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Smart Antenna-Based Wideband Spectrum Detection in Cognitive Radio Networks

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ABSTRACT

Wideband spectrum sensing is a critical requirement in cognitive radio networks to reliably identify spectrum holes while ensuring minimal interference to licensed users. Conventional energy- and eigenvalue-based detection techniques often suffer from degraded performance under low signal-to-noise ratio (SNR) conditions and in dynamic spectral environments. In this paper, a smart antenna–based wideband detection framework for cognitive radio networks is proposed using the Hannan–Quinn (HQ) information criterion. The proposed system exploits the spatial diversity of smart antenna arrays to enhance signal reception and interference suppression, while the HQ criterion is employed for robust model order selection to accurately determine the presence of primary user signals across multiple frequency subbands. By jointly integrating spatial processing with information-theoretic detection, the proposed approach achieves improved detection reliability, particularly in low SNR and multi-signal scenarios. Extensive simulation results demonstrate that the proposed method outperforms conventional spectrum sensing techniques in terms of probability of detection, false alarm rate, and wideband detection accuracy. The results confirm the effectiveness of the HQ criterion–based smart antenna design as a viable solution for efficient wideband spectrum sensing in cognitive radio networks.

KEYWORDS—Cognitiveradio, DOA, MEV, MLM, HQ .

INTRODUCTION

In present day wireless communication has become the most popular communication. Because of this growing demand on wireless applications has put a lot of constraints on the available radio spectrum which is limited and precious. In fixed spectrum assignments there are many frequencies that are not being properly used. So cognitive radio helps us to use these unused frequency bands which are also called as “White Spaces”. This is a unique approach to improve utilization of radio electromagnetic spectrum. Spectrum sensing is essential and vital to cognitive radio. In Cognitive radio (CR)[1] has attracted worldwide attention and is capable of promoting efficient utilization of frequency resources. In CR networks, secondary users (SUs) sense the spectrum holes and then perform dynamic spectrum access without interfering with primary users (PUs).Here smart antenna[6] is using for detection of mobile user. Detection algorithms are two types classical and subspace. In classical detection namely Bartlett Cognitive Method and Maximum Likelihood Method and Maximum Eigen Value Method are presented. In subspace method HQ algorithm is proposed.

PROBLEM FORMULATION

Signal model

Let us consider system model with uniform linear array (ULA) consisting of ‘L’ isotropic sensors. Let ‘m’ (m<L) be the unconstrained signal with frequency f_o impinging on a ULA. Consider, ‘d’ as element spacing between array elements and its value in this work is $\lambda/2$. Here, $\lambda = c/f_o$, where ‘c’ is the speed of light and f_o is the frequency of received signals respectively. Consider Cx1 dimension steering vector for directions $\theta(\theta_1, \theta_2, ..., \theta_m)$ in far fields.

Let $A = [a(\theta_1), a(\theta_2), ..., a(\theta_m)]$ is the steering matrix with steering vector:

$a(\theta) = [1, e^{j2\pi \sin(\theta) d/\lambda}, ..., e^{j2\pi(N-1)\sin(\theta) d/\lambda}]$.

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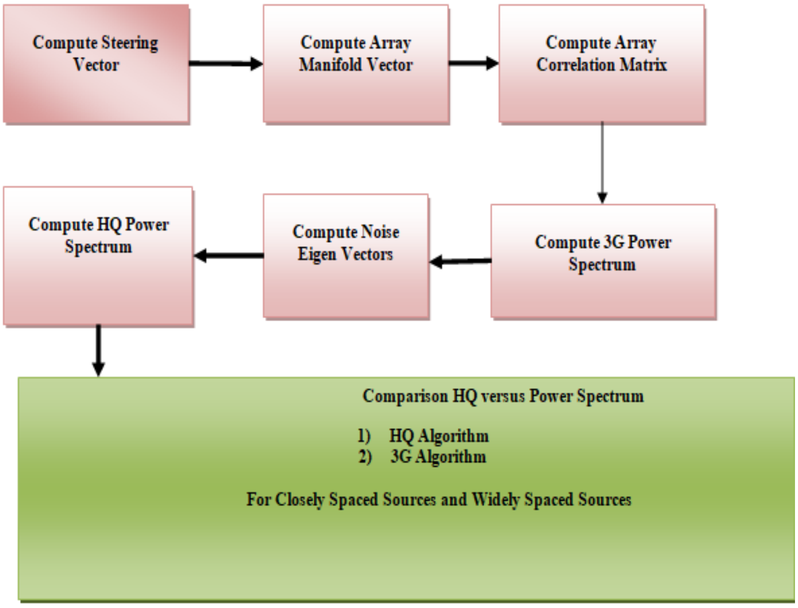
CLASSICAL METHODS

