The Application of Distributed Spectrum Sensing and Available Resource Maps to Cognitive Radio Systems

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***Abstract*—In order for cognitive radio systems to fulfill their potential of enabling more efficient spectrum utilization by means of opportunistic spectrum use, significant advances must be made in the areas of spectrum sensing and "cognitive" spectrum access. In this paper, we discuss two research efforts relevant to these areas; namely the development of distributed (cyclic feature-based) spectrum sensing algorithms and of available resource maps-based cognitive radio systems. It is shown that distributed spectrum sensing is a practical and efficient approach to increase the probability of signal detection and correct modulation classification and/or to reduce sensitivity requirements of individual radios. Additionally, numerical results are presented that show significant reduction of harmful interference and greater spectrum utilization efficiency of available resource maps-based cognitive radio systems.**

I. Introduction

Cognitive radios can be broadly defined as radios that are capable of learning about their environment, resources, and requirements, adapting their behavior, and optimizing their performance subject to pre-defined rules [1], [2]. It is due to their learning and adaptation capabilities that a great deal of research has focused on the use of cognitive radios to achieve more efficient spectrum utilization. In this context, cognitive radios have been considered to act either as secondary users of spectrum (by means of opportunistic spectrum reuse, as is currently being evaluated by the IEEE 802.22 working group) or as users of unlicensed spectrum (possibly co-existing and even interoperating with other unlicensed systems) [1]-[3].

In this paper, we address two problems which are at the heart of cognitive radio systems when used in spectrum-sharing scenarios: spectrum sensing and "cognitive" spectrum access. More specifically, we give an overview of two projects currently underway at Wireless @ Virginia Tech: the design and analysis of algorithms and methods for *distributed* spectrum sensing (i.e., multiple radios performing signal detection and modulation classification collaboratively) based on cyclic feature analysis, and the development of an approach to cognitive radio systems based on the use of available resource maps (ARMs). Our goal here is to discuss key concepts and present some key results of such projects; the reader is referred to [4]-[7] for a more detailed description and further results of this research.

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II. Spectrum Sensing: Distributed Cyclic-feature Analysis for Signal Detection and Modulation Classification

Cognitive radio systems have the potential to achieve a more efficient spectrum utilization by estimating the radio spectrum activity in its surroundings (*spectrum sensing*) and transmitting on unused frequency bands. In this paper, we define spectrum sensing as the combination of signal detection and modulation classification, and use the general term Automatic Modulation Classification (AMC) to denote this combined process.

Cognitive radios must perform AMC with no a priori knowledge of received signal characteristics, such as the bandwidth, carrier frequency, and chip-rate. In this scenario, it is known that cyclic feature-based AMC is a possible approach with many advantages, including reduced sensitivity to unknown and changing noise levels and the capability to differentiate temporally and spectrally overlapping signals. This approach exploits the statistical characteristics of communication signals that vary periodically with time.

In order to take advantage of radio signal variability, and therefore allow for more reliable sensing, we present a *distributed* approach to cyclic feature-based AMC in which spectrum sensing is performed collaboratively by a network of radios. The distributed AMC system to be considered is seen in Fig. 1. In this system, we assume the radios are comprised of two stages: an AMC stage and a Decision Making (DM) stage. In the AMC stage, we utilize a cyclic spectrum feature-based method and a feed-forward back-propagation neural network. The output of this AMC stage, y_n ($1 \leq n \leq N$), is then used by the radios DM stage to make the local decision u_n ($1 \leq n \leq N$). The local decisions from all radios are sent to a fusion center that makes a global decision based on the output of its own AMC stage, y_0, as well as the radios' decisions. In order to optimize this global decision, a nonlinear Gauss-Seidel iterative algorithm is used to develop "person-by-person" optimal decision rules for the fusion center and DM stages of the system.

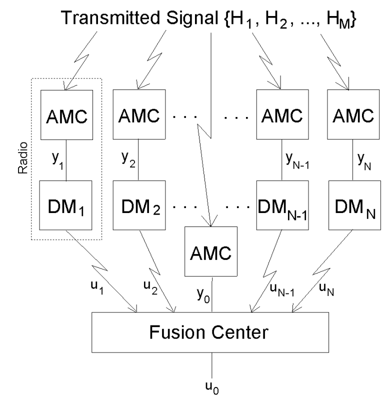

Fig. 1. Distributed AMC system block diagram.

