Performance of Massive MIMO systems in cognitive spectrum sensing

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Abstract. Cognitive radio is a revolutionary technology that guarantees a viable solution to the spectrum scarcity problem. This prominent new technology has the power to change future technological developments forever if intelligently applied. In Cognitive Radio Networks, secondary (unlicensed) user uses the licensed spectrum band opportunistically, without creating any interference with primary user (licensed) transmission. Spectrum sensing is a vital challenge for spectrum usage and to prevent harmful interference with licensed users. Energy detection has been for a long, constituting the most widely known sensing technique in cognitive radio systems. In this paper, Neyman - Pearson criterion-based detection rules are used to incorporate the local probabilities of detection and false alarm to analyse an energy detector sensing behaviour over additive white Gaussian (AWGN) channel, fading channel and massive multiple input multiple output (MIMO) cases. Closed-form solutions for the probabilities of false alarm and detection were derived. The analytical results were verified by numerical computations using the Monte Carlo method with MATLAB.

1. INTRODUCTION

With the tremendous increase in technological innovations and new wireless technology services spectrum resources increase day by day. Much of the licensed spectrum remains unused both in time and in frequency. In [1], authors presented the optimal detection rules and the corresponding performance analysis for cooperative spectrum sensing in multiuser MIMO cognitive radio networks, considering both perfect and imperfect CSI scenarios. The allocation of the static spectrum strategy to licensed users is very intransigent where licensed users are solely entitled to perform in the allotted frequency band [2]. Cognitive Radio (CR) has emerged as an appealing solution because it can clear up the spectral crowding hassle by opportunistic use of frequency bands, which is no longer occupied by licensed users at that particular instant and aids in ‘Bandwidth Harvesting’. It enables secondary users to utilize the licensed spectrum’s unoccupied portions (spectrum holes) while guaranteeing no intervention with primary user transmissions. FCC (Federal communication commission) defines CR [3] as “a transceiver that monitors its operational radio environment and adjusts its radio operating parameters autonomously and dynamically”. Therefore, one of the important features of CR is to provide new ways to spectrum access by autonomously exploiting locally unutilized spectrum. In CR terminology, the Primary user (PU) can be termed as the user who is licensed to use a particular range of frequencies of the available spectrum. Secondary users (SU) also known as CR users don’t have any license to use the spectrum but incessantly monitors the licensed users’ activity for detecting spectrum holes. CR user jumps to another frequency band when PU arrives without affecting primary users interference [4]-[7].
Efficient exploitation of the spectrum requires the ability to exploit the instantaneous opportunities. For cognitive networks to operate efficiently, secondary users should exploit the radio spectrum used by the primary network. Spectrum sensing is the primary task for sensing the spectrum for finding spectrum hole, decide to use the spectrum band or not. To identify the presence of PU transmission, there are many techniques that have been introduced. Among them, energy detection is mostly used since it doesn’t need any apriori knowledge of the PU signals, and compared to other methods, it has less implementation complexity[8]–[12].

The contribution in this paper is spectrum sensing in cognitive radio in a massive MIMO setup. Here, the secondary users with single antenna node communicates the availability of spectrum to a base station with massive antennas. Due to the power scaling property of massive MIMO, secondary users can transmit with very low power. Also the detection at the base station is done by Neyman pearson criteria. In this paper performance of the energy detection technique is studied. This paper is organized as follows: spectrum sensing model is presented in section II. Section III explains the system model, and Section IV provides simulation results and discussion. The conclusion is finally drawn in section V.

2. SYSTEM MODEL

The spectrum sensing is the primary and fundamental step in CR networks. The problem of detection of primary signal at the secondary user may be modeled as binary hypothesis

\[ H_0 : \ y[n] = w[n] \]
\[ H_1 : \ y[n] = x[n] + w[n] \]

(1)

Where w(n) are the samples of the additive white Gaussian noise (AWGN) with zero mean and variance and x(n) are the samples of the primary signal and y(n) is the received signal samples. Hypothesis \( H_0 \) corresponds to the presence of noise signal only, i.e., absence of the primary user signals. Hypothesis \( H_1 \) corresponds to the presence of the primary user signal. Depending on the decision statistic being either lesser or greater than the threshold, the hypothesis is determined.

