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Novel Spectrum-Sensing Algorithms for Cognitive Radio Based on with and without Signal Information

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ABSTRACT

In first module presents a spectrum monitoring algorithm for Orthogonal Frequency Division Multiplexing (OFDM) based cognitive radios by which the primary user reappearance can be detected during the secondary user transmission. The proposed technique reduces the frequency with which spectrum sensing must be performed and greatly decreases the elapsed time between the start of a primary transmission and its detection by the secondary network. In second module the statistical covariance of the received signal and noise are usually different, they can be used to differentiate the case where the primary user's signal is present from the case where there is only noise. In second module, spectrum-sensing algorithms are proposed based on the sample covariance matrix calculated from a limited number of received signal samples. Two test statistics are then extracted from the sample covariance matrix. A decision on the signal presence is made by comparing the two test statistics. Theoretical analysis for the proposed algorithms is given. Detection probability and the associated threshold are found based on the statistical theory. The methods do not need any information about the signal, channel, and noise power a priori. In addition, no synchronization is needed. Simulations based on narrow-band signals, captured digital television (DTV) signals, and multiple antenna signals are presented to verify the methods.

KEYWORDS: *Communication, communication channels, covariance matrices, signal detection, signal processing.*

I. Introduction

Nowadays, static spectrum access is the main policy for wireless communications. Under this policy, fixed channels are assigned to licensed users or primary users (PUs) for exclusive use while unlicensed users or secondary users (SUs) are prohibited from accessing those channels even when they are unoccupied. The idea of a cognitive radio (CR) was proposed to achieve more efficient utilization of the RF spectrum [1]. One of the main approaches utilized by cognitive networks is the overlay network model [2] in which SUs seek to opportunistically use the spectrum when the PUs are idle. Primary and secondary users are not allowed to operate simultaneously. In this method, secondary users must sense the spectrum to detect whether it is available or not prior to communication. If the PU is idle, the SU can then use the spectrum, but it must be able to detect very weak signals from the primary user by monitoring the shared band to quickly vacate the occupied spectrum. During this process, the CR system may spend a long time, known as the sensing interval, during which the secondary transmitters are silent while the frequency band is sensed. Since the CR users do not utilize the spectrum during the detection time, these periods are also called quiet periods (QPs) [3]. In the IEEE 802.22 system, a quiet period consists of a series of consecutive spectrum sensing intervals using energy detection to determine if the signal level is higher than a predefined value, which indicates a non-zero probability of primary user transmission. The energy detection is followed by feature detection to distinguish whether the source of energy is a primary user or noise [4], [5]. This mechanism is repeated periodically to monitor the spectrum. Once the PU is detected, the SU abandons the spectrum for a finite period and chooses another valid spectrum band in the spectrum pool for communication.

OFDM is a multi-carrier modulation technique that is used in many wireless systems and proven as a reliable and effective transmission method. For these reasons, OFDM is utilized as the physical layer modulation technique for many wire- less systems including DVB-T/T2, LTE, IEEE 802.16d/e, and IEEE 802.11a/g. Similar to other wireless networks, OFDM is preferred for cognitive networks and has been already in use for the current cognitive standard IEEE 802.22. On the other hand, OFDM systems have their own challenges that need special treatment [10]. These challenges include its sensitivity to frequency errors and the large dynamic range of the time domain signal. Moreover, the finite time-window in the receiver DFT results in a spectral leakage from any in-band and narrow band signal onto all OFDM sub-carriers.

The paper is organized as follows. Section II summarizes the overall system model. In Section III, the *energy ratio* technique is discussed. In addition, we present performance analysis for AWGN channels under perfect synchronization and neglecting power leakage in Section IV. OFDM challenges and non-perfect synchronization environment are considered in Section V. Further, we extend the analysis and study to frequency selective fading channels and multi-antenna systems in Section VI. The complexity of the *energy ratio* is analyzed and architecture is also proposed in Section VII. Finally, the performance is evaluated with computer simulations in Section VIII.

