An Improved Covariance Spectrum Sensing Algorithm Establish on AD Test

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Abstract. Owing to no need for prior knowledge of signal, blind spectrum sensing has received wide attention. Covariance Absolute Value (CAV) detection algorithm, one of the most popular blind sensing algorithms, considers the correlation of signal samples. However, its detection performance is restricted by the uncertain threshold calculation. To optimize the performance of CAV, we propose a new method based on a new statistic and goodness of fit test. The statistic is constructed from the off-diagonal of covariance matrix firstly, then Anderson-Darling (AD) test is used to estimate the existence or absence of primary user. The proposed method not only achieves blind detection but also improves the sensing performance of CAV. Experimental results manifest the effectiveness of the proposed scheme.

Keywords: Blind spectrum sensing · Covariance absolute value · New statistic Anderson-darling test

1 Introduction

As a vital technology in cognitive radio, spectrum sensing is devoted to the appearance or absence detection of the primary user (PU) for possible improvement of spectrum utilization [1]. Recently, Covariance spectrum detection algorithms are prevailing [2, 3]. Because they take the correlation of signal samples into consideration and do not require the information about signal and noise.

CAV detection algorithm [4] as one of covariance detection has the advantages mentioned above all. However, its capability is limited by the multiple approximate solutions in the process of threshold estimation. To optimize its performance, some methods have been proposed. [5] put forward a two-stage spectrum sensing algorithm on the basis of energy and CAV detection. In [6], features are extracted from covariance matrix and put into support vector machine to achieve the improvement of detection

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performance. Nevertheless, the above methods do not solve uncertain estimated threshold in essence.

To fundamentally improve the performance of spectrum sensing, some literatures prefer to use the goodness of fit testing [7, 8]. The goodness of fit testing, a nonparametric hypothesis testing problem, consists of Anderson-Darling (AD), Cramervon Mises(CM) and Kolmogorov-Smirnov(KS). What's more, [8] verifies the superiority of AD test. Thus, this paper puts forward a modified covariance matrix-based spectrum sensing scheme. It constructs new statistics from the off-diagonal elements of covariance matrix firstly, and then AD test is used to determine the existence or absence of PU.

The structure of this paper is as follows. In Sect. 2, the system model of spectrum sensing and CAV is introduced. Section 3 gives the construction of statistics and the process of AD test. Experimental results and analysis are given in Sect. 4 and conclusion are drawn in Sect. 5.

2 Theoretical Principle

2.1 Spectrum Sensing

The core role of Spectrum sensing is to obtain the state of PU, which can be presented as follows [9]

$$\begin{cases} H_1: & y(k) = s(k) + n(k) \\ H_0: & y(k) = n(k) \end{cases} \qquad k = 1, 2, \ldots K \tag{1}$$

Where, H_0 and H_1 separately represent the absence and existence of PU. $y(k)$, $s(k)$ and $n(k)$ indicate the signal obtained by SU, signal of PU and noise. K denotes the samples.

The testing performance of sensing algorithm can be measured by the detection probability P_d and the probability of false alarm P_{fa}, which are formulated as

$$P_d = \mathrm{P}(H_1 | \mathrm{H}_1) \tag{2}$$

$$P_{fa} = \mathrm{P}(H_1 | \mathrm{H}_0) \tag{3}$$

Obviously, a good detection method has large P_d and small P_{fa}. However, these two indicators are mutually restricted. In practice, the receiver operating characteristic curve (ROC) is used as the main measure.

2.2 CAV Sensing Model

Assume that noise is a Gaussian signal of independent and identically distributed with a mean zero and variance σ_n^2.

