A Novel Primary User Detection Method for Multiple-Antenna Cognitive Radio

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Abstract— **As we know, cognitive radios should not interfere with the primary users and so, should detect them and vacate the frequency bands when required. In this paper, we propose a novel multiple-antenna receiver diversity scheme based on cyclostationary detection, in order to improve the reliability of primary user detection. We derive closed-form expressions for the probabilities of detection and false alarm in the proposed scheme. The performance is probed by computer simulations and compared to the conventional spectrum sensing methods. The results show the performance enhancement of the proposed spectrum sensing method over the conventional ones.**

I. Introduction

Access to the radio spectrum is currently granted exclusively to individual telecom operators, or completely does not require any license. But, investigations of spectrum utilization show that not all the spectrum is in use for all of the time. Measurements show that in some locations or at some times of day, 15% to 85% of the allocated spectrum may be sitting idle [1], meaning that there is no shortage of radio spectrum, only a dearth of affordable communications infrastructure [2]. In fact, the problem is not the scarceness of the radio spectrum, but it's the way that the spectrum is used, and this has put a great pressure on the radio spectrum managers to utilize the spectrum in a more efficient, economical, rational and equitable way. The solution lies with the so-called Cognitive Radios (CR), devices that figure out which frequencies are currently not in-use and pick one or more over which to transmit and receive data [2]. Cognitive radio was coined firstly in a doctoral thesis submitted in May 2000 by Joseph Mitola III [3], [4]. It is an unlicensed intelligent wireless communication system that is aware of, learns from and adapts to the statistical variations of its environment [5]. This technology has found an attracting and exploding interest in the development process of IEEE 802.22 WRAN (Wireless Regional Area Network) standard [6]. However, as cognitive radios are considered to be of lower priority or secondary users (SU) of spectrum allocated to a primary user (PU), a fundamental requirement is to avoid interference to potential primary users in their vicinity. One of the challenges to implement such a system is the detection of vacant frequency bands in the radio spectrum [7]. This requires CRs to sense the presence of the spectrum holes (temporarily-unused spectrum), i.e., equivalently, detect the presence of the PUs [4]. Therefore, the essential function of a cognitive radio is its spectrum sensing function to sense whether a particular band is being used and, if it is not, to utilize the spectrum without interfering with the other licensed transmitters.

In general, spectrum sensing can be accomplished by energy-based or feature-based detection schemes. If nothing is known about the target PU signal, the energy-based approach is usually preferred [1]. When the target signal contains some known characteristics, e.g., DTV or NTSC signals, the feature-based method will be used [8]. In this case, because the required signal is of telecommunication type, a cyclostationary model is employed rather than a stationary one for the PU signal. This model is particularly attractive when the noise is of stationary type [7].

In this article, we assume that the CRs have some knowledge about PU signal and employ cyclostationary feature detection. A robust cyclostationary feature detection algorithm has been introduced in [10] and based on this, some spectrum sensing techniques were proposed [11],[12]. We also employ the algorithm in [10], but improve it by detecting multiple cycles at the same time.

Energy-based spectrum sensing with multiple-antenna CRs has almost been investigated [9]; however, cyclostationarity-based methods with multiple-antenna applications have not been studied so far. By employing multiple antennas at the CR, we can further improve the performance of the proposed spectrum sensing CR. In fact, K receivers, each with an associated antenna, are to be employed in parallel to achieve a diversity gain. We derive closed form expressions for the probabilities of detection and false alarm for multiple-antenna CR based on multi-cycle cyclostationary detection. Also, we simulate the detection performance of the proposed CR in terms of the detection rate given a sustainable false-alarm rate and a certain SNR. Results show that this multiple-antenna CR has good performance even in low SNR regimes. Because of the nature of cyclostationary detection, this device can distinguish among different PUs if their signals have distinct cycle frequencies. These two important requirements could not be satisfied by conventional energy detectors [13], [14]. Therefore, this spectrum sensing scheme is a great improvement over energy-based schemes.

