SkyTel provides a discussion herein as to its concept to use High Accuracy Location ("HALO") of the radios in a Cognitive Radio Network, to substantially improve and extend the Available Resoure Maps (AMRs) that are the focus of this paper on moving towards Cogntive Radio Systems or Networks (as opposed to simply Cognitive Radios).

There is no question that Cogntive Radio Newtorks are the future of wireless and are especially needed, and cost justified even now, for: Smart Transport, Energy, Environment Radio (STEER) and complimentary wireless (e.g., precision agriculture and resouce manangemnet use and protection) for core infrastructure and wide-georgraphy industries for the US and all nations.

Distributed Spectrum Sensing for Cognitive Radio Systems

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Also, radios in a mesh net can receive and send more effectively, when their receivers-antennas are synchronized and coordinated, using mesh nets.

***Abstract*— Cognitive radio is a candidate technology for more efficient spectrum utilization systems based on opportunistic spectrum sharing. Because this new technology does not rely on traditional license-based spectrum allocation policies, it could disrupt existing systems if the spectrum utilization decision is based on unreliable spectral estimation. Distributed sensing methods have the potential to increase the spectral estimation reliability and decrease the probability of interference of cognitive radios to existing radio systems. In this paper, we consider different aspects of the processing and fusion of spectrum sensing information of cognitive radio systems. The use of cyclic feature-based methods for distributed signal detection and classification is discussed and recent results are presented.**

I. Introduction

Aiming at more efficient spectrum utilization, the FCC is currently revisiting traditional licensed-based policies and moving toward the adoption of "spectrum sharing" strategies such as ultra-wideband (UWB) and cognitive radio. While UWB systems achieve a more efficient spectrum utilization by overlaying existing narrowband systems, cognitive radios opportunistically find and use empty frequency bands. Cognitive radios rely on the fact that a significant portion of the spectrum allocated to licensed services show little usage over time. A recent spectrum occupancy measurement project shows that the average spectrum occupancy taken over multiple locations is 5.2%, with a maximum occupancy of 13.1% [1].

Originally introduced by Mitola [2]-[3], cognitive radios are capable of sensing their environment, learning about their radio resources and user/application requirements, and adapting behavior by optimizing their own performance in response to user requests [4]. Cognitive radios are therefore a powerful tool for solving the spectrum usage problem. Such radios are capable of sensing spectrum occupancy, and, in conformity with the rules of the FCC, opportunistically adapting transmission to utilize empty frequency bands without disrupting other systems. However, this departure from traditional license-based spectrum allocation policies could disrupt existing systems if the spectrum utilization decision is based on unreliable spectral estimation.

One possible approach to increase the spectral estimation reliability and decrease the probability of interference of cognitive radios to existing radio systems is by using *distributed spectrum sensing*. In such a distributed approach, the spectrum occupancy is determined by the joint work of cognitive radios, as opposed to being determined individually by each cognitive radio. In this paper, we consider different aspects of the processing and fusion of spectrum sensing information of cognitive radio systems. A new system architecture that combines cognitive radios and *available resource maps* is also discussed. A major focus of this paper is on the use of cyclic feature-based methods for distributed signal detection and classification.

This work was supported in part by a gift from Texas Instruments Inc.

II. Distributed Spectrum Sensing: Overview

In application scenarios involving geographically distributed radios, such as a wireless communication system, distributed spectrum sensing approaches are worth considering due to the variability of the radio signal, as suggested in [5]-[7]. Such methods may significantly increase the reliability of the spectrum estimation process, at the expense of computational complexity and power/bandwidth usage for the transmission of spectrum sensing information.

needed in mesh net anyway, especially mobile ad hoc mesh net

In this paper, we model the cognitive radio system with a standard parallel fusion network commonly used in decentralized detection problems, shown in Fig. 1. In this model, each cognitive radio (CR node) obtains some relevant information y_i, $i = 1, \ldots, N$, on the spectrum occupancy. Each CR node processes this information and then sends a summary of its own observations to a fusion center, in the form of a message u_i, $i = 1, \ldots, N$, taking values in a finite alphabet. The fusion center then generates a global spectrum usage decision u_0 based on the messages it has received [8]. The objective in this Bayesian hypothesis testing problem is to obtain the set of decision rules that minimize the average cost of making a decision of the overall system. Taking a person-by-person optimization methodology [9], and assuming that the observations at the local detectors are conditionally independent and that the local decisions are binary, the local decision rules reduce to threshold tests given by

$$\frac{p\left(y_k|H_1\right)}{p\left(y_k|H_0\right)} \underset{u_k=0}{\overset{u_k=1}{\gtrless}} \frac{P\left(H_0\right)}{P\left(H_1\right)}\gamma_k, \tag{1}$$

where

$$\gamma_k = \frac{\sum_{\mathbf{u}^k}\left\{P\left(u_0=1|\mathbf{u}^{k_1}\right) - P\left(u_0=1|\mathbf{u}^{k_0}\right)\right\}\prod_{i=1,i\neq k}^{N} P\left(u_i|H_0\right)}{\sum_{\mathbf{u}^k}\left\{P\left(u_0=1|\mathbf{u}^{k_1}\right) - P\left(u_0=1|\mathbf{u}^{k_0}\right)\right\}\prod_{i=1,i\neq k}^{N} P\left(u_i|H_1\right)},$$

