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# Cyclostationarity-Based Cooperative Spectrum Sensing for Cognitive Radio Networks

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*Abstract*— **In order to ensure trustworthy coexistence of unlicensed cognitive radio (CR) networks with licensed primary networks, CR spectrum sensing function must be able to detect licensed users even at very low SNR values. But, non-cooperative spectrum sensing methods are not so reliable and result in a low probability of detection. In this paper, we propose some cooperative detection schemes in order to improve the spectrum sensing performance in the CR networks. Because cyclostationary detectors can differentiate between modulated signals, interference, and noise even in low SNRs; in the proposed method a powerful multi-cycle detector is employed. Results of the simulations show that cooperative sensing based on multi-cycle detection outperforms conventional methods even in low SNR conditions.**

## I. Introduction

Radio transmitters are traditionally restricted to operate within those frequency bands that have been allocated them by regulatory bodies. But with many traditional technologies present, and many new incoming wireless standards, the 1-10 GHz frequency spectrum is expeditiously becoming saturated. The latest measurements, however, disclose that the actual spectrum usage varies between 15% and 85%, based on the location and time of the day [1]. This has put forth the notion of dynamic/opportunistic spectrum use. The enabling technology of this idea, cognitive radio (CR), is an emergent smart wireless communications technology that is capable of identifying temporary unused frequencies (white spaces) and using them opportunistically, until a licensed primary user (PU) needs them. In December 2003, FCC specifies cognitive radio as the candidate for implementing opportunistic spectrum sharing [2]. In response to this, IEEE has established the 802.22 Working Group to develop a standard for wireless regional area networks (WRAN), which reuse the TV bandwidth by CR technology (IEEE 802.22 standard) [3]. In such a network, CRs should be able to jump from a radio frequency band that is occupied by licensee to a free one, to complete a transmission link. This necessity asserts that all the primary signals in secondary networks must be detected reliably. If the CR wrongly concludes that there is no PU in the band and starts transmitting, it will destroy the primary signal.

The primary user's signal might be severely attenuated due to multipath and shadowing before it reaches the secondary user (SU) [4]. This makes difficulties in PU signal detection and as a consequence, each CR must be able to detect very weak PU signals (i.e. in very low SNR regimes) [4]. In the case that there is not sufficient information about the PU signal, the energy detector is employed. But to detect the PU reliably, it may need to receive data over a long period of time. Moreover, it requires the correct estimate of the noise variance to perform properly. At low SNRs, cognitive radio will estimate the noise variance by taking a large number of samples. But there will still be uncertainty in the estimating of the noise variance [4] and the threshold selection for energy detection is highly influenced by the changing background noise and interference level [5]. Another challenging issue in the context of energy detection is that it cannot discriminate between different SUs sharing the same channel [5].

In wireless communication networks, there is usually some information about the statistical or structural properties of the PU signal, including the modulation scheme, coding scheme, symbol rate, pilot signals, etc. [6]. These properties could be exploited in the design of the detectors that operate in very low SNRs. The most important of such detectors is cyclostationary detector [6], [10] that operates much better than energy one, but it is more complex.

Cooperative sensing is the process of making a final decision for the overall network, based on the sensing data collected from spatially distributed secondary users [5], [7]. This scheme can improve the probabilities of detection and false alarm. However, most of the researches in cooperative spectrum sensing are conducted on the basis of energy detection at each node [5], [7], [8]. In this paper, we propose some cooperative sensing algorithms based on cyclostationary detection. Given a target probability of detection for the network, we study the achievable (system-level) false alarm rate in the network. From the other point of view, the usage level of the vacant channels are fixed by setting the false alarm probability at a definite value and then, the detection probability is investigated.

This paper is organized as follows. In Section II, we overview the concept of cyclostationary signals and detection hypothesis. Section III gives the review of proposed cooperative sensing schemes. In Section IV, performance evaluations and comparisons are given. The conclusions are drawn in Section V. Section VII introduces the future works.

## II. Cyclostationary Detection

Most of the signals in wireless communications and radar

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systems can be treated as the cyclostationary random processes [6]. The cyclostationary processes are the random processes in which their statistical properties, such as the mean and autocorrelation, change periodically as a function of time [9]. Examples of the processes that are appropriately modeled as the cyclostationary processes are the familiar modulated signals AM, FM, ASK, PSK, FSK, PAM, OFDM, etc [10]. If the signal of the PU exhibits cyclostationary properties, it can be detected even at very low SNR values [5]. Before dealing with the detection problem, we must overview the concept of the cyclostationarity in order to provide the better understanding of the subsequent sections.