This paper is organized as follows. In Section II, we describe

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the employed detection scheme. In Section III, we propose our multiple-antenna spectrum sensing CR. In Section IV, performance evaluations and comparisons are given. The conclusions are drawn in Section V.

II. Signal Detection Method

The first step in the opportunistic exploitation of radio spectrum is the detection of unused spectral bands, or equivalently, detection of PUs [14]. One solution is that the cognitive radio devices measure the RF energy in a channel or monitors the received signal strength indicator to determine whether the channel is idle or not (energy detection approach). But this approach has a problem in that wireless devices can only sense the presence of a PU if and only if the energy detected is above a certain threshold. It is true that one cannot arbitrarily lower the threshold as this would result in non-detection because of the presence of noise. In the feature detection approach, which has been used in the military to detect the presence of weak signals, the wireless device uses cyclostationary signal processing to detect the presence of primaries. If a signal exhibits strong cyclostationary properties, it can be detected at very low Signal-to-Noise Ratios (SNR) [14].

Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading, hoping sequences, or cyclic prefixes which result in built-in periodicity [1]. Even though the data is a stationary random process, these modulated signals are characterized as cyclostationary, since their statistics, mean and autocorrelation, exhibit periodicity [1]. This periodicity is typically introduced intentionally in the signal format so that a receiver can exploit it for: parameter estimation such as carrier phase, pulse timing, or direction of arrival. This can then be used for detection of a random signal with a particular modulation type in a background of noise and other modulated signals [1]. Therefore, cyclostationarity feature detection can be used for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. A stochastic process is said to be (second-order) cyclostationary (in the wide sense) if its mean and autocorrelation functions are periodic with some period T [15]. Because of the periodicity of the autocorrelation function, with the assumption of its convergence, it can be represented by its Fourier series expansion [15]:

$$R_{xx^*}\left(t+\tau/2,\, t-\tau/2\right)=\sum_{\alpha\in A} R_{xx^*}(\tau)e^{j2\pi\alpha t} \qquad (1)$$

where the sum is taken over the integer multiples of fundamental frequencies α (i.e. $A=\{\alpha=m/T_0\}$, m integer). The coefficients $\{R_{xx^*}(\tau)\}$ are generally referred to as Cyclic Autocorrelation (CA) function and the frequencies α are called cycle frequencies. A process $x(t)$ is said to be exhibited cyclostationarity at cycle frequency α, if $R_{xx^*}(\tau)\neq 0$ [15] for some τ. The discrete-time consistent estimation of this conjugate cyclic autocorrelation function is given as [10], [11],

$$R^{\alpha}_{xx^*}(\nu)\overset{\Delta}{=}\frac{1}{T_0}\sum_{i=1}^{T_0} x[i]x^*[i+\nu]e^{-j2\pi\alpha i} \qquad (2)$$

where ν is the discrete version of the lag parameter τ, $x[i] = x(iT_{st})$ with the sampling time T_{st} . In order to examine for the presence of a cycle frequency in a set of time lags at the same time, we consider multiple values of $\hat{R}^{\alpha}_{xx^*}(\nu)$ rather than a single value [10]. In this article, we deploy the detection algorithm for the fixed set of lags $\{\nu_1, \nu_2, \ldots, \nu_N\}$.

If the hypothesis H_0 represents the case where the PU is not in the frequency band of interest, and the hypothesis H_1 represents the case where the PU is in the band, the signal detection problem can be modeled by a simple binary hypothesis testing problem as follows [13], [14], [7]:

$$\begin{cases} H_0 : y[n]=w[n] \\ H_1 : y[n]=x[n]+w[n] \end{cases} \quad , n=1,2,\ldots,T_0 \qquad (3)$$

where $y[n]$ is received signal at the SU (i.e. CR), $x[n]$ is the transmitted signal from the PU with $E[x[n]]=0$, $w[n]$ is additive white Gaussian noise (AWGN) and T_0 denotes the number of samples. The solution to this problem, largely studied in the past, depends on the degree of knowledge we have on the signal to be detected and/or the noise [7]. In the case of spectrum sensing based on cyclostationarity, the detection problem (3) is reduced to that of testing for the presence of cyclostationarity in the received signal [7]:

$$\begin{cases} \mathrm{H}_0 : \alpha \text{ is not a cycle frequency of } y(n) \\ \mathrm{H}_1 : \alpha \text{ is not a cycle frequency of } y(n) \end{cases} \qquad (4)$$