Here the observed phenomenon is the spectrum to be sensed. Now K number of secondary users with single antenna forward this information to the base station with M number of antennas. Here M is large compared to K. By using the Neyman-Pearson decision rule, likely hood ratio test (LLR), spectrum availability is determined. Let y=[y(1), ……..y(k)] denotes the observation from K number of sensors at the base station. For n=1,…….,k, the likely hood ratio, logarithm of the ratio of conditional probability density functions(PDF) are compared with a threshold. If the observation y during \( H_1 \) transmission is more than \( H_0 \) transmission, then the ratio of conditional PDF will be greater than the threshold, and decisions are made in favor of \( H_1 \) otherwise \( H_0 \). Using the Neyman-Pearson (NP) criterion that aims to maximize the detection probability for a given probability of false alarm, the log likelihood ratio (LLR) \( T(Y) \) for the observation matrix \( Y \) defined as

\[ T(Y) = \ln \left[ \frac{P(Y|H_1)}{P(Y|H_0)} \right] \]

(2)

where \( \gamma \) denotes the decision threshold. The quantities \( P(Y|H_1) \) and \( P(Y|H_0) \) in the above expression represent the probability density functions (PDFs) of the received matrix \( Y \) under the alternative and null hypotheses, respectively.

(a) Energy Detection in CSI uncertainty

If the channel state information (CSI) are unknown, one can use Energy detectors(ED). This paper proposes energy detection technique based on a non-coherent detection approach as the primary user
doesn't require any prior knowledge of the PU signal to detect whether or not the channel is occupied. The acquired signal is first bandpass filtered and then converted with an ADC to discrete samples. These discrete samples are then squared and integrated to achieve the energy of the received signal, which is the actual decision statistic, \( X' \) given as:

\[
X' = \frac{1}{N} \sum_{n=0}^{N-1} |y(n)|^2
\]  

(3)

Detection probability \( (P_D) \) and the probability of false alarm \( (P_F) \) can be computed respectively as below.

\[
P_D = P (X' > \gamma | H_1)
\]  

(4)

\[
P_F = P (X' > \gamma | H_0)
\]  

(5)

Where \( \gamma \) is termed decision threshold. False alarm probability can be expressed in terms of PDF as

\[
P_F = \int_{\gamma}^{\infty} F_{X'}(x) \, dx
\]  

(6)

From (5) we get

\[
P_F = \frac{1}{2^d \Gamma(d)} \int_{\gamma}^{\infty} x^{d-1} e^{-\frac{x^2}{2}} \, dx
\]  

(7)

Multiplying and dividing the RHS of the above equation by \( 2^{d-1} \), we get

\[
P_F = \frac{1}{2^d \Gamma(d)} \int_{\gamma/2}^{\infty} (x/2)^{d-1} e^{-\frac{x^2}{4}} \, dx
\]  

(8)

Substituting \( t = x/2 \) and \( dt = dx/2 \) and change the limits of integration to \( (\gamma/2, \infty) \) then,

\[
P_F = \frac{1}{2^d \Gamma(d)} \int_{\gamma/2}^{\infty} t^{d-1} e^{-t} \, dt
\]  

(9)

\[
P_F = \frac{\Gamma(d, \frac{\gamma}{2})}{\Gamma(d)}
\]  

(10)

Where \( \Gamma(\cdot) \) is the incomplete gamma function. Detection Probability can be expressed in terms of cumulative distribution function (CDF) as given by

\[
P_D = 1 - F_{X'}(\gamma)
\]  

(11)

Then CDF of \( X' \) can be computed as

\[
F_{X'}(x) = 1 - Q_d(\sqrt{\lambda}, \sqrt{\gamma})
\]  

Using (4) and (11) probability of detection is

\[
P_D = Q_d(\sqrt{\lambda}, \sqrt{\gamma})
\]  

(12)
Q_d(.) is the generalized Marcum-Q function, and this expression is used for evaluating detection probability over the AWGN channel.