A. Bartlett Cognitive method

Bartlett Cognitive method is also called Ordinary Beam forming Method (OBM). This method estimates the mean power $P_B(\theta)$ by steering the array in θ direction. The power spectrum in BartlettCognitive method is given by:

$$P_B(\theta) = \frac{a_\theta^H R a_\theta}{L^2} \qquad (1)$$

Where, 'a_θ' denotes the steering vector associated with the direction θ, 'R' is the array correlation matrix. 'L' denotes the number of elements in the array. In detection estimation, a set of steering vectors $\{S_\theta\}$ associated with various direction θ is often referred to as the **array manifold**. In practice, it may be measured at the time of array calibration. From the array manifold and an estimate of the array correlation matrix, $P_B(\theta)$ is computed. Peaks in $P_B(\theta)$ are then taken as the directions of the radiating sources. The steps are as follows.



Algorithm

1. The steering vector '$a(\theta)$' for an antenna array comprising of L elements is calculated by using equation

$$a(\theta) = \begin{bmatrix} 1 \\ e^{i2\pi d\sin\theta} \\ \vdots \\ \vdots \\ e^{i2\pi d(L-1)\sin\theta} \end{bmatrix} \qquad (2)$$

2. The signal amplitude vector's' is a column vector of order Mx1 given by:

$$s = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ \vdots \\ a_M \end{bmatrix} \qquad (3)$$

3. The Hermitian transpose 's^H' of signal vector S is given by

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$$s^H = \begin{bmatrix} a_1^* & a_2^* & \dots & \dots & a_M^* \end{bmatrix} \quad (4)$$

4. The signal correlation matrix 'P' is given by

$$P = E[ss^H] \quad (5)$$

$$p = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ \vdots \\ a_M \end{bmatrix} * \begin{bmatrix} a_1^* & a_2^* & \dots & \dots & a_M^* \end{bmatrix} = \begin{bmatrix} a_1a_1^* & a_1a_2^* & \dots & \dots & a_1a_M^* \\ a_2a_1^* & a_2a_2^* & \dots & \dots & a_2a_M^* \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ a_Ma_1^* & a_Ma_2^* & \dots & \dots & a_Ma_M^* \end{bmatrix}$$

5. The signal vector 'S' is MxM diagonal matrix comprising of only diagonal elements of matrix 'P' given by

$$S = \begin{bmatrix} a_1a_1^* & 0 & \dots & \dots & 0 \\ 0 & a_2a_2^* & \dots & \dots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & \dots & a_Ma_M^* \end{bmatrix} \quad (6)$$

6. The Signal subspace is a LxL matrix given by

$$R_s = ASA^H \quad (7)$$

7. The Noise subspace is LxL matrix given by

$$R_n = \sigma^2 I = \sigma^2 \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} = \begin{bmatrix} \sigma^2 & 0 & \dots & 0 \\ 0 & \sigma^2 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & \sigma^2 \end{bmatrix}$$

Where, σ^2 is variance of noise and I is identity matrix

8. The array correlation matrix is given by

$$R = R_S + R_n$$

Where, R_S is signal subspace and R_n is noise subspace.

9. Compute the steering vector by using equation 2

10. The value of the power spectrum is found by using equation 1.This power spectrum is computed by keeping array correlation matrix R constant and varying 'θ' in the range –π/2< θ+0.001< π/2.