A. Radio-level AMC stage

The radios' AMC stage, seen in more detail in Fig. 2, can be broken up into two main functions, feature extraction, in which the received signal's α-profile is estimated, and pattern matching, in which a trained feed-forward back-propagation neural network performs pattern matching on the α-profile. The α-profiles, first defined for use in AMC in [8] and [9], are extracted from an estimate of the limit cyclic spectrum (often abbreviated to cyclic spectrum) of the received signal $x(t)$, defined as [10]

$$\hat{S}_x^\alpha(f) = \lim_{T\to\infty} \lim_{\Delta t\to\infty} \frac{1}{\Delta t}\int_{-\Delta t/2}^{\Delta t/2} \frac{1}{T} U_T(t,f) V_T^*(t,f)dt \quad (1)$$

where

$$U_T(t,f) = \int_{t-T/2}^{t+T/2} x(u)e^{-j2\pi(f+\alpha/2)u}du \quad (2)$$

and

$$V_T^*(t,f) = \int_{t-T/2}^{t+T/2} x(u)e^{j2\pi(f-\alpha/2)u}du. \quad (3)$$

Here we estimate the cyclic spectrum through the use of a time-smoothing algorithm known as the FFT accumulation algorithm. For more details on this process, please refer to [4] and [11].

Once the cyclic spectrum of the received signal has been estimated, the α-profile is created by taking the maximum value along the spectral location parameter f for each spectral separation parameter α of the cyclic spectrum,

$$profile(\alpha) = \max_f[\hat{S}_x^\alpha(f)]. \quad (4)$$

This process greatly reduces the size of the data to be used, as compared to using the cyclic spectrum itself, allowing for a more computationally efficient pattern matching algorithm without significantly reducing performance. In Fig. 3, typical α-profiles can be seen for BPSK, FSK, MSK, and QPSK modulations, assuming square pulses and an E_b/N_o value of 10dB.

After the α-profile is created, a trained two-layer feed-forward back-propagation neural network is used in order to perform pattern matching on the profile. This neural network

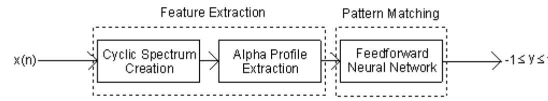

Fig. 2. AMC stage block diagram.

is trained on a set of α-profiles, with E_b/N_o values in the dB range of interest, through the use of a Delta-Bar-Delta adaptive learning rate algorithm (see [12]) to give a modulation dependent output between -1 and 1.

As an example of the functionality of a radio's AMC stage, we assume a case in which there are four possible modulation schemes; BPSK, QPSK, FSK, MSK, as well as the case in which no signal is present. The neural network is trained with α-profiles in the -2 to 5dB E_b/N_o range to yield the following outputs: -1 for BPSK, -0.5 for FSK, 0 for noise only, 0.5 for MSK, and 1 for QPSK. Conditional probability density functions of the output of the AMC stage trained in this way are shown in Fig. 4 for an E_b/N_o of -2dB. From this figure it can be observed that the probability density functions, conditioned on each of the possible 5 hypotheses, have a relatively small overlap even at this low E_b/N_o value. From this result, it is clear that the proposed feature-based scheme has the potential to be of great use in detecting and classifying signals.

B. Distributed system setup and optimization

The configuration of the distributed AMC system considered can be seen in Fig. 1. In this system, we assume that each radio uses a cyclic spectrum feature-based AMC stage to obtain y_n and then sends a local decision u_n to a fusion center in the form of messages that take on values in a finite alphabet (i.e., $1 \le u_n \le M$, where M is the number of hypotheses). For this system, assuming that the local decisions made by the DMs are conditionally independent and that each radio can observe all possible hypotheses, we have the following person-by-person optimal decision rules for the fusion center

$$u_0 = arg \min_{i\in(1,\ldots,M)} \sum_{j=1}^{M} p(y_0|H_j) \prod_{n=1}^{N} P(u_n|H_j)P(H_j)C_{ij} \quad (5)$$

and the DMs

$$u_n = arg \min_{k\in(1,\ldots,M)} \sum_{i=1}^{M}\sum_{j=1}^{M} P(u_0 = i|u_n = k, H_j)p(y_n|H_j) \cdot P(H_j)C_{ij}; \quad (6)$$

where C_{ij} is the cost of deciding $u_0 = i$ given H_j (the actual modulation scheme of the received signal) and $P(H_j)$ is the probability of occurrence of H_j [13].