3. FADING CHANNEL

Let \(x_1, x_2, \ldots, x_m\) denote the fading coefficient of transmitted \(m\) pilot symbols, and \(h\) denote the fading coefficient. The corresponding input-output model is

\[ y_1 = hx_1 + n_1, \quad y_2 = hx_2 + n_2, \quad \ldots, \quad y_m = hx_m + n_m \]

The above model can be vectorized as follows.

\[
\begin{bmatrix}
    y_1 \\
    y_2 \\
    \vdots \\
    y_m \\
\end{bmatrix} = \begin{bmatrix}
    x_1 \\
    x_2 \\
    \vdots \\
    x_m \\
\end{bmatrix} h + \begin{bmatrix}
    n_1 \\
    n_2 \\
    \vdots \\
    n_m \\
\end{bmatrix}
\]

This can be represented as

\[ y = hx + n \quad \text{(13)} \]

The binary hypothesis testing problem for spectrum sensing is

\[ H_0: y = n \quad \text{(14)} \]
\[ H_1: y = hx + n \quad \text{(15)} \]

One can perform matched filtering by multiplying with

\[ h^* x^H \]

The output corresponding to both hypotheses is given as

\[ H_0: \quad y = \frac{h^* x^H}{|h| \|x\|} \quad \text{(16)} \]
\[ H_1: \quad y = \frac{h^* x^H}{|h| \|x\|} (hx + n) = |h| \|x\| + n \quad \text{(17)} \]

The output is compared with a threshold to yield the detector

\[ y \geq \frac{1}{2} |h| \|x\| \Rightarrow H_1 \quad \text{(18)} \]
\[ y < \frac{1}{2} |h| \|x\| \Rightarrow H_0 \quad \text{(19)} \]
4. SIMULATION RESULTS AND DISCUSSION

By depicting the ROC curves, the receiver performance is analyzed. ROC curves show the probability of miss detection versus probability of false alarm. For plotting ROC curves one of the parameters is varied while the other parameter is fixed.

The overall concept for detecting energy is consistent because this method delivers optimum performance with increased signal power (high SNR).

Fig.1: Complementary ROC curves ($P_M$ vs. $P_{FA}$) over AWGN.

Fig.1 shows the complementary ROC curve over a non-fading (AWGN) channel (a case where the form of interference is only noise). This depicted the relationship between the probability of false alarm $P_{FA}$ and missed detection $P_M$, for an SNR = -15dB, sample size $N = 1000$ respectively. The miss detection probability is a complement of the probability of detection.

Fig.3: ROC curves ($P_D$ vs $P_M$) over AWGN.
Fig. 3 shows the ROC curve represents the variation of detection probability with false alarm probability. Theoretical and simulation results are plotted for an SNR = -10dB, sample size N = 1000. For this case, detection probability increases with false alarm probability while $P_{FA}$ is increased from 0.01 to 1.

![ROC curve for different SNR over AWGN](image)

Fig. 4: ROC curves for different SNR over AWGN

Fig. 4 shows the relationship between the probability of false alarm $P_{FA}$ and the probability of detection $P_{D}$, for -25dB to +5 dB average SNR, sample size N = 1000 respectively. The probability of detection improves rapidly with increasing SNR. This buttresses the point made earlier that an SNR increase produces greater detection performance for a non-fading channel.

![ROC curves for fading channel](image)

Fig.5: ROC curves for fading channel.
Fig. 5 shows the ROC curve for the fading channel. Here the channel is modeled as a rayleigh fading channel. Assuming that there is no line of sight (LOS) component in the signal propagation path. In the fading channel probability of detection is less compared to the AWGN channel. Fig. 6 shows the ROC curve for MIMO. With MIMO systems, ROC performance is improved and behaves almost similar to the AWGN channel.

5. CONCLUSION

Radiofrequency spectrum is a limited and precious asset in wireless communication systems and became a fundamental basis for research and development efforts over the past years. To address spectrum shortage and employ the spectrum opportunistically, cognitive radio has become preeminent and propitious technology. Sensing the unoccupied spectrum possibilities is one of the indispensable factors of cognitive radio. Among the methodologies explored so far the energy detection approach has proven to be less complex, viable, but sub-optimal. In this paper, the performance of an energy detector for detecting spectrum holes was evaluated. This study incorporates a theoretical background, wherein closed-form mathematical expressions for false alarm probabilities and probability of detection under non-fading (AWGN) channel. With the help of Receiver Operating Characteristics (ROC) curves, performance is analyzed. Simulation results show that performance of energy detector improves depending on the AWGN channel’s threshold, for various average values of SNR. From the results it is concluded that probability of detection increases with SNR for a single user detector node in a channel with no fading. Also by using multiple antennas at both receiver and transmitter can improve the performance of the system.
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