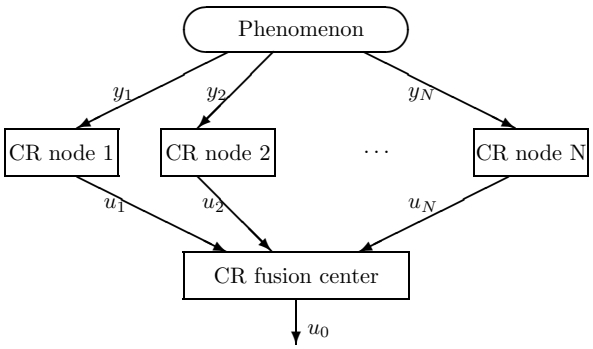

Fig. 1. Block diagram of a parallel fusion network.

$\mathbf{u}^k = (u_1, \ldots, u_{k-1}, u_{k+1}, \ldots, u_N)^T$ and $\mathbf{u}^{k_j} = (u_1, \ldots, u_{k-1}, u_k = j, u_{k+1}, \ldots, u_N)^T$, $j = 0, 1$. The fusion rule is also a threshold test, and is given by

$$\sum_{i=1}^{N} \left(u_i \log \left(\frac{1 - P_{M_i}}{P_{F_i}} \right) + (1 - u_i) \log \left(\frac{P_{M_i}}{1 - P_{F_i}} \right) \right) \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \log \left(\frac{P(H_0)}{P(H_1)} \right). \quad (2)$$

Thus, the person-by-person optimization solution to the binary decentralized Bayesian hypothesis testing problem is given by a system of nonlinear coupled equations. It is well-known that the computational effort required to solve a system of nonlinear coupled equations increases rapidly with the number of detectors. Tsitsiklis and Athans show in their classic paper [10] that even the simplest problems of decentralized decision making are hard from an algorithmic viewpoint, and that it becomes an NP-complete problem if the measurements at each sensor are not independent.

As the testing functions at both the local detectors and at the data fusion center have the form of a likelihood ratio, the decision thresholds are the only free parameters. Therefore, the distributed detection problem reduces to the search of the optimal threshold. One possible way to find these optimal thresholds is by using iterative computational algorithms. For example, a nonlinear Gauss-Seidel iterative algorithm derived in [11] allows for the solution of reasonably large-sized problems, at the expense of requiring messages to be transmitted among fusion center and CR nodes. Other possible iterative algorithms can be found in [9].

III. Distributed Signal Detection Using Single-Cycle Detectors

Cognitive radios must be able to detect spectrum usage with no a priori knowledge of modulation format and characteristics, such as the bandwidth, carrier frequency, and chip-rate, of primary systems. The most conventional approach for the detection of an unknown deterministic signal in AWGN is the radiometer, which is simply a measure of received energy in time and frequency. However, it is well-known that such a method is highly susceptible to unknown and changing noise levels and interference [12]. Cyclic-feature detection techniques are an alternative approach for the unknown signal detection problem that have many advantages, including signal classification capabilities and reduced sensitivity to unknown and changing background noise. Such techniques exploit timing or phase properties of digitally modulated signals, and have been receiving a great deal of attention by the IEEE 802.22 work group [13].

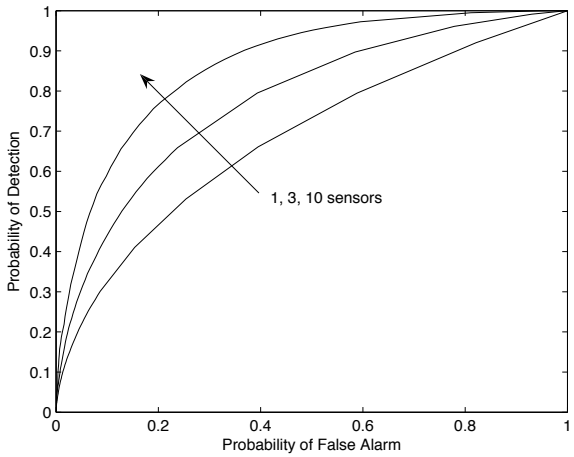

Fig. 2. Distributed detection of a known signal in AWGN using single-cycle detectors ($E_b/N_o = 3$ dB).