Supposing the smoothing factor is M, the vectors and covariance matrixes of signal and noise can be written as [9].

$$Y = [\, y(k)\ \ y(k-1)\ \ \ldots\ \ y(k-M+1)\,]^T \tag{4}$$

$$S = [\, s(k)\ \ s(k-1)\ \ \ldots\ \ s(k-M{+}1)\,]^T \tag{5}$$

$$N = [\, n(k)\ \ n(k-1)\ \ \ldots\ \ n(k-M{+}1)\,]^T \tag{6}$$

$$R_Y = E\left[Y \cdot Y^H\right] \tag{7}$$

$$R_s = E\left[S \cdot S^H\right] \tag{8}$$

$$R_Y = R_s + \sigma_n^2 I_M \tag{9}$$

Traditional covariance-based spectrum sensing algorithm constructs statistics based on the criterion that whether the covariance matrix of the receiver is a diagonal matrix. However, multiple approximate solutions in the process of computing threshold may limit its performance.

3 The Proposed Algorithm

To alleviate the problem of covariance-based method, this paper proposes an improved algorithm. A new statistic is constructed first and then AD test is used to determine the state of PU. The specific processes are shown in the following.

3.1 The Construction of Statistics

Suppose that the power of the signal is σ_s^2. Define the sample autocorrelations of the received signal [3] as

$$\lambda(m) = \frac{1}{K}\sum_{k=0}^{K-1} y(k)\ *\ y(k-m) \qquad m = 0, 1, \cdots, M-1 \tag{10}$$

Then the $M \times M$ statistic covariance of SU can be written as

$$R_Y = \begin{bmatrix} \lambda(0) & \lambda(1) & & \lambda(M-1) \\ \lambda(1) & \lambda(0) & & \lambda(M-2) \\ & & \ddots & \\ \lambda(M-1) & \lambda(M-2) & & \lambda(0) \end{bmatrix} \tag{11}$$

As verified in [4], the distribution off-diagonal elements of R_Y in the situation of H_1 and H_0 can be represented as follows

$$\left\{\begin{array}{ll} H_1: & \begin{array}{c} E(\lambda(m)) = \alpha_m \sigma_s^{\ 2} \\ \mathrm{var}(\lambda(m)) = \mathrm{var}(\frac{1}{K} s(k)^T s(k-m+1) + \frac{\sigma_n^{\ 2}}{K}(\sigma_n^{\ 2} + 2\sigma_s^{\ 2} + \frac{2(K-1)\alpha_{2m}}{K}\sigma_s^{\ 2})) \end{array} \\ H_0: & \begin{array}{c} E(\lambda(m)) = 0 \\ \mathrm{var}(\lambda(m)) = \frac{1}{K}\sigma_n^4 \end{array} \end{array} \quad m = 1, 2, \ldots M-1 \right\} \tag{12}$$

Where $\alpha_m = E(s(n) * s(n-m))/\sigma_s^2$ [4] denotes the normalization correlation of sample points.

From (12), we know that in H_0 the distribution of the whole off-diagonal elements of obeying the normal distribution otherwise, they deviate from the normal distribution.

Based on the conclusions mentioned above, this paper constructs statistics. The specific process is denoted as follows.

(1) Remove the diagonal elements R_Y to form a new $(M-1) \times M$ matrix R and calculate the mean and variance of each column of R. Thus, we can get M mean-variance pairs, which can be represented as $(\overline{X}_i, S_i^2)$. The range of i is 1 to M.

(2) Construct statistics T_i, which can be calculated as follows

$$T_i = \frac{\overline{X}_i}{S_i/\sqrt{n}} \tag{13}$$

Where $n = M - 1$. According to (13), we can get that in, T_i is students t distribution with degree n − 1, namely $T_i \sim t(n-1)$. However, in H_1, T_i deviates significantly from $t(n-1)$. Therefore, the state of PU can be judged by the distance between the distribution function of observations and the cumulative distribution function of $t(n-1)$.

3.2 AD Test

Suppose the empirical distribution function of observations $T_i (i = 1, 2 \cdots M)$ and the cumulative distribution function of $t(n-1)$ respectively as $F_M(\mathrm{y})$ and $F_0(\mathrm{y})$.