It can be seen from (5) and (6) that these person-by-person optimal rules form a system of nonlinear coupled equations. Tsitsiklis and Athans show, in [14], that decentralized decision making is hard from an algorithmic viewpoint even for the simplest of systems. Therefore, in order to avoid the "brute-force" approach to solving for these rules, we use an iterative

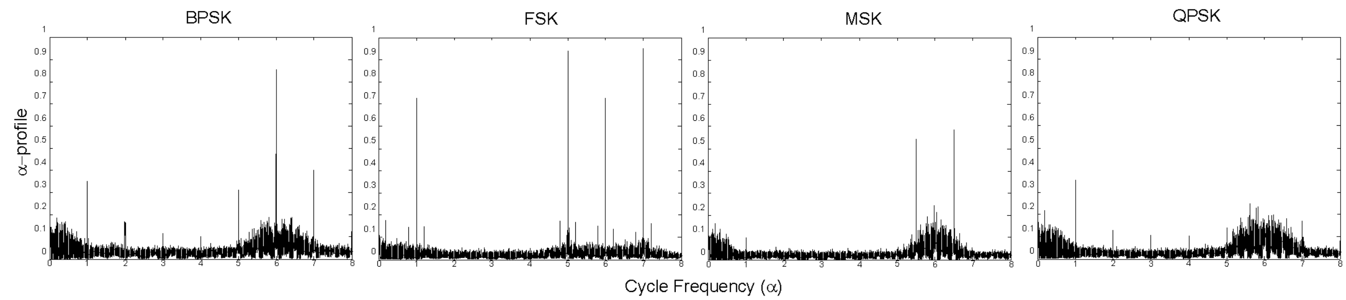

Fig. 3. α-profiles for BPSK, FSK, MSK, and QPSK at an E_b/N_o of 10dB.

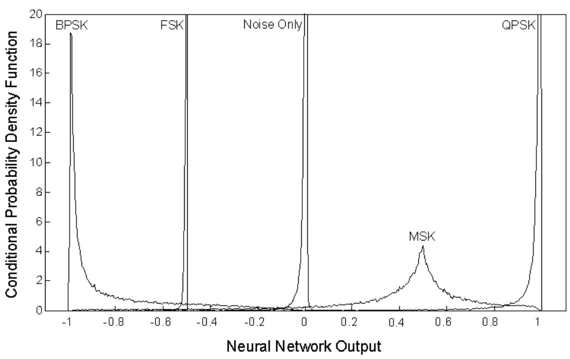

Fig. 4. Conditional probability density functions for the output of the AMC stage at an E_b/N_o of -2dB.

TABLE I
PROBABILITY OF CLASSIFICATION FOR THE SINGLE RADIO CASE

	Hypothesis				
	Noise	BPSK	QPSK	FSK	MSK
Noise	0.9721	0.0020	0.0003	0.0000	0.0150
BPSK	0.0062	0.9780	0.0015	0.0067	0.0780
QPSK	0.0000	0.0000	0.9357	0.0000	0.0420
FSK	0.0001	0.0103	0.0001	0.9933	0.0022
MSK	0.0216	0.0097	0.0624	0.0000	0.8628

TABLE II
PROBABILITY OF CLASSIFICATION FOR THE DISTRIBUTED CASE (3 RADIOS WITH FUSION CENTER)

	Hypothesis				
	Noise	BPSK	QPSK	FSK	MSK
Noise	0.9985	0.0000	0.0000	0.0000	0.0000
BPSK	0.0001	0.9998	0.0000	0.0008	0.0003
QPSK	0.0000	0.0000	0.9949	0.0000	0.0027
FSK	0.0000	0.0000	0.0000	0.9992	0.0000
MSK	0.0014	0.0002	0.0051	0.0000	0.9970

method known as the Gauss-Seidel algorithm. This algorithm, defined in detail in [13], allows for these rules to be solved in a computationally efficient manner, at the expense of requiring messages to be passed between the radios and the fusion center [4].

In order to show the effects of performing distributed AMC, using the defined person-by-person decision rules and the Gauss-Seidel algorithm, over a single radio case, we expand on the AMC stage example given in Sect. II.A. Using the empirical conditional density functions shown in Fig. 4, we obtain the results shown in Tables I and II. From these tables, it can be seen that performing AMC in a distributed manner greatly improves the detection and classification of signals over the single radio system. This can be seen by observing the average probability of classification error. In the single radio case this error is approximately 5.16% but drops to approximately 0.21% for the distributed case with three radios and fusion. As another example, in the case of classifying MSK, the probably of correct classification rises from 86.28% for the single radio case to 99.70% for the distributed case with three radios and fusion.