### *A. Cyclostationarity*

The process $x(t)$ is said to be (second-order) cyclostationary (in the wide sense) if its mean and autocorrelation functions are periodic with some period, say $T_0$ [9], [11]. Because of the periodicity of the autocorrelation function, it can be represented by its Fourier series expansion [9]. Therefore, with the assumption of its convergence, we can write:

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

where $R_{xx^*}(t+\tau/2,t-\tau/2)$ is the conjugate auto-correlation function and the sum is taken over the integer multiples of fundamental frequencies $\alpha$ (i.e. $A=\{\alpha=m/T_0\}$, $m$ integer). The Fourier coefficients, which depend on the lag parameter $\tau$, can be calculated as [9]:

$$R_{xx^*}^{\alpha}(\tau)\overset{\Delta}{=}\frac{1}{T_0}\int_{-T_0/2}^{T_0/2}R_{xx^*}\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)e^{-j2\pi\alpha t}\,dt \tag{2}$$

These coefficients are generally referred to as Cyclic Autocorrelation (CA) function and the frequencies $\alpha$ are called cycle frequencies. More generally, a stochastic process $x(t)$ is said to be exhibited cyclostationarity at cycle frequency $\alpha$, if $R_{xx^*}(\tau)\neq 0$ [9].

### *B. Detection Algorithm*

The discrete-time version of the consistent estimation of the conjugate cyclic autocorrelation function is given as [10]:

$$\hat{R}_{xx^*}^{\alpha}(\nu)\overset{\Delta}{=}\frac{1}{T_0}\sum_{i=1}^{T_0}x(i)x^*(i+\nu)e^{-j2\pi\alpha i} \tag{3}$$

$$=R_{xx^*}^{\alpha}(\nu)+\Delta_{xx^*}^{\alpha}(\nu) \tag{4}$$

where $\nu$ is the discrete version of the lag parameter $\tau$, $x[i]=x(iT_{st})$ with the sampling time $T_{st}$ and $\Delta_{xx^*}^{\alpha}(\nu)$ is the estimation error, which vanishes as $T_0\to\infty$ [10], [11]. In order to examine for the presence of a cycle frequency in a set of time lags $\nu$ at the same time, we consider multiple values of $\hat{R}_{xx^*}^{\alpha}(\nu)$ rather than a single value [11]. Using the fixed set of lags $\{\nu_1, \nu_2, \ldots, \nu_N\}$, we defined a row vector consisting of conjugate cyclic autocorrelation estimates at the candidate cycle frequency $\alpha=\alpha_0$ (Re{} and Im{} are the real and imaginary parts, respectively):

$$\begin{aligned}\hat{r}_{xx^*}\overset{\Delta}{=}\Big[&\operatorname{Re}\{\hat{R}_{xx^*}^{\alpha}(\nu_1)\},\ldots,\operatorname{Re}\{\hat{R}_{xx^*}^{\alpha}(\nu_N)\},\\&\operatorname{Im}\{\hat{R}_{xx^*}^{\alpha}(\nu_1)\},\ldots,\operatorname{Im}\{\hat{R}_{xx^*}^{\alpha}(\nu_N)\}\Big]_{1\times 2N}\end{aligned} \tag{5}$$

The true value of the above vector is then [11],

$$\begin{aligned}r_{xx^*}\overset{\Delta}{=}\Big[&\operatorname{Re}\{R_{xx^*}^{\alpha}(\nu_1)\},\ldots,\operatorname{Re}\{R_{xx^*}^{\alpha}(\nu_N)\},\\&\operatorname{Im}\{R_{xx^*}^{\alpha}(\nu_1)\},\ldots,\operatorname{Im}\{R_{xx^*}^{\alpha}(\nu_N)\}\Big]_{1\times 2N}\end{aligned} \tag{6}$$

and the estimation error vector is [11],

$$\begin{aligned}\underline{\Delta}_{xx^*}\overset{\Delta}{=}\Big[&\operatorname{Re}\{\Delta_{xx^*}^{\alpha}(\nu_1)\},\ldots,\operatorname{Re}\{\Delta_{xx^*}^{\alpha}(\nu_N)\},\\&\operatorname{Im}\{\Delta_{xx^*}^{\alpha}(\nu_1)\},\ldots,\operatorname{Im}\{\Delta_{xx^*}^{\alpha}(\nu_N)\}\Big]_{1\times 2N}\end{aligned} \tag{7}$$