Several work, and in particular [10], are devoted to this kind of problem and propose various tests of cyclostationarity over a given set of cyclic frequencies. Although the hypothesis testing scheme proposed in [10] is computationally extensive, but this test exhibits good performances and can be applied when the transmission parameters of the PU are known to the CR receiver. For the purpose of testing the hypotheses (4), an algorithm has been deployed in [10] which ends to the following result:

$$\begin{cases} \text{If } \Gamma < \Gamma_{th} \Rightarrow \text{Detector decides hypothesis } \mathrm{H}_0 \\ \text{If } \Gamma > \Gamma_{th} \Rightarrow \text{Detector decides hypothesis } \mathrm{H}_1 \end{cases} \qquad (5)$$

where Γ is the test statistics and Γ_{th} is the threshold of hypothesis testing. Statistical tests for the presence of a single cycle frequency have been proposed in [10], and it is shown that irrespective of the distribution of the input data, the asymptotic distribution of the test statistic Γ under the hypothesis H_0 is central chi-squared with $2N$ degrees of freedom and normal under the hypothesis H_1,

$$\Gamma \sim \begin{cases} \chi^2_{2N} & ,\text{Under hypothesis } \mathrm{H}_0 \\ \mathrm{N}(\mu,\sigma^2) & ,\text{Under hypothesis } \mathrm{H}_1 \end{cases} \qquad (6)$$

where μ and σ^2 are defined, calculated and estimated in [10]. Hence, for a given threshold, the detection probability (P_d) can be calculated regardless of the particular input signal, for large enough observation lengths T_0. In this article, this cyclostationary detection scheme is called single-cycle (SC) detection.

Despite SC detection is much better than energy detection [16], however, by detecting multiple cycles at the same time (MC detection); we can improve the performance of detection. For this end, we propose the following test statistics for MC detection problem:

$$\Gamma_{MC} = \sum_{i=1}^{S} \Gamma^{\alpha_i} \tag{7}$$

where $\{\alpha_i\}_{i=1}^{S}$ are the cycles that we are interested in to detect, Γ^{α_i} is the corresponding test statistic for detecting α_i and S is the number of cycles. We assume that the CA estimates for different candidate cycle frequencies are independent, so the asymptotic distributions of Γ_{MC} are,

$$\Gamma_{MC|H_0} \sim \chi^2_{2NS} \tag{8}$$

$$\Gamma_{MC|H_1} \sim \mathrm{N}\left(\mu_{MC}, \sigma^2_{MC}\right) \tag{9}$$

where $\mu_{MC} = \sum_{i=1}^{S} \mu_i$, $\sigma^2_{MC} = \sum_{i=1}^{S} \sigma_i^2$ and μ_i and σ_i^2 are the parameters of testing for α_i defined in (6).

III. PROPOSED MULTIPLE-ANTENNA COGNITIVE RADIO

As mentioned before, spectrum sensing (SS) is the most important function of a cognitive radio. If CR falsely decides that the PU is not in the band and starts to transmit, it destroys the incumbent signal. Therefore we need an accurate PU detection algorithm. Multiple antennas can be used to exploit the spatial dimension of spectrum space to improve the efficiency. In essence, multi-antenna systems can help to find spectral opportunities in the spatial domain and can help to exploit these opportunities fully [14].