B. Maximum Likelihood Method

The Maximum Likelihood estimate is known as a Minimum Variance Distortion less Response (MVDR). It is also alternatively a maximum likelihood estimate of the power arriving from one direction while all other sources are considered as interference. Thus the goal is to maximize the Signal to Interference Ratio (SIR) while passing the signal of interest undistorted in phase and amplitude. The source correlation matrix R_{ss} is assumed to be diagonal. This maximized SIR is accomplished with a set of array weights given by

$$w_{MVDR} = \frac{R_{xx}^{-1}\, a(\theta)}{a^H(\theta)\, R_{xx}^{-1}\, a(\theta)}$$

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Where, R_{xx}^{-1} is the inverse of un-weighted array correlation matrix R_{xx} and $a(\theta)$ is the steering vector for an angle θ . The MLM pseudo spectrum is given by

$$P_{MLM} = \frac{1}{a^H(\theta) R_{inv}\, a(\theta)}$$

Where, $a^H(\theta)$ is the hermitian transpose of $a(\theta)$ and R_{inv} is the inverse of autocorrelation matrix.

C. Maximum Eigen Value (MEV) Method

This method finds a power spectrum such that its Fourier transform equals the measured correlation subjected to the constraint that its entropy is maximized. For estimating DOA from the measurements using an array of sensors, the Maximum Eigen value(ME) method finds a continuous function $P_{MEv}(\theta) > 0$ such that it maximize the entropy function[4-5].

The Maximum Eigen Value (MEV) method power spectrum is given by

$$P_{MEV} = \frac{1}{a^H(\theta) E_S E_s{}^H a(\theta)}$$

$$a^H(\theta) = Hermitiantransposeof\ steeringvector$$

PROPOSED METHOD FOR HIGH RESOLUTION ESTIMATION

A. Hanan Quenon (HQ) Method

HQ is an acronym which stands for Hanan Quenon. HQ promises to provide unbiased estimates of the number of signals, the angles of arrival and the strengths of the waveforms. HQ makes the assumption that the noise in each channel is uncorrelated making the noise correlation matrix diagonal. The incident signals may be correlated creating a non diagonal signal correlation matrix. However, under high Signal correlation the traditional HQ algorithm breaks down and other methods must be implemented to correct this weakness. The Eigen values and eigenvectors for correlation matrix R is found. M eigenvectors associated with the signals and L−M eigenvectors associated with the noise are separated. The eigenvectors associated with the smallest Eigen values are chosen to calculate power spectrum. For uncorrelated signals, the smallest Eigen values are equal to the variance of the noise. The L× (L− M) dimensional subspace spanned by the noise eigenvectors is given by

$$E_N = [e_1\, e_2\, e_3 \ldots\ldots\ldots\ldots\ldots\ e_{L-M}]$$

Where, e_i is the ith Eigen Value.

The noise subspace Eigen vectors are orthogonal to the array steering vectors at the angles of arrival $\theta_1, \theta_2, \ldots\ldots\ldots \theta_M$. Because of this orthogonality condition, one can show that the Euclidean distance $d^2 = a(\theta)^H E_N E_N^H a(\theta) = 0$ for each and every angle of arrival $\theta_1, \theta_2, \ldots\ldots\ldots \theta_M$ .Placing this distance expression in the denominator creates sharp peaks at the angles of arrival. The HQ pseudo spectrum is given by

$$P_{HQ} = \frac{1}{a(\theta)^H E_N E_N^H a(\theta)}$$

Where, $a(\theta)$ is steering vector for an angle θ and E_N is L x L-M matrix comprising of noise Eigen vectors.

SIMULATIONS

The proposed algorithms are simulated using MATLAB software. The parameters used in the simulations are tabulated in Table I.