Hence, we can write [11],

$$\hat{r}_{xx^*}=r_{xx^*}+\underline{\Delta}_{xx^*} \tag{8}$$

It is shown that [10],[11]:

$$\lim_{T_0\to\infty}\sqrt{T_0}\,\underline{\Delta}_{xx^*}\overset{D}{=}\mathrm{N}(0,\Sigma_{xx^*}) \tag{9}$$

where $\overset{D}{=}$ denotes the convergence in distribution and $\mathrm{N}(0,\Sigma_{xx^*})$ is a multivariate normal distribution with zero mean and covariance matrix $\Sigma_{xx^*}$ which is given by [11]:

$$\Sigma_{xx^*}=\begin{bmatrix}\operatorname{Re}\left\{\dfrac{Q+Q^{(*)}}{2}\right\} & \operatorname{Im}\left\{\dfrac{Q-Q^{(*)}}{2}\right\}\\ \operatorname{Im}\left\{\dfrac{Q+Q^{(*)}}{2}\right\} & \operatorname{Re}\left\{\dfrac{Q^{(*)}-Q}{2}\right\}\end{bmatrix} \tag{10}$$

The $(m,n)^{th}$ entries of the complex covariance matrices $Q^{(*)}$ and $Q$ can be approximated as [11]:

$$\begin{aligned}\hat{Q}(m,n)\approx\frac{1}{T_0L}\sum_{s=-(L-1)/2}^{(L-1)/2}\Big(&W(s)\times\\&F_{\nu_n}\left(\alpha-\frac{2\pi s}{T_0}\right)\times F_{\nu_m}\left(\alpha+\frac{2\pi s}{T_0}\right)\Big)\end{aligned} \tag{11}$$

and,

$$\begin{aligned}\hat{Q}^{(*)}(m,n)\approx\frac{1}{T_0L}\sum_{s=-(L-1)/2}^{(L-1)/2}\Big(&W(s)\times\\&F_{\nu_n}^{*}\left(\alpha+\frac{2\pi s}{T_0}\right)\times F_{\nu_m}\left(\alpha+\frac{2\pi s}{T_0}\right)\Big)\end{aligned} \tag{12}$$

where $W(s)$ is a spectral window of length $L$ (odd) and,

$$f_{\nu}[i] = x[i] \times x[i+\nu] \tag{13}$$

If the hypothesis $H_0$ represents the case where the PU signal is not present, and the hypothesis $H_1$ represents the case where the PU signal is present, we can formulate the following binary hypothesis testing problem based on (8) [10], [11]:

$$\begin{cases} H_0 : \alpha \text{ not a cycle frequency} \Rightarrow \hat{r}_{xx^*} = \underline{\Delta}_{xx^*} \\ H_1 : \alpha \text{ a cycle frequency} \quad \Rightarrow \hat{r}_{xx^*} = r_{xx^*} + \underline{\Delta}_{xx^*} \end{cases} \tag{14}$$

or in the other word,

$$\begin{cases} H_0 : \alpha \notin \mathrm{A}, \forall \{\nu_n\}_{n=1}^{N} \quad \Rightarrow \hat{r}_{xx^*} = \underline{\Delta}_{xx^*} \\ H_1 : \alpha \in \mathrm{A}, \text{for some} \{\nu_n\}_{n=1}^{N} \quad \Rightarrow \hat{r}_{xx^*} = r_{xx^*} + \underline{\Delta}_{xx^*} \end{cases} \tag{15}$$