III. AVAILABLE RESOURCE MAPS: CONCEPT AND APPLICATIONS TO IMPROVING THE PERFORMANCE OF SPECTRUM-SHARING COGNITIVE RADIO SYSTEMS

Available Resource Maps (ARMs) are defined as databases containing multi-domain information, such as the locations and activities of radios, spectral regulations, and geographical features, that characterize the spectral environment in a given geographical area [5]-[7]. The application of ARMs to cognitive radio systems was first proposed in the context of unlicensed wireless WAN in [15] and [16]. Cognitive radios use the information present in the ARM to make situation-aware adaptations in various layers, such as transmit frequency, power, timing, and routing protocol, to optimize their performance according to pre-established rules.

ARMs can be divided into two categories, depending on the origin and extent of the information it contains. A *global* ARM contains a global view of the spectral environment, with information obtained by the spectrum sensing of multiple cognitive radios and by possible connections between the global ARM and control entities of other cognitive or non-cognitive systems. Cognitive radios can access the contents of the global ARM through a dedicated control channel, for example. While global ARMs contain information on the spectral environment in the geographical area in which a cognitive radio system is deployed, *local* ARMs are generated individually by each radio from its own spectrum sensing, and contain information that characterize the spectral environment in the vicinity of that individual cognitive radio only. Using the shared-spectrum system simulation platform presented in [17], we present link-level and network-level performance results of

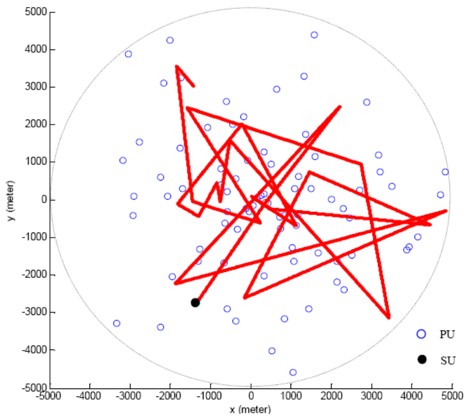

Fig. 5. Typical link-level simulation scenario.

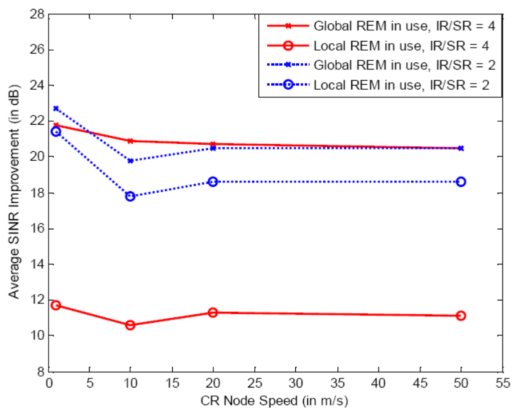

Fig. 6. Performance comparisons under different IR/SR ratios.

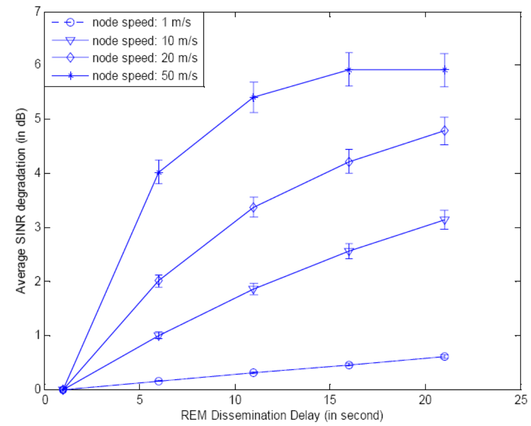

Fig. 7. Average SINR degradation comparison under various PU moving speeds.

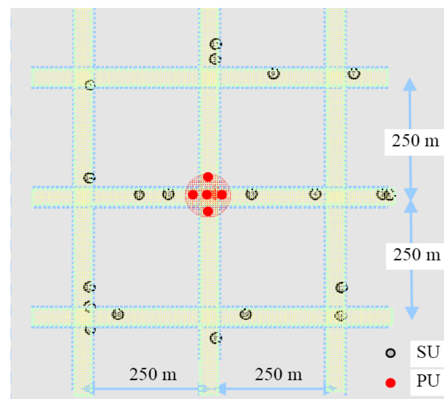

Fig. 8. Network-level simulation scenario.

global and local ARM-based cognitive radio systems.

