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Spectrum sensing algorithm based on sample variance in multi-antenna cognitive radio systems

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ABSTRACT

The most significant feature that cognitive radio systems must include in order to operate properly is spectrum sensing. In this paper, we investigate the problem of designing accurate and efficient spectrum sensing algorithms in multi-antenna cognitive radio systems. Existing algorithms require an excessive number of sampling points to achieve the desired detection performance, and we address this issue by proposing a spectrum sensing algorithm based on sample variance that requires significantly fewer sampling points in multiple input multiple output (MIMO) scenarios. The proposed method uses the row vector of the sampling covariance matrix as the sample, and then uses the sample variance to construct the detection statistics. The judgment threshold is derived according to the false alarm probability. This algorithm makes full use of the relational structure of the signal, which allows it to reduce the number of sampling points while simultaneously enhancing the detection ability. Compared with existing algorithms, the proposed algorithm is more accurate and efficient. The superior performance of the proposed algorithm is demonstrated by Monte Carlo simulations in both Rayleigh and additive white Gaussian noise (AWGN) channels. These simulation results also show that the proposed algorithm has wider applicability than existing algorithms.

1. Introduction

Cognitive radio technology is capable of secondary utilization of licensed spectrum without affecting the primary users by looking for unused regions in the radio frequency spectrum. Essentially, existing spectrum is reused by exploiting the randomness in the communications of the primary users. As such, cognitive radio is an emerging technology with the potential of significantly improving spectrum efficiency [1–3]. To function properly, cognitive radio systems need an efficient and accurate method of spectrum sensing in order to avoid causing interference to primary users and improve the quality of service (QoS) [4–6].

In recent years, research into spectrum sensing algorithms has given rise to a number of techniques such as cyclostationary feature detection, matched filter detection, and energy detection. In [7], results showed that matched filter detection methods have the best detection performance under the condition that all the prior information of the primary users is known. However, this is a difficult requirement to satisfy in practical applications. The cyclostationary feature detection method proposed in [8–10] only needs to know part of the primary users' prior information to achieve spectrum sensing, but its computational complexity is relatively high. It has been shown in [11–13] that energy detection is easy to implement and it achieves good performance in the case where the noise power is known noise. Similarly to the issue with matched filter methods, the noise power is generally unknown in the practical applications. The problem of determining the noise power has been solved by noise power estimation methods (e.g., [14]), however, the detection performance was sacrificed in this solution.

Multi-antenna spectrum sensing technology has been proposed in order to solve the spectrum sensing problems stated above. This technology uses the correlation between different receiving antennas in the cognitive radio to determine the occupancy of licensed spectrum. The reasoning behind this judgment is as follows: when the spectrum is idle, the signals on each receiving antenna will simply be noise, and there will be no correlation between them; when the spectrum is occupied, there is a strong correlation between each receiver antenna signal. By assuming that the noise from the receiver antennas is uniform, detection algorithms based on the likelihood ratio was proposed in [15–16,21–22], such as maximum-minimum eigenvalue detection algorithm (MME) [15,21], arithmetic to geometric mean detection algorithm (AGM)

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[22] and the mean-max detection (MMD) algorithm was proposed in [16]. This latter algorithm finds the mean and maximum eigenvalue of the covariance matrix and uses their ratio to construct the statistics. The performance of this detection algorithm is relatively good under the uniform noise assumption, but it deteriorates significantly in a nonuniform noise environment. In order to improve the detection performance in nonuniform noise environments, the volume-based detection (VD) algorithm and covariance absolute value detection algorithm (CAV) were proposed in and [17,23–24]. This method constructs statistics based on the determinant of the sampling covariance matrix. Since this algorithm operates without the constraints of consistent noise power, it can effectively overcome the effects of nonuniform noise. However, both of the above two algorithms require a relatively large number of sampling points to achieve suitable detection performance. This significantly reduces the efficiency of the spectrum sensing process, and new methods that achieve both efficient and high performance detection are highly desirable.