Since $r_{xx^*}$ is non-random, the distribution of $\hat{r}_{xx^*}$ under $H_0$ and $H_1$ differs only in mean. The asymptotic complex normality of $\hat{r}_{xx^*}$ allows the formulation of the following generalized likelihood function as the test statistic for the binary hypothesis test [11]:

$$\Gamma_{xx^*} = T_0 \hat{r}_{xx^*} \hat{\Sigma}_{xx^*}^{-1} \hat{r}_{xx^*}^{t} \tag{16}$$

where $t$ denotes the transpose of the matrix and the estimated covariance matrix is represented by $\hat{\Sigma}_{xx^*}$. To set a threshold for hypothesis testing, we need the asymptotic distribution of $\Gamma_{xx^*}$. In [11], it is shown that the asymptotic distribution of the test statistic under the hypothesis $H_0$ is central chi-squared with $2N$ degrees of freedom (irrespective of the distribution of the input data):

$$\lim_{T_0 \to \infty} \Gamma_{xx^*} \overset{D}{=} \chi_{2N}^2 \tag{17}$$

and under the hypothesis $H_1$ it has the normal asymptotic distribution:

$$\begin{aligned} \lim_{T_0 \to \infty} \Gamma_{SC-CSD} &\overset{D}{=} \lim_{T_0 \to \infty} \sqrt{T_0} \left( \hat{r}_{xx^*} \hat{\Sigma}_{xx^*}^{-1} \hat{r}_{xx^*}^{t} - r_{xx^*} \Sigma_{xx^*}^{-1} r_{xx^*}^{t} \right) \\ &= \mathrm{N}\left(0, 4 r_{xx^*} \Sigma_{xx^*}^{-1} r_{xx^*}^{t}\right) \end{aligned} \tag{18}$$

For $T$ large enough, we may approximately write the distribution of $\Gamma_{xx^*}$ as [11]:

$$\Gamma_{xx^*} \sim \mathrm{N}\left(T_0 r_{xx^*} \Sigma_{xx^*}^{-1} r_{xx^*}^{t}, 4 T_0 r_{xx^*} \Sigma_{xx^*}^{-1} r_{xx^*}^{t}\right) \tag{19}$$

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 practice, the probability of detection can be evaluated by substituting for $r_{xx^*}$ and $\Sigma_{xx^*}$ in (19) by their estimates [11].

### *C. Multi-Cycle Detection*

Simultaneous detection of multiple cycle frequencies can improve performance of the detector [13]. In order to detecting multiple cycle frequencies of interest $\alpha$ at the same time, we propose the following test statistics:

$$\Gamma_{M.C.} = \sum_{\alpha_i} \Gamma_{xx^*}^{\alpha_i} \qquad , i = 1, 2, \ldots, s \tag{20}$$

We assume that the CA estimates for different candidate cycle frequencies are independent, so the asymptotic distribution of $\Gamma_{M.C.}$ under the null hypothesis is $\chi_{2N.S}^2$, where $S$ is the number of cyclic frequencies to be tested, and under the hypothesis $H_1$ is normally distributed. This detector is the one that we employ in each CR node of the network.

## III. COOPERATIVE DETECTION

Cooperative communications has been recently recognized as a powerful solution that can conquer some limitations in wireless systems. Specially, in view of the low reliability of single SU sensing, a cooperative spectrum sensing scheme is employed [5], [7], [8]. Cooperative sensing is done by combining the individual observations of SUs and making a final decision at the secondary BS. This procedure is somewhat analogous to distributed decision making in wireless sensor networks (WSNs) [12], where each sensor makes a local decision based on its own observations and those decision results are reported to a Fusion Center (FC) to give a final decision under some fusion rule. In this paper, the fusion center is a secondary access point (AP) in a wireless LAN or a secondary base station (BS) in a cellular network.

We consider two decision combining techniques at the secondary base station. Cooperative spectrum sensing will go through two successive channels, first the sensing channel (from the PU to CRs); and second the reporting channel (from the CRs to the secondary BS). Perfect reporting channels are assumed for simplicity.

### *A. Soft Decision Combining (SDC)*

In SDC cooperative detection, each CR forwards its decision statistics to the secondary BS. Based on these statistics, BS makes the final decision about the spectrum occupancy. In this case, we simply propose the following cyclostationary based test statistic for the hypothesis testing problem at the BS:

$$\Gamma_{SDC} = \sum_{j=1}^{N_c} \Gamma_{M.C_j}(j) \tag{21}$$

It is obvious that with the assumption of conditional independence, the asymptotic distribution of the test statistic $\Gamma_{SDC}$ is chi-squared under the null hypothesis, with $2NSN_c$ degrees of freedom ( $\chi_{2NSN_c}^2$ ).

### *B. Hard Decision Combining (HDC)*

In SDC scheme, as the number of cognitive radios increases, reporting their sensing results to the common receiver will require much bandwidth. But if CRs process their own observations and then transmit condensed information to the BS, the required bandwidth decreases (Fig. 1). This scheme is recognized as the parallel distributed detection [12].