II. Covariance-Based Detections

Let $x_c(t)=s_c(t)+\eta_c(t)$ be the continuous-time received signal, where $s_c(t)$ is the possible primary users signal and $\eta_c(t)$ is the noise. $\eta_c(t)$ is assumed to be a stationary processsatisfying $E(\eta_c(t))=0$, and $E(\eta^2{}_c(t))=\sigma^2{}_\eta$,and $E(\eta_c(t)\eta_c(t+\tau))=0$ for any $\tau\neq 0$. Assume that we are interested in thefrequency band with central frequency f_c and bandwidth W. We sample the received signal at a sampling rate f_s where $f_s\geq W$. Let $T_s=\frac{1}{f_s}$ be the sampling period. For notationsimplicity, we define $x(n)\triangleq x_c(nT_s)$, $s(n)\triangleq s_c(nT_s)$,and $\eta(n)\triangleq\eta_c(nT_s)$ .There are two hypotheses: 1) H_o ,i.e., thesignal does not exist, and 2) H_1, i.e., the signal exists. The received signal samples under the two hypotheses are given by [11], [12], [15], and [16]

$$\mathrm{H}_o : x(n)=\eta(n) \quad (1)$$

$$\mathrm{H}_1 : x(n)=s(n)+\eta(n) \quad (2)$$

respectively, where $s(n)$ is the transmitted signal samples that passed through a wireless channel consisting of path loss, multipath fading, and time dispersion effects; and $\eta(n)$ is the white noise, which is i.i.d., having mean zero and variance $\sigma^2{}_\eta$. Note that $s(n)$ can be the superposition of the received signals from multiple primary users. No synchronization is needed here.

Two probabilities are of interest for spectrum sensing: 1) probability of detection P_d which defines, at hypothesis H_1, the probability of the sensing algorithm having detected the presence of the primary signal, and 2) probability of false alarm P_{fa} which defines, at hypothesis H_o, the probability of thesensing algorithm claiming the presence of the primary signal.

A. CAV Detection

Let us consider L consecutive samples and define the follow-ing vectors:

$$x(n) = \begin{bmatrix} x(n) & x(n-1) & \dots & x(n-L+1) \end{bmatrix}^T$$

$$s(n) = \begin{bmatrix} s(n) & s(n-1) & \dots & s(n-L+1) \end{bmatrix}^T$$

$$\eta(n) = \begin{bmatrix} \eta(n) & \eta(n-1) & \dots & \eta(n-L+1) \end{bmatrix}^T$$

Parameter L is called the smoothing factor in the following. Considering the statistical covariance matrices of the signal and noise defined as

$$R_x = E\left[x(n)x^T(n)\right] \qquad (6)$$

$$R_s = E\left[s(n)s^T(n)\right] \qquad (7)$$

We can verify that

$$R_x = R_s + \sigma_\eta^2 \mathrm{I}_L \qquad (8)$$

If signal $s(n)$ is not present, $R_s = 0$. Hence, the off-diagonal elements of Rx are all zeros. If there is a signal and the signal samples are correlated, R_s is not a diagonal matrix. Hence, some of the off-diagonal elements of R_x should be nonzeros. Denote r_{nm} as the element of matrix Rx at the nth row and mth column, and let

$$T_1 = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}| \qquad (9)$$

$$T_2 = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}| \qquad (10)$$

Then, if there is no signal, T1/T2 = 1. If the signal is present, T1/T2>1. Hence, ratio T1/T2can be used to detect the presence of the signal.

In practice, the statistical covariance matrix can only be calculated using a limited number of signal samples. Define the sample autocorrelations of the received signal as

$$\lambda(l) = \frac{1}{N_S}\sum_{m=0}^{N_S-1} x(m)x(m-l), \qquad l = 0,1,\dots\dots,L-1$$

where N_s is the number of available samples. Statistical covariance matrix R_x can be approximated by thesample covariance matrix defined as

$$\hat{R}_x(N_s) = \begin{bmatrix} \lambda(0) & \lambda(1) & \dots & \lambda(L-1) \\ \lambda(1) & \lambda(0) & \dots & \lambda(L-2) \\ \vdots & \vdots & \ddots & \vdots \\ \lambda(L-1) & \lambda(L-2) & \dots & \lambda(0) \end{bmatrix}$$

Note that the sample covariance matrix is symmetric and Toeplitz. Based on the sample covariance matrix, we propose the following signal detection method:

Algorithm 1: Covariance Absolute Value (CAV) DetectionAlgorithm

Step 1) Sample the received signal, as previously described.