Calculating the distance A_M^2 between $F_M(\mathrm{y})$ and $F_0(\mathrm{y})$.

$$A_M^2 = n \int_{-\infty}^{+\infty} [F_M(\mathrm{y}) - F_0(\mathrm{y})]^2 \frac{dF_0(\mathrm{y})}{F_0(\mathrm{y})(1 - F_0(\mathrm{y}))} \tag{14}$$

In [10], A_M^2 can be simplified as

$$A_M^2 = \frac{\sum_{i=1}^{M} (2 * i - 1)(\ln z_i + \ln(1 - z_{n+1-i}))}{M} - M \tag{15}$$

Where $z_i = F_0(T_i)$

Then, According to A_M^2 and threshold γ, the state of PU can be determined as

$$\begin{cases} H_1 \colon A_M^2 > \gamma \\ H_0 \colon A_M^2 < \gamma \end{cases} \tag{16}$$

As proved in [11], the distribution of A_M^2 under H_0 converges to a limiting distribution when M >= 5 and it is independent of F_0(y). Thus, the value of γ at a given P_{fa} can be calculated using the limiting distribution of A_M^2. For example, when $P_{fa} = 0.05,\ \gamma = 2.492$ and when $P_{fa} = 0.1,\ \gamma = 1.933$.

4 Experimental Results and Analysis

In the experiments, it is assumed that the modulation type of PU is OFDM, the noise is AWGN. The frequency of the carrier and are respectively set at 100 MHz and 400 MHz [9]. The value of M is set to 10. Then we discuss the performance of proposed method and CAV.

The sampling point is 100 in this paper without special instructions. At a certain $P_{fa} = 0.05$, Fig. 1 compares theirs under different SNR. It shows that the proposed algorithm outperforms CAV. When SNR is between −15 dB and −10 dB, the performance of proposed method exceeds CAV more than 2 dB.

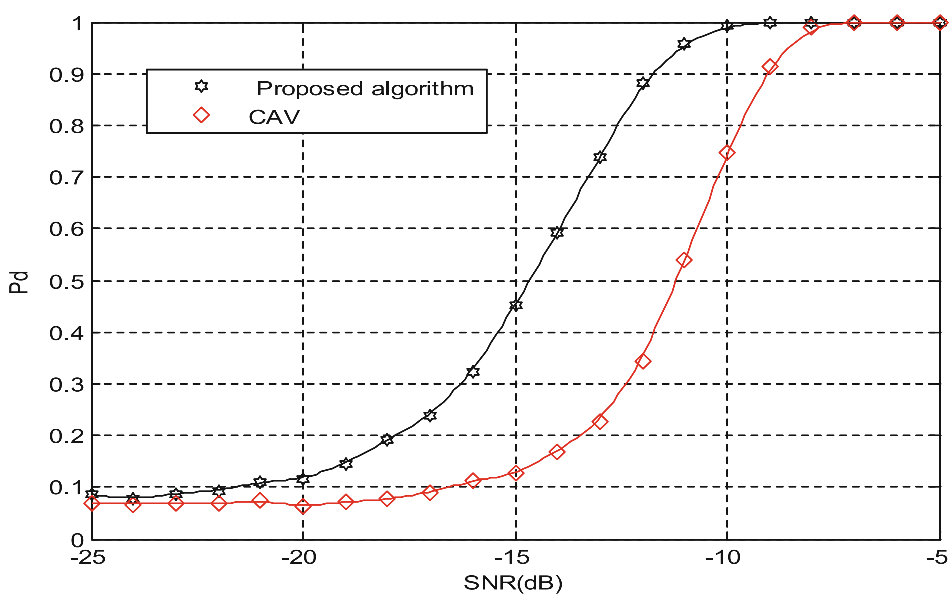

Fig. 1. The comparison of P_d at different SNR

The setting value of K to100, Fig. 2 compares their ROC at different SNR of both algorithm. It is obvious that the detection performance of proposed algorithm is better than CAV. The performance of proposed algorithm at -14 dB even outperforms CAV at −12 dB, which conforms with the result of Fig. 1.