Methods that use the standard deviation of an image to analyze the contrast in a specific region have been proposed in the field of image processing [18]. In this paper, we apply this idea to spectrum sensing and propose an algorithm based on sample variance detection (SVD) in multi-antenna cognitive radio systems. The row vector of the signal sampling covariance matrix is considered as the sample in the proposed algorithm. We further use the derived sample variance to construct statistics. Compared with the algorithms in [16,17], the proposed algorithm not only reflects the correlation between signals to overcome the effects of nonuniform noise, but also requires fewer sampling points to achieve the same detection probability. The operation of the algorithm is verified through Monte Carlo simulations, and the results show that superior performance is obtained in both a multiple input multiple output (MIMO) Rayleigh channel and an additive white Gaussian noise (AWGN) channel environment.

The remainder of this paper is organized as follows. Section 2 introduces the relevant background and highlights imperfections in existing representative algorithms. Section 3 describes the model of the proposed algorithm. Simulation results and a performance analysis of the proposed algorithm are presented in Section 4, and conclusions are provided in Section 5.

2. Problem description

The cognitive radio detection system considered here operates in a MIMO environment consisting of one primary user with K transmitting antennas, and one cognitive user with L receiving antennas. N is the number of sampling points, and $w_l(n) \sim CN(0, \sigma_{w_l}^2)$ is the complex Gaussian noise. The noise and the signal are assumed to be independent of each other. The variable $\boldsymbol{H}$ is the $K \times L$ dimensional fading channel matrix. The signal at the cognitive user's receiver at the Nth sampling time can be written as

$$\begin{cases} \mathrm{H}_0: & \boldsymbol{x}(n) = \boldsymbol{w}(n) \\ \mathrm{H}_1: & \boldsymbol{x}(n) = \boldsymbol{Hs}(n) + \boldsymbol{w}(n) \end{cases}, \tag{1}$$

where $\boldsymbol{w}(n) = [w_1(n), \ldots, w_l(n), \ldots w_L(n)]^{\mathrm{T}}$, $\boldsymbol{x}(n) = [x_1(n), \ldots, x_l(n), \ldots, x_L(n)]^{\mathrm{T}}$, and $\boldsymbol{s}(n) = [s_1(n), \ldots, s_k(n), \ldots, s_K(n)]^{\mathrm{T}}$.

The signals $x_l(n)$ and $s_k(n)$ are the lth receiving antenna signal of the cognitive user and the kth transmitting antenna signal of the primary user, respectively.

2.1. Existing spectrum sensing algorithms in a uniform noise environment

The sampling covariance matrix is used to represent the correlation of each signal in a multi-antenna receiver in a uniform noise ($\sigma = \sigma_{w_l}, l = 1, 2, \ldots, L$) environment. The sampling covariance matrix is given by

$$\hat{\boldsymbol{C}} = \frac{1}{N}\boldsymbol{XX}^{\mathrm{H}}, \tag{2}$$

where $\boldsymbol{X} = [\boldsymbol{x}(0), \cdots, \boldsymbol{x}(n), \cdots, \boldsymbol{x}(N-1)]$.Thus, we can rewrite (2) as

$$\hat{\boldsymbol{C}} = \frac{1}{N}\sum_{n=0}^{N-1}\boldsymbol{x}(n)\boldsymbol{x}^{\mathrm{H}}(n). \tag{3}$$

From (1), the sampling covariance matrix for the conditions of H_0 and H_1 can be written as

$$\begin{cases} \mathrm{H}_0: & \hat{\boldsymbol{C}} = \sigma^2\boldsymbol{I} \\ \mathrm{H}_1: & \hat{\boldsymbol{C}} = \boldsymbol{HC}_S\boldsymbol{H}^{\mathrm{H}} + \sigma^2\boldsymbol{I} \end{cases}, \tag{4}$$

where σ^2 is the uniform noise power, $\boldsymbol{I}$ is the Lth dimensional identity matrix, and $\boldsymbol{C}_S$ is the primary user signal covariance matrix.