Step 2) Choose a smoothing factor L and a threshold γ_1, where γ_1 should be

Chosen to meet the requirement for the probability of false alarm. This will be discussed in the next section.

Step 3) Compute the autocorrelations of the received signal $\lambda(l), l = 0,1,\dots\dots,L-1$, and form the sample co-variance matrix.

Step 4) compute

$$T_1(N_s) = \frac{1}{L}\sum_{n=1}^{L}\sum_{m=1}^{L}|r_{nm}(N_s)| \qquad (13)$$

$$T_2(N_s) = \frac{1}{L}\sum_{n=1}^{L}|r_{nn}(N_s)| \qquad (14)$$

Where $r_{nn}(N_s)$ are the elements of the sample covariance matrix $\hat{R}_x(N_s)$.

Step 5) Determine the presence of the signal based on $T_1(N_s)$, $T_2(N_s)$, and threshold γ_1.That is, if $T_1(N_s)/T_2(N_s) > \gamma_1$,the signal exists; otherwise, the signal does not exist.

B. Theoretical Analysis for the CAV Algorithm

The proposed method only uses the received signal samples. It does not need any information of the signal, channel, and noise power *a priori*. In addition, no synchronization is needed. The validity of the proposed CAV algorithm relies on the assumption that the signal samples are correlated, i.e., R_s is not a diagonal matrix. (Some of the off-diagonal elements of R_s should be non zeros.) Obviously, if signal samples $s(n)$ are i.i.d., then $R_s = \sigma_s^2 \mathrm{I}_L$. In this case, the assumption is invalid, and the algorithm cannot detect the presence of the signal.

However, usually, the signal samples should be correlated due to three reasons.

1)The signal is oversampled. Let T_0 be the Nyquistsam-pling period of signal $s_c(t)$ and $s_c(nT_0)$ be the sampled signal based on the Nyquist sampling rate. Based on the sampling theorem, signal $s_c(t)$ can be expressed as

$$s_c(t) = \sum_{n=-\infty}^{\infty} s_c(nT_o) g(t - nT_o) \quad (15)$$

Where $g(t)$ is an interpolation function. Hence, the signal samples $s(n) = s_c(nT_s)$ are only related to $s_c(nT_0)$. If the sampling rate at the receiver $f_s > 1/T_0$, i.e., $T_s < T_0$, then, $s(n) = s_c(nT_s)$ must be correlated. An example of this is a narrow-band signal, such as the wireless microphone signal. In a 6-MHz-bandwidth TV band, a wireless microphone signal only occupies about 200 kHz. When we sample the received signal with a sampling rate of not lower than 6 MHz, the wireless microphone signal is actually oversampled and, therefore, highly correlated.The propagation channel has time dispersion; thus, the actual signal component at the receiver is given by

where $s_0(t)$ is the original transmitted signal, and $h(t)$ is the response of the time-dispersive channel. Since sampling period T_s is usually very small, the integration (16) can be approximated as

$$s_c(t) \approx T_s \sum_{k=-\infty}^{\infty} h(kT_s) s_o(t - kT_s) \quad (17)$$

Hence

$$s_c(nT_s) \approx T_s \sum_{k=k_0}^{K_1} h(kT_s) s_o((n-k)T_s) \quad (18)$$

Where $[K_0 T_s, K_1 T_s]$ is the support of channel response $h(t)$, i.e., $h(t) = 0$for $t \notin [K_0 T_s, K_1 T_s]$. For the time-dispersive channel, $K_1 > K_2$; thus, the signal samples $S_c(nT_s)$ are correlated, even if the original signal samples $S_o(nT_s)$could be i.i.d.

1. The original signal is correlated. In this case, even if the channel is a flatfading channel and there is no oversampling, the received signal samples are correlated.