Assuming that there are $N_c$ cognitive radios and each one performs local spectrum measurements independently, then the binary decisions are as follow:

$$q_i = \begin{cases} 1 & \text{, if i}^{th} \text{ CR decides } \mathrm{H}_1 \\ 0 & \text{, if i}^{th} \text{ CR decides } \mathrm{H}_0 \end{cases} \quad , i = 1,2,...,N_c \qquad (22)$$

Afterwards, all the CRs forward their binary decisions to the secondary BS. Then the secondary BS combines those binary decisions and according to a fusion rule makes a final decision $q_0$ to infer the absence or presence of the PU in the observed band [5], [12]. The fusion rule is a logical function with $N_c$ binary inputs and one binary output of the BS:

$$q_0 = \begin{cases} 1 & \text{, if } \mathrm{H}_1 \text{ decided at the BS} \\ 0 & \text{, if } \mathrm{H}_0 \text{ decided at the BS} \end{cases} \qquad (23)$$

Hence there are $2^{2^{N_c}}$ different fusion rules. The optimum decision fusion rule is Chair-Varshney rule, which is based on log-likelihood ratio test [8]. However to avoid complexity in secondary BS we propose the following suboptimum Max rule for hypothesis testing problem at the secondary BS:

$$\begin{cases} \text{if } \ max\,\{q_1, q_2, ..., q_{N_c}\} = 0 \ \Rightarrow \text{BS decides } H_0 \\ \text{if } \ max\,\{q_1, q_2, ..., q_{N_c}\} = 1 \ \Rightarrow \text{BS decides } H_1 \end{cases} \qquad (24)$$

If $P_{M_j}$ and $P_{fa_j}$ be the probabilities of miss detection and false alarm for the $j^{\text{th}}$ CR, with the assumption of independence of different decisions, we can formulate the probability of detection of the network as follows:

$$\begin{aligned} P_d &= \text{Prob}(max\,\{q_1, q_2, \ldots, q_{N_c}\} = 1 | H_1) \\ &= 1 - \text{Prob}(max\,\{q_1, q_2, \ldots, q_{N_c}\} = 0 | H_1) \\ &= 1 - \text{Prob}(q_1 = 0 | H_1) \times \cdots \times \text{Prob}(q_{N_c} = 0 | H_1) \\ &= 1 - P_{M_1} \times P_{M_2} \times \cdots \times P_{M_{N_c}} = 1 - \prod_{i=1}^{N_c} \left(1 - P_{d_i}\right) \end{aligned} \qquad (25)$$

Similarly, we can derive:

$$P_{fa} = 1 - \prod_{i=1}^{N_c} \left(1 - P_{fa_i}\right) \qquad (26)$$

If a guaranteed usability rate of vacant channels is needed, the $P_{fa}$ of the network has to be fixed and the $P_d$ of the network is maximized as much as possible. This is referred to as constant false alarm rate (CFAR) requirement. In the Max

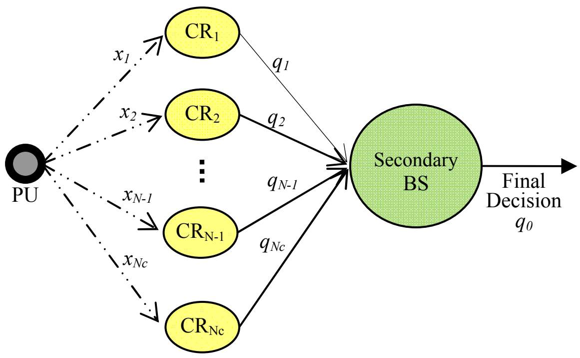


Fig. 1. Parallel centralized PU detection scheme. The k$^{\text{th}}$ local CR observes $x_k$ and sends its decision $q_k$ to the BS.

fusion rule, to achieve a target probability of false alarm for the network ($P_{fa}$), we propose that the individual SUs satisfy the following average probability of false alarm, $\overline{P}_{fa_i}$ (is drawn from (26)),

$$\overline{P}_{fa_i} = 1 - \sqrt[N_c]{1 - P_{fa}}\,, \quad i = 1,2,\ldots,N_c \qquad (27)$$

From the other point of view, the probability of detection can be fixed at a target value $P_d$. This is defined as constant detection rate (CDR) requirement. Using the Max rule at the BS, we can set the individual SUs' average probability of detection as,

$$\overline{P}_{d_i} = 1 - \sqrt[N_c]{1 - P_d}\,, \quad i = 1,2,\ldots,N_c \qquad (28)$$

Therefore the proposed HDC scheme, in spite of SDC approach, lowers the sensitivity requirements on individual CRs.

