearly chain the data received by the array elements to attain single output signal

$$Y(t) = w^H X(t) \qquad (29)$$

The total output power over N snapshots of an array can be stated as

$$P(w) = \frac{1}{N}\sum_{n=1}^{N}|Y(t_n)|^2 = \frac{1}{N}\sum_{n=1}^{N} w^H X(t_n) X^H(t_n) \quad (30)$$

A measure Rxx of the covariance matrix is attained and its eigenvectors are split into signal and noise subspace (E_S, E_N) and the DOA is obtained from one of these subspaces by the MUSIC algorithm and the MUSIC spectrum is given by [15]

$$PMU(\theta) = \frac{\vec{a}(\theta)^H.\vec{a}(\theta)}{\vec{a}(\theta)^H \vec{E}_N \vec{E}_N^H \vec{a}(\theta)} \qquad (31)$$

where$a(\theta)^H E_N E_N^H a(\theta)$ represents Euclidean distance, EN is the noise subspace and is composed of K–D eigenvectors associated with the noise.

H= ''Hermitian" means conjugate transpose

IV. SIMULATION RESULTS

In this section, we provide simulation results for the of the proposed strategy against the normal detection methods.

Fig.7 compares proposed strategy with single stage methods used in our scheme. The equations (3), (14) and (17) are plotted. The comparison is done for i.i.d. signal for SNR between -30 dB and 0 dB, N = 5,000; L = 10; and P_{fa} = 0.1. Clearly the proposed strategy has outperformed the other method

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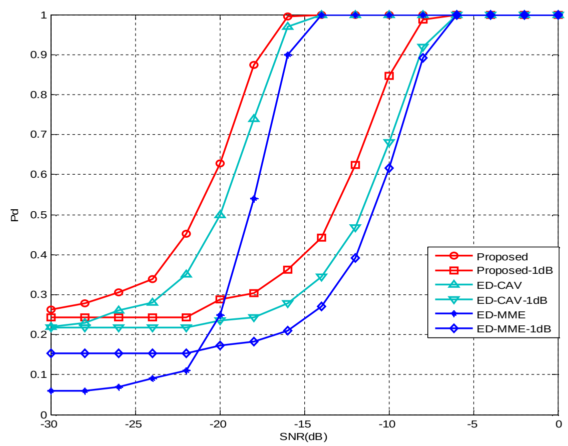

Fig. 7 Comparison of probability of detection for SNR between −30 dB and 0 dB and P_{fa} = 0.1.

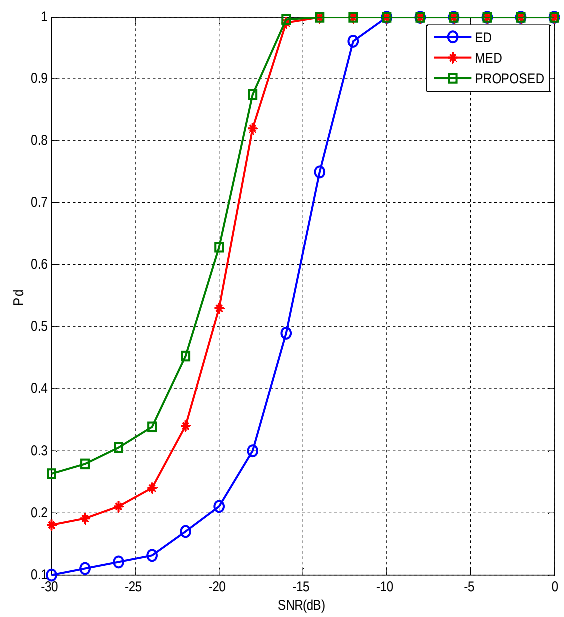

Fig. 8 Comparison of probability of detection against SNR between −30 dB and 0 dB and P_{fa} = 0.1. with and without noise uncertainty.

Fig.8 compares proposed strategy with single stage methods used in our scheme. The comparison is made by introducing 0dB and 1dB noise uncertainty. The comparison is again done for i.i.d. signal for SNR between -30 dB and 0 dB, N = 5,000; L = 10; and P_{fa} = 0.1. Here also the proposed strategy has outperformed the other methods.