Another assumption for the algorithm is that the noise samples are i.i.d. This is usually true if no filtering is used. However, if a narrow-band filter is used at the receiver, thenoise samples will sometimes be correlated. To deal with this case, we need to prewhiten the noise samples or pretransform the covariance matrix. A method is given in the Appendix to solve this problem.

The computational complexity of the algorithm is given as follows: Computing the autocorrelations of the received signal requires about LN_s multiplications and additions. Computing $T_1(N_s)$ and $T_2(N_s)$ requires about L^2 additions. Therefore,the total number of multiplications and additions is about $LN_s + L^2$.

C. Generalized Covariance-Based Algorithms

Based on the same principle as CAV, generalized covariance-based methods can be designed to detect the signal. Let φ_1 and φ_2 be two nonnegative functions with multiple variables. Assume that

$$\varphi_1(a) > 0, \quad for \ a \neq 0 \quad \varphi_1(0) = 0$$

$$\varphi_2(b) > 0, \quad for \ b \neq 0 \quad \varphi_2(0) = 0$$

Then, the following method can be used for signal detection:

Algorithm 2: Generalized Covariance-Based Detection

Step 1) Sample the received signal, as previously described.

Step 2) Choose a smoothing factor L and a threshold γ_2 , where γ_2 should be chosen to meet the requirement for the probability of false alarm.

Step 3) Compute sample covariance matrix $\hat{R}_x(N_s)$.

Step 4) Compute

$$T_4(N_s) = \psi_2 \ (r_{nn}(Ns), n = 1, \ldots, L) \quad (19)$$

$$T_3(N_s) = T_4(N_s) + \psi_1 \ (r_{nm}(N_s), n \neq m). \quad (20)$$

Step 5) Determine the presence of the signal based on $T_3(N_s)$, $T_4(N_s)$, and threshold γ_2. That is, if $T_3(N_s)/T_4(N_s) > \gamma_2$, the signal exists; otherwise, the signal does not exist.

Obviously, the CAV algorithm is a special case of the generalized method when φ_1 and φ_2 are absolute summation functions. As another example, we can choose $\psi_1(a) = a^T a$ and $\psi_2(b) = b^T b$. For this choice

$$T_3(N_s) = \frac{1}{L} \sum_{n=1}^{L} \sum_{m=1}^{L} \left| r_{nm}(N_s) \right|^2 \quad (21)$$

$$T_4(N_s)=\frac{1}{L}\sum_{n=1}^{L}\left|r_{nn}(N_s)\right|^2 \qquad (22)$$

D. Spectrum Sensing Using Multiple Antennas

Multiple-antenna systems have widely been used to increase the channel capacity or improve the transmission reliability in wireless communications. In the following, we assume that there are M>1 antennas at the receiver and exploit the received signalsfromtheseantennas forspectrumsensing.Inthis case, the received signal at antenna i is given by

$$H_o: x_i(n)=n_i(n) \qquad (23)$$

$$H_1: x_i(n)=S_i(n)+n_i(n) \qquad (24)$$

$$X(n)=[x_1(n)\ \cdots\ x_M(n)x_1(n-1)\ \cdots\ x_M(n-1)\ \cdots\ x_1(n-L+1)\ \cdots\ x_M(n-L+1)\,]^T \qquad (25)$$

$$S(n)=[s_1(n)\ \cdots\ s_M(n)s_1(n-1)\ \cdots\ s_M(n-1)\ \cdots\ s_1(n-L+1)\ \cdots\ s_M(n-L+1)\,]^T \qquad (26)$$

$$\eta(n)=[\eta_1(n)\ \cdots\ \eta_M(n)\eta_1(n-1)\ \cdots\ \eta_M(n-1)\ \cdots\ \eta_1(n-L+1)\ \cdots\ \eta_M(n-L+1)\,]^T \qquad (27)$$

In hypothesis H_1, $S_i(n)$ is the signal component received by antenna i. Since all $S_i(n)$'s are generated from the same source signal, the $S_i(n)$'s are correlated for i.