## IV. Simulation Results

In this section we present some computer simulation results to evaluate the performance of proposed algorithms under both CFAR and CDR requirement. Also these results demonstrate the performance of the multi-cycle (MC) cyclostationary based cooperative spectrum sensing in the low SNR conditions. The test signal is a base-band QPSK signal with symbol rate $1/T_s$. This signal exhibits cyclostationarity with cycle frequencies of $\alpha = k/T_s$, k = 0, ±1, ±2, … . The cycle frequencies employed by the detectors are $1/T_s$ and $2/T_s$. Single-cycle (SC) detectors use $1/T_s$ and multi-cycle detectors use both. Each detector uses zero time-lag ($\nu$=0). Performances of cyclostationary detectors are examined in additive white Gaussian noise (AWGN) channel. All the curves are averages over 1500 experiments. Five CRs are assumed in the network and each one receives the same PU signal with different AWGN noise.

The Performances of the different cooperative and non-cooperative techniques are compared in Fig. 2 (at low SNR conditions). This figure, which is known as the receiver operating characteristics (ROC), plots the probability of detection versus the probability of false alarm for SNR of -12 dB. Results indicate that the performance of the cooperative techniques is better than the single node schemes. Also, the multi-cycle detections lead to higher performance.

Furthermore, hard decision combining centralized detection has the best performance. The probability of detection $P_d$ versus SNR for different schemes is given in Fig. 3. The local and global decision thresholds of the SDC are chosen based on constant false alarm (CFAR) test, such that $P_{fa}$ = 0.03. But in the case of HDC, the probability of false alarm for the network is set to 0.03 and local probabilities of false alarm for CRs computed by equation (27). The results demonstrate an improvement in the probability of detection when cooperative schemes are used and specially, hard decision combining achieves the best performance for all SNRs. In either cooperative or non-cooperative spectrum sensing, it is the multi-cycle detector that has better performance than the single-cycle detector. Results of the CDR test are given in Fig. 4. The target probability of detection $P_d$ of the network is set at 0.99.

In this case, HDC has higher probability of false alarm than the SDC. But the bandwidth required for HDC is much lower than the other scheme, so the HDC is of interest. Fig. 5 illustrates HDC cooperative sensing in a network with different number of SUs. We can see that the detection performance improves, when the number of collaborating SUs increaseses. Finally, Fig. 6 represents the detection probability of the overall network when the number of cooperating SUs in the network increases (SNR = -12 dB).

## V. Concluding Remarks

As the interest in the cognitive radio technology has been exploded recently, the proper spectrum sensing functionality has been recognized as a key issue. In this paper, two cooperative detection schemes based on cyclostationarity have

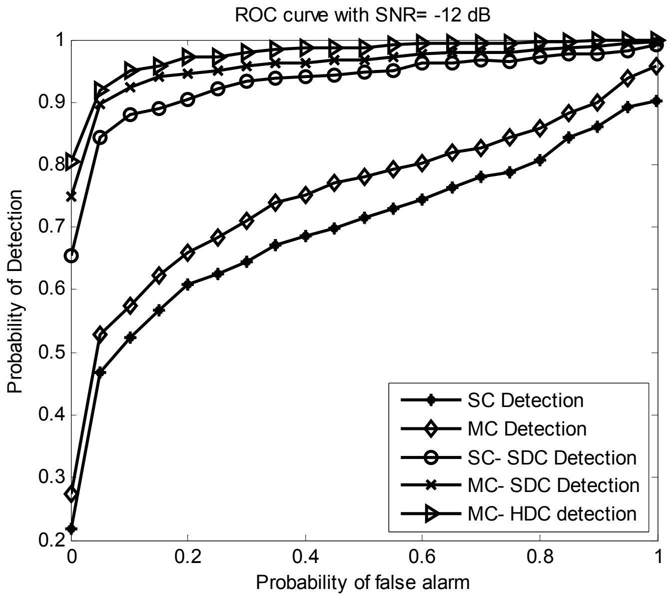


Fig. 2. ROC curve for different detection proposed methods.