In this section, we present a parallel multiple-antenna spectrum sensing unit based on MC detection. In order to achieve spatial receiver diversity gain, we assume that antennas are separated more than half of the wavelength. First, the primary signal is received and sampled by each antenna and then is passed to a MC detector. At there, the MC detection algorithm is performed and finally, the test statistics is produced. After that, all of the test statistics are summed together and the result is sent to the final decision-making unit. The proposed scheme is illustrated in Fig. 1.

The final test statistics is,

$$\Gamma_{MA} = \sum_{j=1}^{K} \Gamma_{MC_j} \tag{10}$$

where K is the number of antennas. It is obvious that the asymptotic distributions of the Γ_{MA} under the two hypotheses

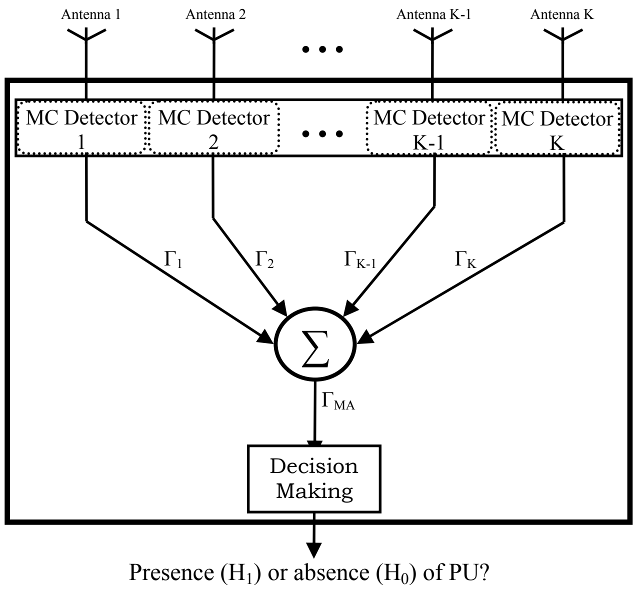

Fig. 1. Proposed multiple-antenna cognitive radio.

are,

$$\Gamma_{MA|H_0} \sim \chi^2_{2NSK} \tag{11}$$

$$\Gamma_{MA|H_1} \sim \mathrm{N}(\mu_{MA}, \sigma^2_{MA}) \tag{12}$$

where,

$$\mu_{MA} = \sum_{j=1}^{K} \mu_{MC_j} \tag{13}$$

$$\sigma^2_{MA} = \sum_{j=1}^{K} \sigma^2_{MC_j} \tag{14}$$

The performance of the proposed scheme can be evaluated by the probabilities of false alarm and detection. In this case, the false alarm probability is calculated as below,

$$\begin{aligned} P_F &= \text{prob}\left\{\Gamma_{MA} > \Gamma_{th} \mid \mathrm{H}_0\right\} \\ &= 1 - \text{prob}\left\{\Gamma_{MA} < \Gamma_{th} \mid \mathrm{H}_0\right\} \\ &= 1 - F(\Gamma_{th}, 2NSK) \end{aligned} \tag{15}$$

where $F(\xi, \rho)$ is the cumulative distribution function of a chi-squared random variable with ρ degrees of freedom at the point ξ which is [17],

$$F(\xi, \rho) = \frac{\gamma(\rho/2, \xi/2)}{\Gamma(\rho/2)} = P(\rho/2, \xi/2) \tag{16}$$

where $\gamma(g,z)$, $P(g,z)$ and $\Gamma(.)$ are the lower incomplete Gamma function, the regularized Gamma function, and the complete Gamma function, respectively. Also, the detection probability is,

$$P_D = prob\{\Gamma_{MA} > \Gamma_{th} | H_1\} \\ = Q\left(\frac{\Gamma_{th} - \mu_{MA}}{\sigma_{MA}}\right) \quad (17)$$

where $Q(z) = \int_z^{\infty} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$.