It is assumed that the $n_i(n)$'s are i.i.d. for n and i. Let us combine all the signals from the M antennas and definethevectorsin(25)–(27),asshowninthebottomof thepage. Note that (3)–(5) are a special case (M = 1)of the preceding equations. Defining the statistical covariance matrices in the same way as those in (6) and (7), we obtain

$$R_x=R_s+\sigma_n^{\,2}I_{ML} \qquad (28)$$

Except for the different matrix dimensions, the preceding equation is the same as (8). Hence, the CAV algorithm and generalized covariance-based method previously described can directly be used for the multiple-antenna case. Let $S_o(n)$ be the source signal. The received signal at antenna i is

$$S_i(n)=\sum_{K=o}^{N_i}h_i(k)S_o(n-k)+n_i(n), \qquad i=1,2,\ldots,M \qquad (29)$$

III. Comparison with Energy Detection

Energy detection is the basic sensing method, which was first proposed in [14] and further studied in [10]–[12] and [15]. It does not need any information of the signal to be detected and is robust to unknown dispersive channels. Energy detection compares the average power of the received signal with the noise power to make a decision.To guarantee are liable detection, the threshold must be set according to the noise powerandthenumberofsamples[10]–[12].Ontheotherhand, the proposed methods do not rely on the noise power to set the threshold [see (76)]while keeping the other advantages of energy detection. Accurateknowledgeonthenoisepoweristhenthekeyofthe energy detection. Unfortunately, in practice, noise uncertainty is always present. Due to noise uncertainty [10]–[12], the estimated (or assumed) noise power may be different from the real noise power. Let the estimated noise power be $\hat{\sigma}_\eta^{\,2}=\alpha\sigma_\eta^{\,2}$ We define the noise uncertainty factor (in decibels) as

$$B=\sup\{10\log_{10}\alpha\} \qquad (34)$$

It is assumed that α (in decibels) is evenly distributed in an interval [−B,B] [11]. In practice, the noise uncertainty factor of a receiving device normally ranges from 1 to 2 dB [11], [20]. Environment/interferencenoiseuncertaintycanbe much higher [11]. When there is noise uncertainty, the energy detection is not effective [10]–[12], [20]. The simulation presented in the next section also shows that the proposed method is much better than the energy detection when noise uncertainty is present. Hence, here, we only compare the proposed method with ideal energy detection (without noise uncertainty).

To compare the performances of the two methods, we first need a criterion. By properly choosing the thresholds, both methods can achieve any given Pd and Pfa > 0 if a sufficientlylarge number of samples are available. The key point is how many samples are needed to achieve the given Pd and Pfa> 0. Hence, we choose this as the criterion for comparing the two algorithms. For energy detection, the required number of samples is approximately [11]

$$N_e=\frac{2\left(Q^{-1}(P_{fa})-Q^{-1}(P_d)\right)^2}{SNR^2} \qquad (35)$$

Comparing (79) and (82), if we want Nc<Ne, we need

$$\gamma_L>1+\frac{L-1}{\sqrt{\pi}\left(Q^{-1}(P_{fa})-Q^{-1}(P_d)\right)} \qquad (36)$$

For example, if Pd =0 .9 and Pfa =0 .1, we need $\gamma_L>1+(L-1/4.54)$. In conclusion, if t he signal samples are highly correlated such that (83) holds, CAV detection is better than ideal energy detection; otherwise, ideal energy detection is better.

In terms of the computational complexity, the energy detection needs about Ns multiplications and additions. Hence, the computational complexity of the proposed methods is about L times that of the energy detection.

IV. Results

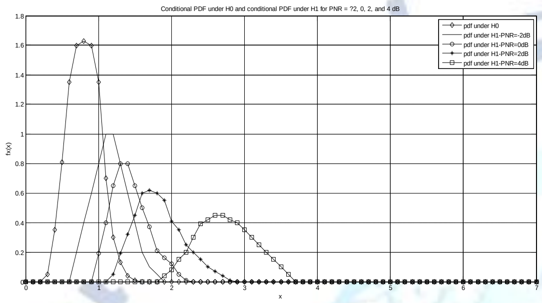

Fig. 1. Conditional PDF under $H0$ and conditional PDF under $H1$ for PNR =−2, 0, 2, and 4 dB.