A. Link-level simulations

Consider the scenario depicted in Fig. 5, where a single cognitive radio randomly moves in an open area (path in red) and shares the spectrum with a primary user (PU) network. Assuming that the ARM-based cognitive radio switches off its transmission once a PU is found to be within its interference range (based on ARM information), the average signal-to-interference-and-noise-ratio (SINR) improvement at the PU receivers (compared to the case in which the cognitive radio is always transmitting) is shown in Fig. 6. In Fig. 6, IR/SR stands for interference-radius-to-sensing-radius. As expected, the performance of local ARM-based systems greatly depends on the IR/SR ratio. However, it is also seen that the global ARM-based system is not as dependent on this parameter; this is due to the fact that the cognitive radio in this case has complete knowledge of the spectrum (as opposed to only in its vicinity)[1].

The performance improvement obtained by having a global ARM comes at the cost of having to first acquire and then broadcast the contents of this global database to all cognitive radios. Obviously, there are a number of practical issues that affect these operations and will ultimately result in performance degradation. In order to better understand the effects of such practical implementation issues, we evaluate the system performance assuming PU mobility and information dissemination delay. The simulation scenario is similar to Fig. 5 but with non-stationary PUs. The average SINR degradation at the PU nodes and the corresponding 95% confidence interval are shown in Fig. 7. As expected, the simulation results indicate that the higher the moving speed of the PU nodes, the greater is the SINR degradation at the PU nodes due to the global ARM dissemination delay. This is due to the fact that the locations of the PUs in the ARM are out of date and the cognitive radio uses this noisy information to adjust its transmissions.

B. Network-level simulations

The network-level simulation scenario is shown in Fig. 8, where twenty cognitive radios are moving along the streets and another twenty PU nodes are stationary and clustered at a street crossing. In this analysis, two typical geographical environments are considered; an open area and a dense urban area, where the two-ray ground reflection model and the Manhattan model are employed, respectively. The simulation parameters can be found in [17]. The following utility function

[1]It should be noted that because we assume the ARM information to be perfect (i.e., no propagation delays or noisy spectrum estimates, for example), the curves in Fig. 6 are expected to be constant. However, due to the limited simulation time used to generate these results, the curves do show some variation.

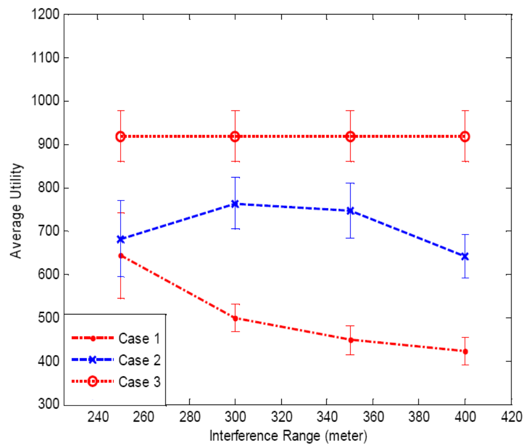

Fig. 9. Network utility comparison when the cognitive radio system uses different adaptation schemes.

is proposed in order to evaluate the performance of the two networks,

$$u = \frac{\text{sum throughput of both primary and cognitive networks}}{\text{average packet delay experienced by the PUs}}.$$

Fig. 9 shows the increased network utility obtained when cognitive radios use the ARM concept, in the context of spectrum sharing with incumbent PUs. As depicted in this figure, three different adaptation schemes are evaluated:

- Case 1: The cognitive radios are unaware of the topographical environment. Therefore, they take a conservative approach; when any PU node falls into their free-space interference range, they stop transmission.
- Case 2: The cognitive radios first estimate the path loss to the PU nodes by using the two-ray ground model and then adaptively adjust their transit power if any PU is within their interference range.
- Case 3: The ARM-enabled cognitive radios are fully aware of the radio environment and apply the Manhattan propagation model for path loss prediction. Based on this estimate, the cognitive radios then adaptively adjust their transit power if any PU is within their interference range.

The Manhattan propagation model differentiates the line-of-sight (LOS) and non-line-of-sight (NLOS) conditions for appropriate path loss prediction. The simulation results show that the high penetration loss due to the buildings in a dense urban area creates many "spectrum holes" that enable much higher spectrum reuse by the ARM-enabled cognitive radios. Therefore, the network utility for Case 3 is higher than that for Cases 1 and 2.