IV. Simulation Results

In this section, we evaluate the performance of the proposed system. The PU signal is a base-band QPSK signal with symbol rate $1/T_s$. This signal exhibits cyclostationarity with cycle frequencies of $\alpha = m/T_s$, (m = 0, ±1, ±2, …). The cycle frequencies employed by MC detectors are $1/T_s$ and $2/T_s$; and SC (Single-cycle) detectors employ $1/T_s$. All detectors use zero time-lag (v=0). The channels are assumed to be additive white Gaussian noise (AWGN). All the curves are averages over 1000 experiments. Each antenna in CR receives the same PU signal with different AWGN noise (channels are independent). The PU detection scenario is illustrated in Fig. 2.

ROC (Receiver Operating Characteristics) curves are shown in Fig. 3 to validate the proposed spectrum sensing scheme. It is obvious that the use of multiple antennas for sensing significantly improves the performance. In Fig. 4, where both MC and SC detections are assumed, P_D as a function of SNR is illustrated (constant sustainable false alarm rate test with P_F fixed at 0.01). This can be confirmed that not only the MC scheme outperforms the SC one, but also increasing the number of antennas can obtain performance gains. In Fig. 5, we compare the false alarm performance of different number of receive antennas, using both SC and MC detection schemes. In Fig. 6, the PU detection probability is evaluated as a function of number of antennas. It can be seen that the performance is enhanced with the number of receive antennas at the CR. As we can see, initially the slope of the curve increases rapidly, but as the number of antennas exceeds 4, the slope decreases. Particularly, MC detection with 3-antennas CR entails $P_D > 0.9$. Hence, as we can see in the figures, the proposed multiple-antenna cognitive radio improves the efficiency of spectrum usage in comparison to the single- antenna CR. Also, employing 2 antennas at CR results in a considerable improvement of about 0.2 in probability of detection, respective to single-antenna one.

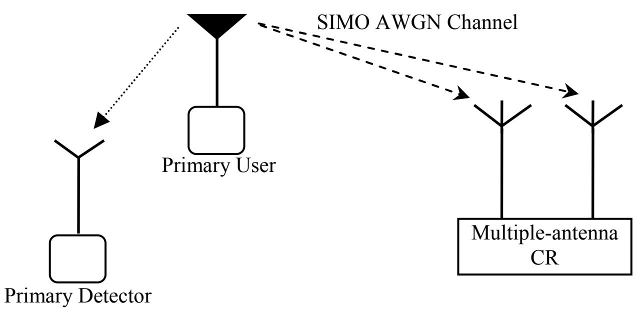

Fig. 2. Spectrum sensing scenario with multiple-antenna CR.

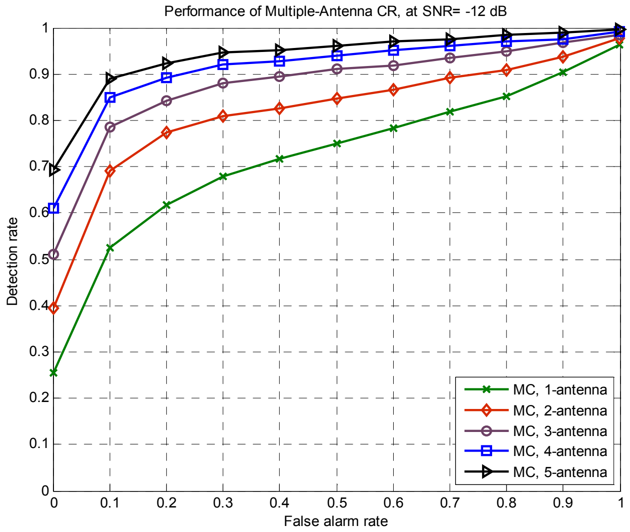

Fig. 3. ROC curves for different number of receive antennas.