From the fig 2 If the noise variance is exactly known (B = 0), the energy detection is better than the proposed method. However, as discussed in [10]–[12], noise uncertainty is always present. Even if the noise uncertainty is only 0.5 dB, the Pd of the energy detection is much worse than that of the proposed method.

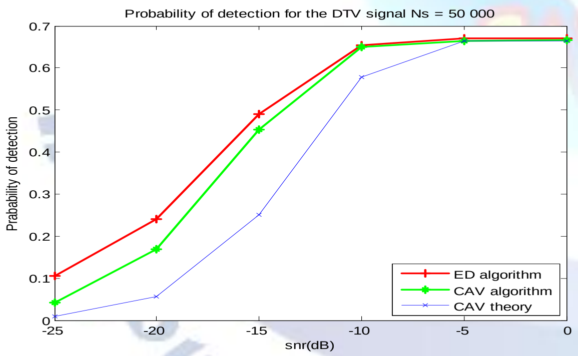

Fig 2: probability of detection for the DTV signal Ns = 50 000.

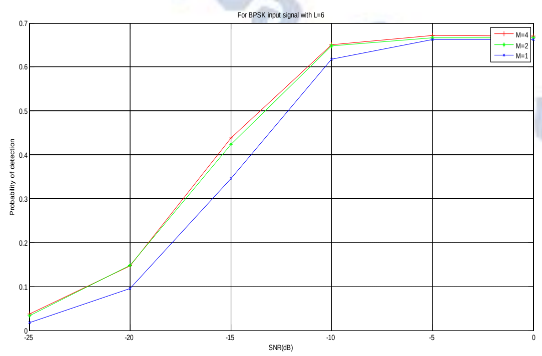

Fig. 3. Probability of detection using multiple antennas: Pfa = 0.1, and Ns = 20, with three source signals.

The channel taps are generated as Gaussian random numbers and different for different Monte Carlo realizations. Source signal $s_0(n)$ is i.i.d. and binary phase-shift keying modulated. From fig 3 The received signal at antenna i is defined in (29). The smoothing factor is L = 6, and the number of samples at each antenna is Ns = 20. We fix the P_{fa} = 0.1 at all cases

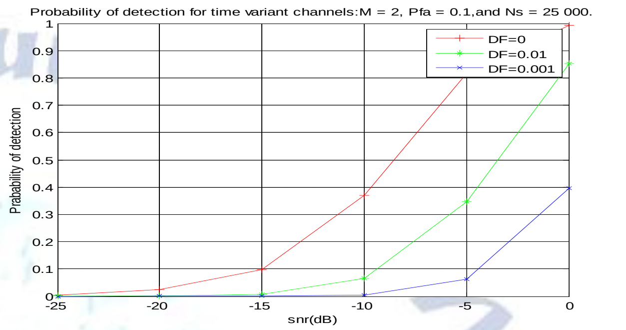

Fig 4:Probability of detection for time variant channels: M = 2, Pfa = 0.1, and Ns = 25 000.

Conclusion

In this paper, sensing algorithms based on the sample covariance matrix of the received signal have been proposed. Statistical theories have been used to set the thresholds and obtain the probabilities of detection. The methods can be used for various signal detection applications without knowledge of the signal, channel, and noise power. Simulations based on the narrow-band signals, captured DTV signals, and multiple antenna signals have been carried out to evaluate the performance of the proposed methods. It is shown that the proposed methods are, in general, better than the energy detector when noise uncertainty is present. Furthermore, when the received signals are highly correlated, the proposed method is better than the energy detector, even if the noise power is perfectly known.

REFERENCES

[1] J.Mitola and G. Q. Maguire, “Cognitive radio: Making softwar radios morepersonal,” IEEE Pers.Commun., vol.6, no.4, pp.13–18,Aug.1999.

[2] S. Haykin, “Cognitive radio: Brain-empowered wireless communications,” IEEE Trans. Commun., vol. 23, no. 2, pp. 201–220, Feb. 2005.

[3] D. Cabric, S. M. Mishra, D. Willkomm, R. Brodersen, and A. Wolisz, “A cognitive radio approach for usage of virtual unlicensed spectrum,” in Proc. 14th IST Mobile Wireless Commun. Summit, Jun. 2005.