Fig.9. compares proposed strategy and other two stage methods. The comparison is made by introducing 0dB and 1dB noise uncertainty. The comparison is carried out for i.i.d. signal for SNR between −30 dB and 0 dB, N = 5,000; L = 10; and P_{fa} = 0.1

Fig.10 gives plot of MUSIC spectrum with different number of array elements ''K'' for number of data samples(N) = 500. inter-element spacing(d)= $\lambda/2$. and angle of incidence $\theta = (10^0, 30^0)$. As the number of array elements 'K' increases, MUSIC spectrum peaks become sharper and gives high accuracy and resolution.

Fig.11 gives the relationship of music spectrum for changing value of 'd'. If the elements are spaced closely the coupling effect will be larger. At the same time if d is larger grating lobes in negative side appear causing wrong estimation

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Fig.9 Comparison of probabilities of detection with other two stage methods. SNR between −30 dB and 0dB and P_{fa} = 0.1. with and without noise uncertainty.

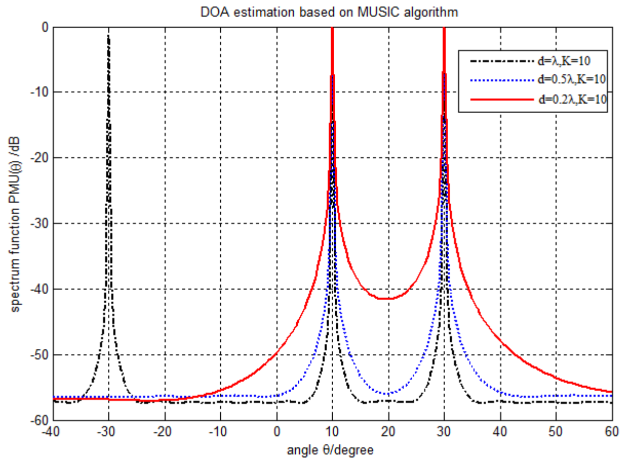


Fig.10 Music spectrum for d=λ/2, and N = 200 θ $= (10^0, 30^0)$ and varying 'K'

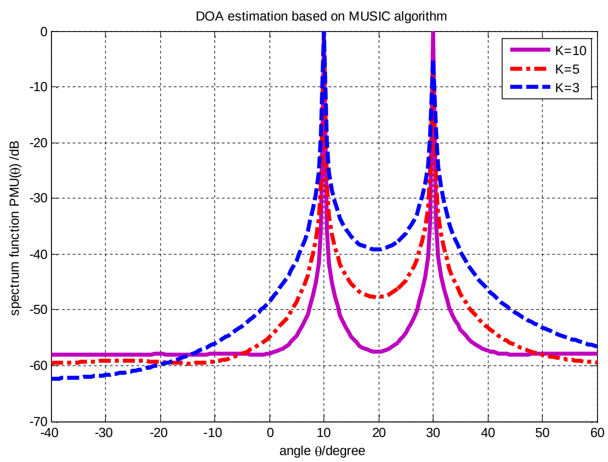
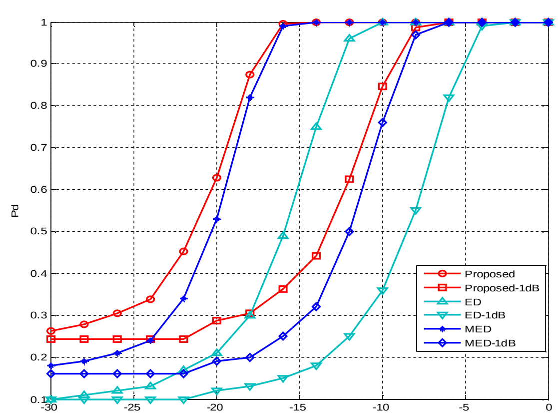


Fig.11. Music spectrum for K=10, and N = 200 θ $= (10^0, 30^0)$ and varying 'd'



V. CONCLUSION

In this paper, three-phase sensing and power allocation are considered. The first phase performs high speed signal detection under high SNR. The sensing goes to the second stage when a signal is not detected due to low SNR. This stage provides accurate sensing using Maximum Eigen Detection(MED) method. The third phase involves direction of arrival detection. The sensing switches between two-stage and three-stage based on the decision statistics of ED-MED. In our proposed technique, the sensing time does not effectively increase with the number of stages, as these stages are pipelined. Further due to three level detection the probability of detection is considerably increased. The presence of malicious users increases the probability of false alarm in ED. If channel is idle, SU runs in overlay mode. If channel is busy due to PU, then SU runs in underlay mode. However, if channel is busy due to miss detection from other SU or a malicious user the then SU functions in channel defense by continuing the channel usage. The miss detection probability is derived and optimum power allocation is studied in both overlay and underlay schemes.