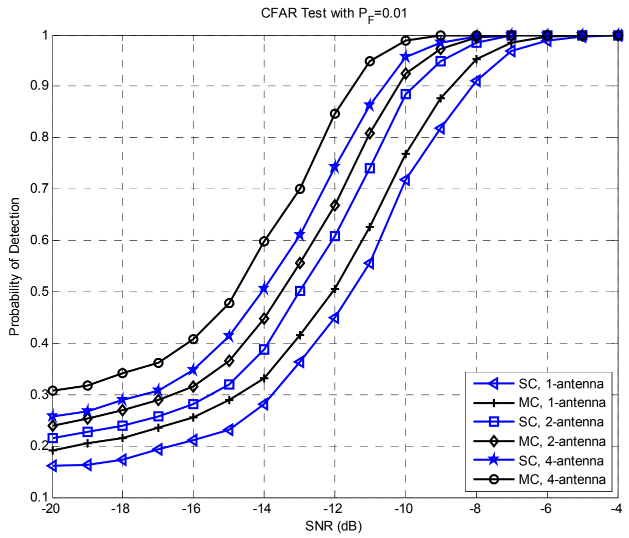

Fig. 4. Detection performance, with P_F=0.01.

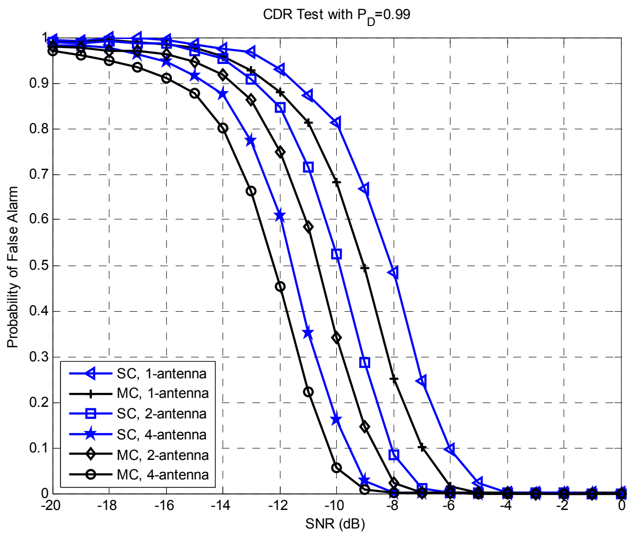

Fig. 5. Simulated probability of false alarm vs. SNR.

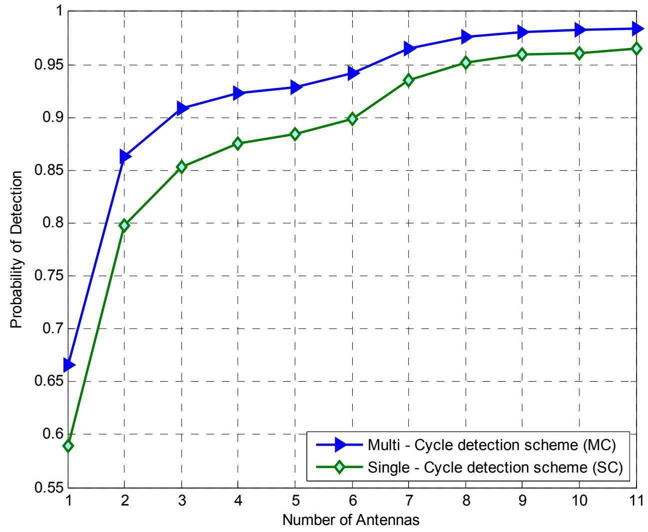

Fig. 6. Detection performance of proposed multiple-antenna CR as the number of antennas increases ($P_F = 0.01$, $SNR = -10$ dB).

V. Concluding Remarks

In this paper, the design of a multiple-antenna cognitive radio for reliable spectrum sensing was considered. At each antenna, a soft decision is made. These decisions are added with unit gains and then sent to a final decision making unit. Each individual receiver employs the proposed multi-cycle detection scheme. Simulation results demonstrate that a considerable detection performance gain is obtained by employing multiple antennas at CR receivers.

VI. Acknowledegment

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