[4] S. M. Mishra, A. Sahai, and R. W. Brodensen, “Cooperative sensing among cognitive radios,” in Proc. IEEE ICC, Istanbul, Turkey, Jun. 2006, pp. 1658–1663.

[5] Y.-C. Liang, Y. H. Zeng, E. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," IEEE Trans Wireless Commun., vol. 7, no. 4, pp. 1326–1337, Apr. 2008.
[6] Fed. Commun. Comm., Facilitating Opportunities for Flexible, Efficient, and Reliable Spectrum use Employing Cognitive Radio Technologies, Notice of Proposed Rule Making and Order, Dec. 2003. FCC 03-322.
[7] 802.22 Working Group, IEEE P802.22/D0.1 Draft Standard for Wireless Regional Area Networks, May 2006. [Online]. Available: http://grouper.ieee.org/groups/802/22/
[8] H.-P. Tan, W. K. G. Seah, and L. Doyle, "Exploring cognitive techniques for bandwidth management in integrated underwater acoustic systems," in Proc. MTS/IEEE Kobe Techno-Ocean (OCEAN), Apr. 2008, pp. 1–7.
[9] J. F. Hauris, "Genetic algorithm optimization in a cognitive radio for autonomous vehicle communications," in Proc. IEEE Int. Symp. Comput.Intell.Robot.Autom., Jacksonville, FL, Jun. 2007, pp. 427–431.
[10] A. Sonnenschein and P. M. Fishman, "Radiometric detection of spreadspectrum signals in noise of uncertainty power," IEEE Trans. Aerosp.Electron. Syst., vol. 28, no. 3, pp. 654–660, Jul. 1992.
[11] A. Sahai, D. Cabric, "Spectrum sensing: Fundamental limits and practical challenges," A tutorial in IEEE Int. Symp. New Frontiers DySPAN, Baltimore, MD, Nov. 2005.
[12] R. Tandra and A. Sahai, "Fundamental limits on detection in low SNR under noise uncertainty," in Proc. WirelessCom, Maui, HI, Jun. 2005, pp. 464–469.
[13] S. M. Kay, Fundamentals of Statistical Signal Processing: Detection Theory, vol. 2. Englewood Cliffs, NJ: Prentice–Hall, 1998.
[14] H. Urkowitz, "Energy detection of unknown deterministic signals," Proc. IEEE, vol. 55, no. 4, pp. 523–531, Apr. 1967.
[15] D. Cabric, A. Tkachenko, and R. W. Brodersen, "Spectrum sensing measurements of pilot, energy, and collaborative detection," in Proc. MILCOM, Oct. 2006, pp. 1–7.
[16] H.-S. Chen, W. Gao, and D. G. Daut, "Signature based spectrum sensing algorithms for IEEE 802.22 WRAN," in Proc. IEEE ICC, Jun. 2007, pp. 6487–6492.
[17] W. A. Gardner, "Exploitation of spectral redundancy in cyclostationary signals," IEEE Signal Process. Mag., vol. 8, no. 2, pp. 14–36, Apr. 1991.
[18] W.A.Gardner,W.A.Brown,III,andC.-K.Chen,"Spectral correlationof modulated signals—Part II: Digital modulation," IEEE Trans. Commun., vol. COM-35, no. 6, pp. 595–601, Jun. 1987.
[19] N. Han, S. H. Shon, J. O. Joo, and J. M. Kim, "Spectral correlation based signal detection method for spectrum sensing in IEEE 802.22 WRAN systems," in Proc. Int. Conf. Advanced Commun. Technol., Phoenix Park, Korea, Feb. 2006, pp. 1765–1770.
[20] S. Shellhammer and R. Tandra, Performance of the Power Detector With Noise Uncertainty, Jul. 2006, IEEE Std. 802.22-06/0134r0.
[21] V. Tawil, 51 Captured DTV Signal, May 2006. [Online]. Available: http://grouper.ieee.org/groups/802/22/
[22] C. Clanton, M. Kenkel, and Y. Tang, Wireless Microphone Signal Simulation Method, Mar. 2007, IEEE Std. 802.22-07/0124r0.