The detection statistics of the MMD, MME and AGM algorithms proposed in [16,21,22] can be written as

$$\Gamma_{\mathrm{MMD}} = \frac{\frac{1}{L}\sum_l \lambda_l}{\lambda_{\max}}, \quad \Gamma_{\mathrm{MME}} = \frac{\lambda_{\max}}{\lambda_{\min}}, \quad \Gamma_{\mathrm{AGM}} = \frac{\frac{1}{L}\sum\limits_l \lambda_l}{\left(\prod_l \lambda_l\right)^{1/L}} \tag{5}$$

where λ_l, $\lambda_{\max}$ and $\lambda_{\min}$ are the lth, maximum and minimum eigenvalue of the sampling covariance matrix $\hat{\boldsymbol{C}}$, respectively.

Under the condition of H_0, $\lambda_l = \lambda_{\max} = \lambda_{\min} = \sigma^2$ and under the condition of H_1, $\lambda_{\max} = \alpha_{\max} + \sigma^2$, $\lambda_{\min} = \alpha_{\min} + \sigma^2$. Where $\alpha_{\max}$ and $\alpha_{\min}$ is the maximum and minimum eigenvalue of $\boldsymbol{HC}_S\boldsymbol{H}^{\mathrm{H}}$, respectively.

We can judge the spectrum occupancy by comparing the detection statistic with the corresponding threshold. The judgment decision is given by

$$\Gamma_{\mathrm{MMD}} \underset{\mathrm{H}_1}{\overset{\mathrm{H}_0}{\gtrless}} \gamma_{\mathrm{MMD}}, \quad \Gamma_{\mathrm{MME}} \underset{\mathrm{H}_1}{\overset{\mathrm{H}_0}{\gtrless}} \gamma_{\mathrm{MME}}, \quad \Gamma_{\mathrm{AGM}} \underset{\mathrm{H}_1}{\overset{\mathrm{H}_0}{\gtrless}} \gamma_{\mathrm{AGM}} \tag{6}$$

2.2. Existing spectrum sensing algorithms in a nonuniform noise environment

In a nonuniform noise environment, the sampling covariance matrix (4) can be rewritten as

$$\begin{cases} \mathrm{H}_0: & \hat{\boldsymbol{C}} = \boldsymbol{G}^2 \\ \mathrm{H}_1: & \hat{\boldsymbol{C}} = \boldsymbol{HC}_S\boldsymbol{H}^{\mathrm{H}} + \boldsymbol{G}^2 \end{cases}, \tag{7}$$

where $\boldsymbol{G}^2 = \mathrm{diag}[\sigma_{w_1}^2, \ldots, \sigma_{w_l}^2, \ldots, \sigma_{w_L}^2]$.

Under the condition of H_0, $\hat{\boldsymbol{C}}$ is a diagonal matrix, and under the condition of H_1, $\hat{\boldsymbol{C}}$ is an off-diagonal matrix.

The algorithms in [17,23,24] proposed the use of the determinant of the sampling covariance matrix to construct the statistics. The judgment decision in the VD and CAV algorithms are given by

$$\Gamma_{\mathrm{VD}} = \mathrm{lgdet}[\mu^{-1}\hat{\mathrm{C}}] \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \gamma_{\mathrm{VD}}, \quad \Gamma_{\mathrm{CAV}} = \frac{\frac{1}{L}\sum_{l=1}^{L}\sum_{m=1}^{L}|c_{lm}|}{\frac{1}{L}\sum_{l=1}^{L}|c_{ll}|} \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \gamma_{\mathrm{CAV}} \tag{8}$$

where $\mu = \mathrm{diag}[\mu_1, \cdots, \mu_l, \cdots \mu_L]$, and μ_l is the row vector norm of the sampling covariance matrix $\hat{\boldsymbol{C}}$.

As stated earlier, the MMD algorithm and the VD algorithm achieve spectrum sensing in a uniform and non-uniform noise environment, respectively. The detection performance of both algorithms for 4 and 6 receiving antennas are shown in Fig. 1 (a) and (b), respectively. Even with a relatively large number of receiving antennas, a large number of sampling points is needed to improve the detection performance as shown in Fig. 1(c).