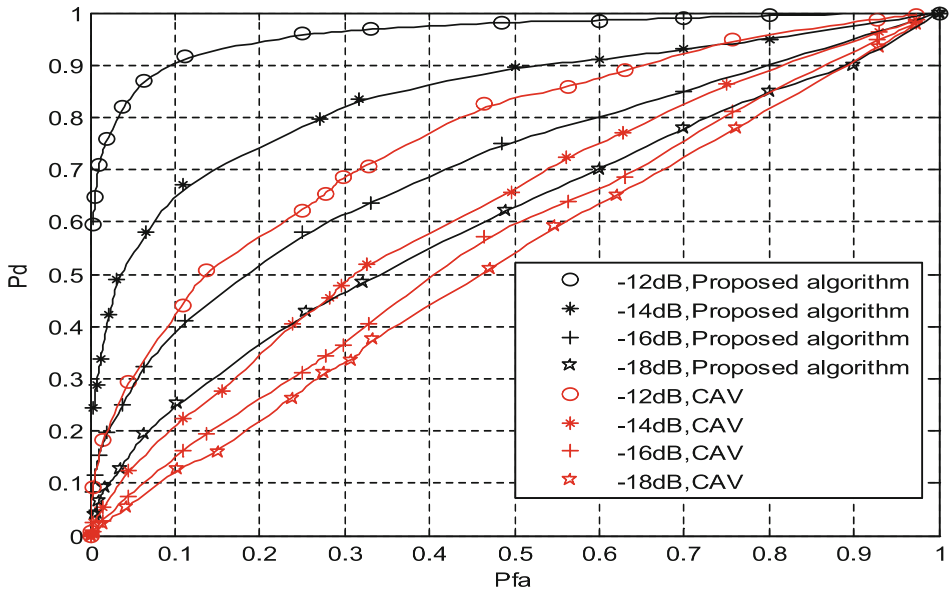

Fig. 2. The comparison of ROC at different SNR

Setting the value of M to 10 and SNR is −16 dB, Fig. 3 compares the ROC curves at different samples of both algorithms. It is can be clearly seen from this figure that when achieving the same detection performance, the proposed algorithm requires fewer samples than CAV.

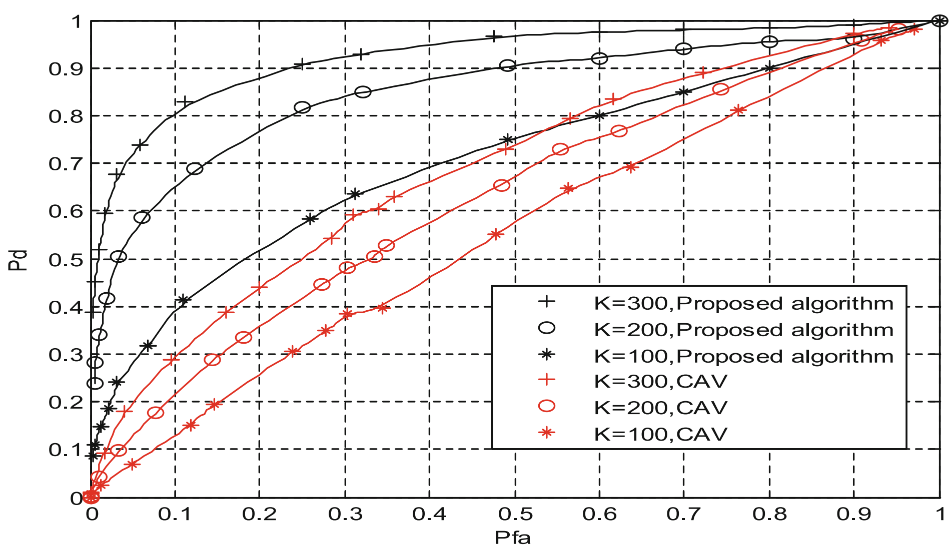

Fig. 3. The comparison of ROC curves at different samples

To sum up, the proposed method is superior to CAV owing to the construction of new statistics and AD test. The above results confirm the stability of AD test and validity of statistics.

5 Conclusion

In this paper, an improved covariance matrix-based spectrum sensing algorithm is considered. Where a new statistic based on covariance matrix-based algorithm is constructed. It preserves the advantages of the CAV algorithm and experiments manifest the improvement of the detection performance.

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