Assume, for example, a basic cyclic-feature detector known as a single-cycle detector. The test statistic of such a detector is given by [14]

$$\left| \int_{-\infty}^{\infty} S_{x_T}^{\alpha}(t, f)\, S_S^{\alpha}(f)\, df \right| \underset{H_0}{\overset{H_1}{\gtrless}} \gamma, \quad (3)$$

where $S_{x_T}^{\alpha}(t, f)$ is the cyclic periodogram of the received (cycloergodic) signal $x(t)$, given by

$$S_{x_T}^{\alpha}(t, f) = \frac{1}{T} \left(\int_{t-\frac{T}{2}}^{t+\frac{T}{2}} x(u)\, e^{-j2\pi\left(f+\frac{\alpha}{2}\right)u} du \right) \times \left(\int_{t-\frac{T}{2}}^{t+\frac{T}{2}} x^*(u)\, e^{j2\pi\left(f-\frac{\alpha}{2}\right)u} du \right), \quad (4)$$

and $S_S^{\alpha}(f)$ is the ideal spectral correlation function.

The performance of a single-cycle detector in a distributed architecture, using the Gauss-Seidel algorithm for data fusion, is shown in Fig. 2. It is seen that when signal detection is performed using 10 sensors instead of using a single sensor, the probability of detection increases from approximately 30% to 60%, for a probability of false alarm equal to 10%.

IV. Signal Classification Using Cyclostationarity

In addition to frequency occupancy estimation, cognitive radio systems may also need to classify the primary system that occupies a given frequency band. For example, the protection (in terms of allowable interference level) that a cognitive radio system may provide to a primary user may be dependent on the primary system. By taking advantage of

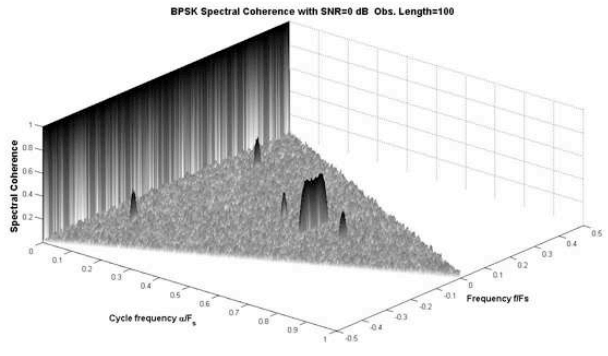

Fig. 3. Spectral coherence function of a BPSK signal.

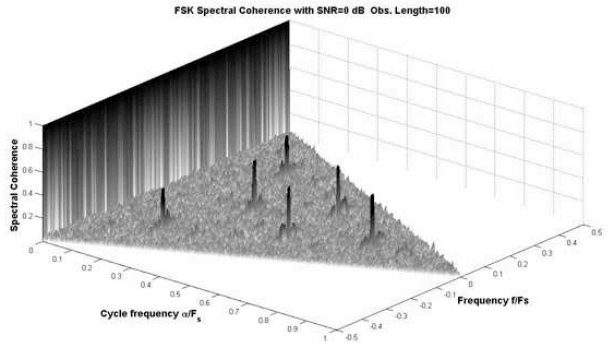

Fig. 4. Spectral coherence function of a BFSK signal.

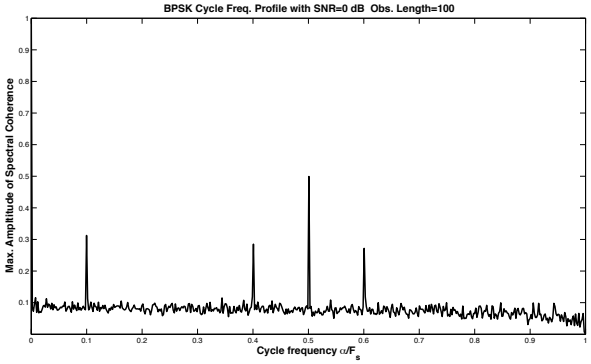

Fig. 5. Cycle frequency domain profile of a BPSK signal.