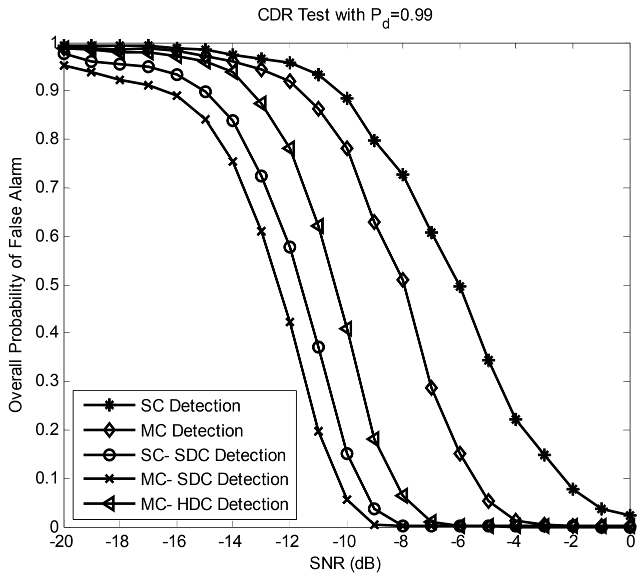


Fig. 4. False alarm probability of network as the SNR increases.

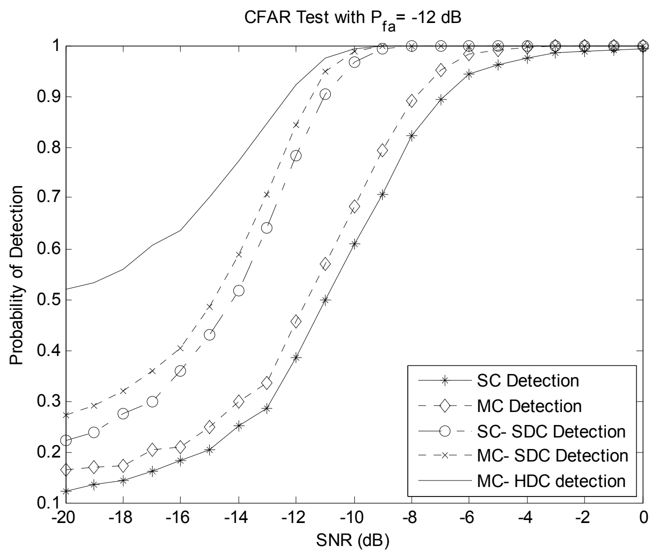


Fig. 3. Probability of detection of the network versus SNR, with fixed probability of false alarm, $P_{fa}$=0.03.

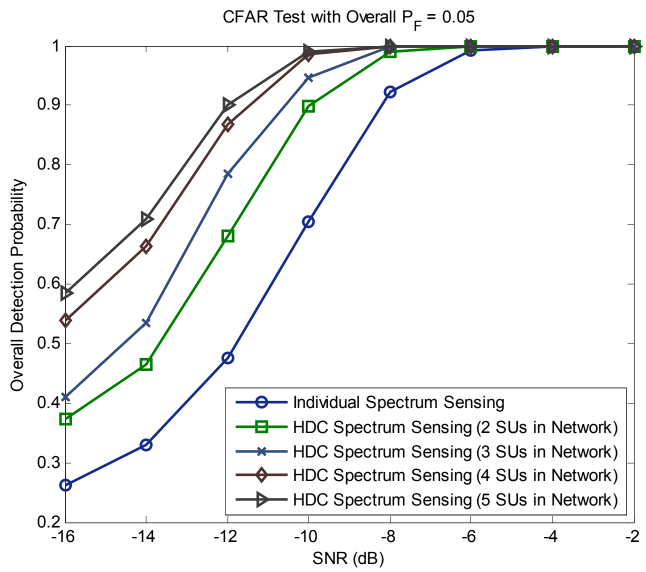


Fig. 5. Detection performance of the secondary network for different number of cooperating SUs.