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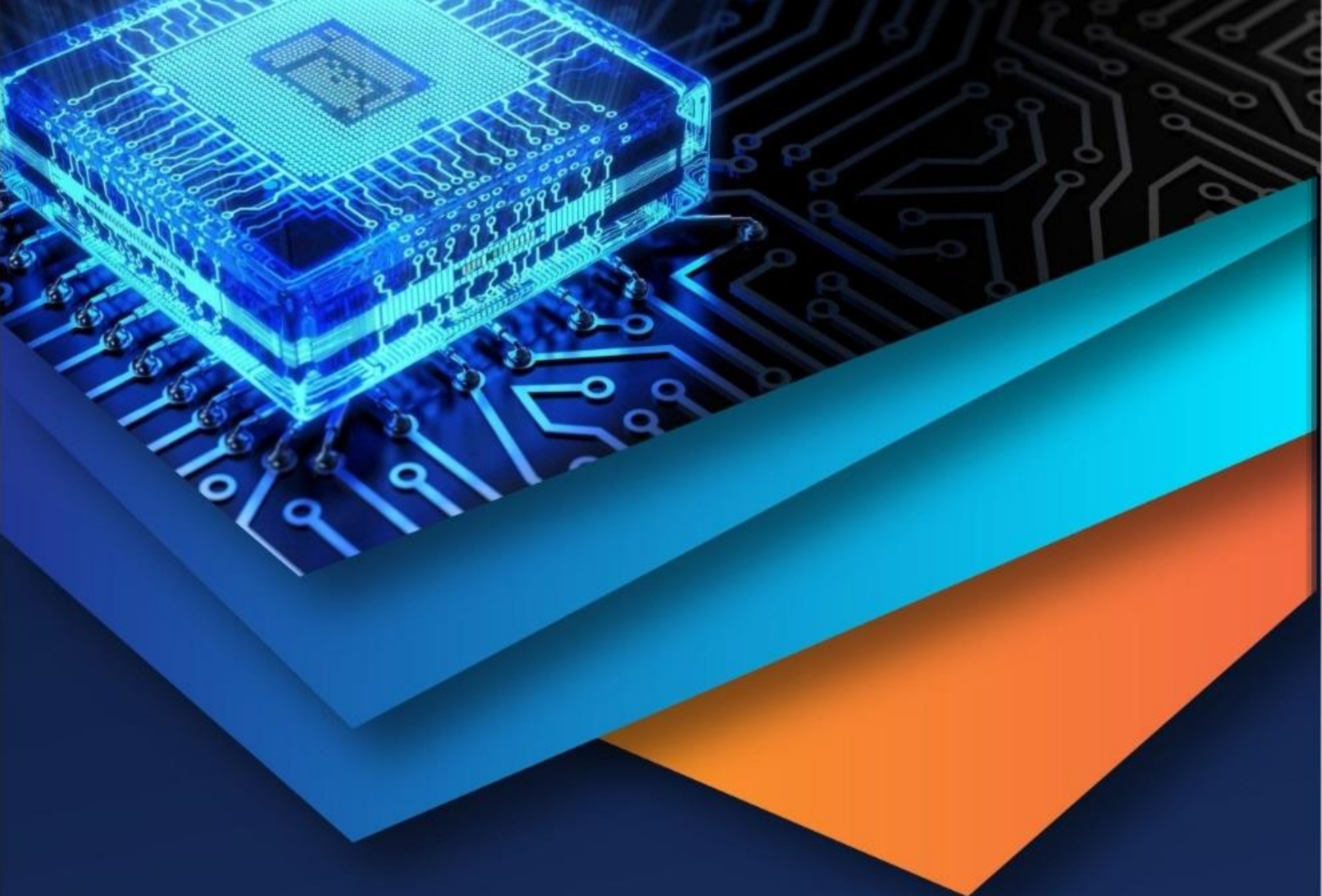

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