IV. Conclusions

Performance analysis demonstrates that distributed spectrum sensing provides a significant increase in the probability of signal detection (there are radios using this frequency at this location) and correct modulation classification (and these signals are from primary users of the spectrum) of a cognitive radio system, at the expense of requiring messages to be exchanged among the radios of the system. This performance improvement ultimately leads to a lower probability of interference among systems, enabling cognitive radio systems to achieve a more efficient utilization of the spectrum. Additionally, in order to achieve a given probability of detection and correct modulation classification for the cognitive radio system, the required sensitivity for each radio (e.g., probability of detection for a given probability of false alarm) reduces as the number of radios collaborating in sensing the spectrum increases. In this paper, we also show that available radio maps-based cognitive radio systems are an efficient approach to achieve a more efficient utilization of the spectrum in both space and time domains, helping to reduce harmful interference between cognitive radio systems and possible primary users of the spectrum.

References

[1] J. Mitola III and G. Q. Maguire Jr., "Cognitive radio: Making software radios more personal," *IEEE Pers. Commun.*, vol. 6, pp. 13-18, Aug. 1999.

[2] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, pp. 201-220, Feb. 2005.

[3] K. E. Nolan, P. D. Sutton, L. E. Doyle, T. W. Rondeau, B. Le, and C. W. Bostian, "Demonstration and analyses of collaboration, coexistence, and interoperability of cognitive radio platforms," in *Proc. IEEE Consumer Commun. Netw. Conf.*, Las Vegas, NV, 2007, pp. 1149-1153.

[4] W. C. Headley, J. D. Reed, and C. R. C. M. da Silva, "Distributed cyclic spectrum feature-based modulation classification," accepted for presentation at *IEEE Conf. Wireless Commun. Netw. Conf.*, Las Vegas, NV, 2008.

[5] Y. Zhao, B. Le, and J. H. Reed, "Network support - The radio environment map," in *Cognitive Radio Technology*, B. Fette, ed., Elsevier, 2006, pp. 337-363.

[6] Y. Zhao, L. Morales, J. Gaeddert, K. K. Bae, J. Um, and J. H. Reed, "Applying radio environment maps to cognitive WRAN systems," in Proc. *IEEE Int. Symp. Dynamic Spectrum Access Netw.*, Dublin, Ireland, 2007.

[7] Y. Zhao, J. Gaeddert, K. K. Bae, and J. H. Reed, "Radio environment map-enabled situation-aware cognitive radio learning algorithms," in Proc. *Software Defined Radio (SDR) Tech. Conf.*, Orlando, FL, 2006.

[8] A. Fehske, J. Gaeddert, and J. H. Reed, "A new approach to signal classification using spectral correlation and neural networks," in *Proc. IEEE Dynamic Spectrum Access Nets.*, 2005, pp. 144-150.

[9] K. Kim, I. A. Akbar, K. K. Bae, J. Um, C. M. Spooner, and J. H. Reed, "Cyclostationary approaches to signal detection and classification in cognitive radio," in *Proc. IEEE Dynamic Spectrum Access Nets.*, 2007, pp. 212-215.

[10] W. A. Gardner, *Statistical Spectral Analysis: A Nonprobabilistic Theory*. Englewood Cliffs, NJ: Prentice-Hall, 1987.

[11] W. A. Gardner, *Cyclostationarity in Communications and Signal Processing*. Piscataway, NJ: IEEE Press, 1994.

[12] L. Fausett, *Fundamentals of Neural Networks - Architectures, Algorithms, and Applications*. Englewood Cliffs, NJ: Prentice-Hall, 1994.

[13] Z. B. Tang, K. R. Pattipati, and D. L. Kleinman, "A distributed M-ary hypothesis testing problem with correlated observations," in *Proc. Conf. Decision and Control*, Tampa, FL, 1989, pp. 562-568.

[14] J. N. Tsitsiklis and M. Athans, "On the complexity of decentralized decision making and detection problems," *IEEE Trans. Automatic Contr.*, vol. AC-30, 1985, pp. 440-446.

[15] A. Batra, W. Krenik, and C. Panasik, "Cognitive radios for unlicensed WANs," presented at the BWRC Cognitive Radio Workshop, 2004.

[16] W. Krenik and A. Batra, "Cognitive radio techniques for wide area networks," in *Proc. Conf. Design Automation*, Anaheim, CA, 2005, pp. 409-412.

[17] Y. Zhao, D. Raymond, C. R. C. M. da Silva, J. H. Reed, and S. F. Midkiff, "Performance evaluation of radio environment map-enabled cognitive spectrum-sharing networks," in *Proc. IEEE Military Commun. Conf.*, Orlando, FL, 2007.