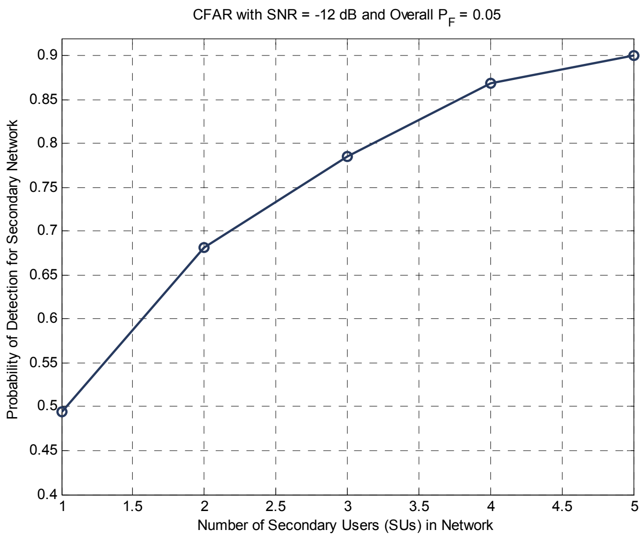


Fig. 6. Detection probability vs. the number of collaborating SUs.

been proposed. The proposed schemes improve the overall reliability of the network (due to cooperative sensing) and can achieve significant performance gains in the low SNR regimes (due to cyclostationary detection). Simulation results confirm this reality.

## VI. Future works

The cooperation scheme we studied here is a form of centralized detection. Future efforts will focus on decentralized schemes, and studying cooperative sensing between multiple-antenna CRs.

## VII. Acknowledegment

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## References

[1] FCC, *Spectrum Policy Task Force Report*, ET Docket No. 02-155, Nov. 2002.

[2] FCC, "Facilitating Opportunities for Flexible, Efficient, and Reliable spectrum Use Employing Cognitive Radio Technologies, Notice of Proposed Rule Making and Order, FCC 03-322," Dec. 2003.

[3] Y. Zeng, Y. C. Liang, "Covariance Based Signal Detection for Cognitive Radios," $2^{nd}$ *IEEE Int. Symp. on New Frontiers in Dynamic Spectrum Access Networks (DySPAN)*, pp. 202-207, Apr. 2007.

[4] R. Tandra and A. Sahai, "Fundamental Limits on Detection in Low SNR Under Noise Uncertainty," *Proc. Wireless Commun. Symp. on Signal Processing*, 2005.

[5] E Hossain, V. K. Bhargava, *Cognitive Wireless Communication Networks*, Springer US, 2007.

[6] N. Han; S. H. Shon, J. H. Chung; J. M. Kim, "Spectral Correlation Based Signal Detection Method for Spectrum Sensing, in IEEE 802.22 WRAN Systems," *8th Int. Conf. on Advanced Communication Technology (ICACT)*, Vol. 3, pp. 6-11, Feb. 2006.

[7] A. Ghasemi and E. S. Sousa, "Opportunistic Spectrum Access in Fading Channels Through Collaborative Sensing," *Journal of Communications*, VOL.2, NO.2, pp.71-82, Mar. 2007.

[8] E. Peh and Y. C. Liang, "Optimization for Cooperative Sensing in Cognitive Radio Networks," *IEEE Wireless Commun. and Networking Conf. (WCNC 2007)*, pp. 27-32, March 2007.

[9] W. A. Gardner, A. Napolitano and L. Paura, "Cyclostationarity: Half a Century of Research," *Signal Processing*, Vol. 86., pp. 639-697, Apr. 2006.

[10] M. Oner and F. Jondral, "Cyclostationarity-Based Methods for the Extraction of the Channel Allocation Information in a Spectrum Pooling System," *IEEE Conf. on Radio and Wireless*, pp.279-282, Sept. 2004.

[11] A. V. Dandawat´e and G. B. Giannakis, "Statistical Tests for Presence of Cyclostationarity," *IEEE Trans. On Signal Processing*, vol. 42, no. 9, pp. 2355–2369, Sep. 1994.

[12] C. Sun, W. Zhang and K. B. Letaief, "Cooperative Spectrum Sensing for Cognitive Radios Under Bandwidth Constraint," *IEEE Wireless Commun. and Networking Conf. (WCNC 2007)*, pp. 1-5, Mar. 2007.

[13] J. Lunden, V. Koivunen, A. Huttunen, and H. V. Poor, "Spectrum Sensing in Cognitive Radios Based on Multiple Cyclic Frequencies," in press. , Available: http://arxiv.org/ abs/0707.0909v1.