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Table I
Simulation Parameters

S. No:	Parameters	Values
1	Type of antenna array	Uniform Linear Array
2	Number of array elements	10
3	Passband Frequency range	(3-4) GHz
4	Voltage range for DOA	(1-5)v
5	Direction range for DOA	0 to $\pm$ 90^0
6	Simulation Language	MATLAB
7	Simulation Version	MATLAB 2008a

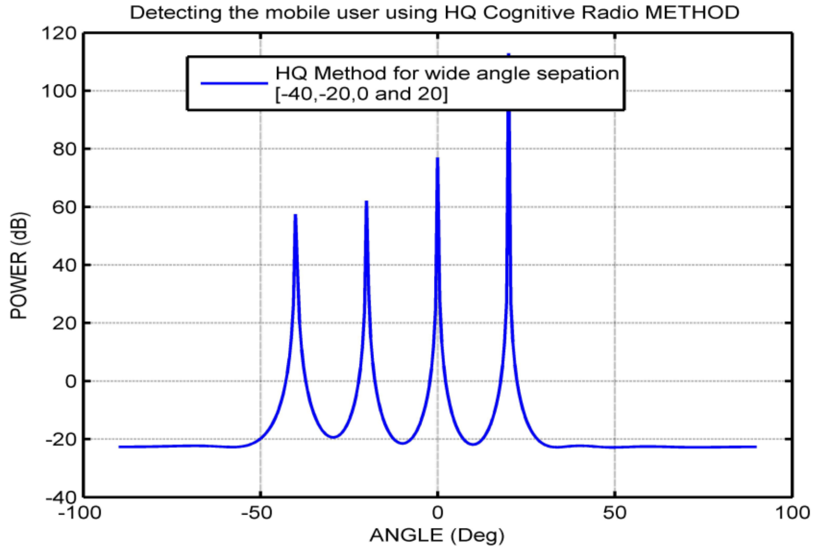

Fig.1: HQ criteria for wide angle separation.

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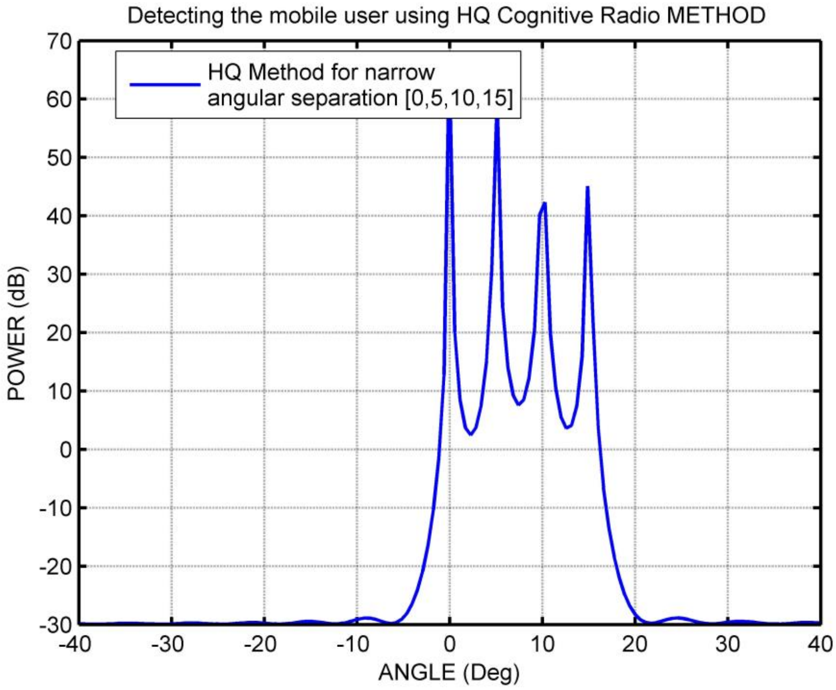

Fig.2: HQ criteria for narrow angle separation.

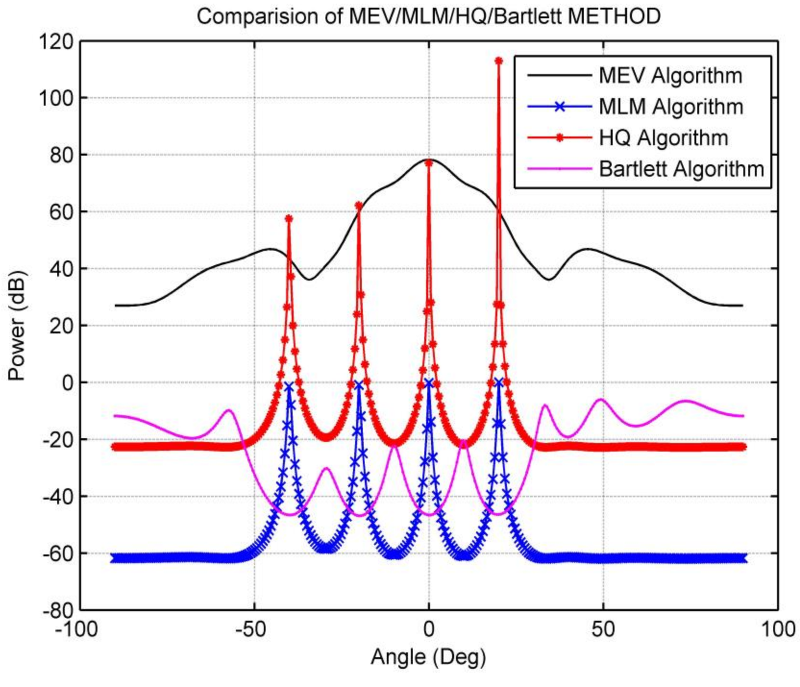

Fig.3: Comparison for proposed and existing methods for wide angle Separation

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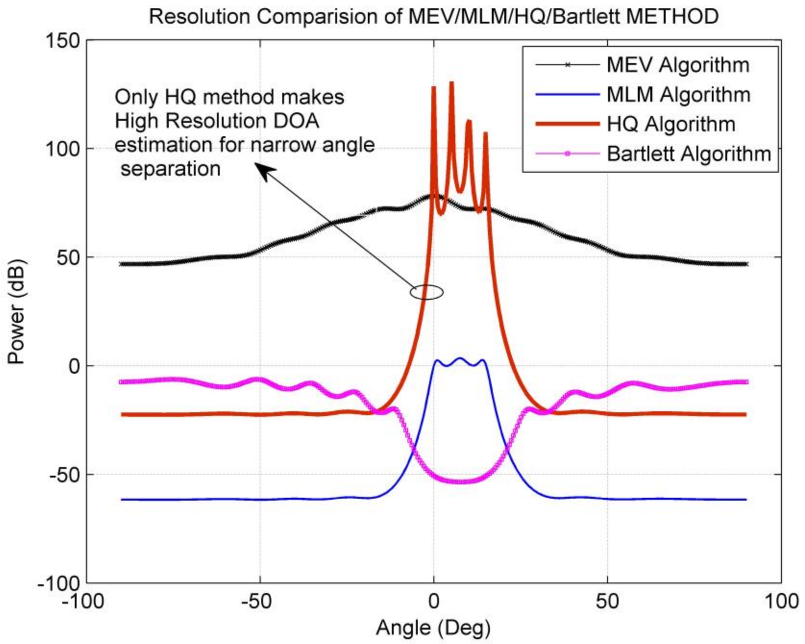

Fig.4: Comparison for proposed and existing methods for narrow band angle separation

From the above figures, it is clear that the smart antennas assisted wideband spectrum sensing algorithm for cognitive radios is operates simultaneously over the total wideband channels rather than one single channel each time. In this approach, the wideband spectrum sensing issue is transformed into estimating the number of occupied channels based on the Hannan-Quinn criterion, and then determining the occupancy status for each channel by the sample power.

CONCLUSION

This paper proposes a wideband sensing algorithm for Cognitive Radio networks based on the HQ criterion. Our approach performs spectrum sensing simultaneously over the whole frequency range instead of one channel each time. Distinct from the classical methods, our approach does not require the estimation of noise power, which is severely deteriorated by noise uncertainty. Also, prior knowledge of the PU signal is not needed, making the proposed algorithm a blind detection technique. This paper presents simulations under various conditions to verify the proposal's performance and the results show that our algorithm is superior to the existing sensing algorithms.

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