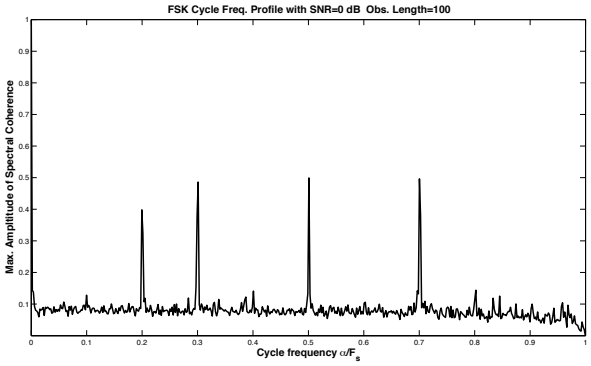

Fig. 6. Cycle frequency domain profile of a BFSK signal.

the inherent cyclostationarity existent in digital signals, cyclic-feature algorithms have the potential to provide reliable signal classification even at low signal-to-noise ratio scenarios.

Cyclic-feature algorithms for signal classification typically use the *spectral coherence function* of the received signal, defined as [15]

$$C_x^\alpha(f) \triangleq \frac{S_x^\alpha(f)}{[S_x^0(f+\alpha/2)S_x^0(f-\alpha/2)]^{1/2}}. \tag{5}$$

This function is of particular interest as it gives a normalized measure of the cross-correlation between signal components at frequencies $f-\alpha/2$ and $f+\alpha/2$. The magnitude of the spectral coherence function ranges from 0 to 1, and is invariant to linear transformations to the incoming signal.

In (5), the spectral correlation function $S_x^\alpha(f)$ is defined as

$$S_x^\alpha(f) = \lim_{\Delta f\to 0}\lim_{T\to\infty} S_{x_T}^\alpha(t,f)_{\Delta f}, \tag{6}$$

where

$$S_{x_T}^\alpha(t,f)_{\Delta f} \triangleq \frac{1}{\Delta f}\int_{f-\Delta f/2}^{f+\Delta f/2} S_{x_T}^\alpha(t,v)dv, \tag{7}$$

and the cyclic periodogram $S_{x_T}^\alpha(t,f)$ is given by (4).

The spectral coherence functions of BPSK and BFSK signals are shown in Figs. 3 and 4, respectively. It is seen that the spectral coherence function corresponding to these modulation techniques have distinct features that ultimately allow for signal classification. It can be shown that most digital signals and some analog signals have distinctive spectral coherence functions.

It is shown in [16] that in order to ease the design of the signal classification algorithm, it is convenient to define the following cycle frequency domain *profile* function

$$I(\alpha) \triangleq \max_f |C_x^\alpha(f)|. \tag{8}$$

The profile functions of BPSK and BFSK signals are shown in Figs. 5 and 6, respectively. As described in [16], an efficient signal classification algorithm is obtained by matching the profile function $I(\alpha)$ of the received signal with a database of profile functions of possible digital and analog modulation schemes. The probability of correct classification for such an algorithm is shown in Fig. 7, assuming a low signal-to-noise ratio environment and a collection of five modulation schemes. It is observed that except for the QPSK modulation (QPSK has only cyclic feature for the symbol rate, and the strength of cyclic feature accounting for the symbol rate is less than the one due to carrier frequency), all other schemes have very good probability of correct classification [16].

V. Cognitive Radio Systems Based on Available Resource Maps

An unlicensed wireless WAN based on the combination of cognitive radio and *available resource maps* (ARM) was

SkyTel believes this sort of AMR-agumented Cognitive Radio (CR) network idea can be much fruther ehanced by the CR radios and network employing near-constant sub-foot-level High Accuracy Location (HALO) in the participating CR radios. HALO determination can be used, with time-matched, near-constant spectrum-use sensing of each radio in all times of day and season. These two correlated measurements can be used to build a map of the wireless network geographic region and how, on a cubic-foot to cubic-foot basis, the radio signals propagate and interacte (including co-channel [CC] and adjacent-channel [AC] RF multipath. With known fixed-station tranceivers, and the mobile received moving in various patterns, this will of course result in a massive database, but those are not cheap to store, build on, and utilze. The resolution / accuracy would improve over time, the more the above paried measurements take place over the whole Network region. (Continued below.)

recently proposed in [17], [18]. ARM-based cognitive radio systems are based on the same operational principles of conventional cellular networks, but with the following fundamental peculiarities:

- Spectrum is shared and a database (ARM) provides spectrum availability,
- A public radio control channel (RCC) is used for session setup, and
- Base transceiver stations (BTSs) report their spectrum usage to the ARM through a wired control channel.

In this architecture, the system infrastructure provides the framework for unlicensed spectrum access and spectrum bartering. The ARM is a real-time map of all spectrum usage updated and maintained by user equipment (UE) and BTSs. Local frequency allocation is managed exclusively by an ARM-based base station. ARM-based cognitive radio networks may operate as a shared resource (secondary user) system in spectrum licensed to a primary system. In this case, primary systems may be connected to the ARM to allow for spectrum sharing and coordination.

In the ARM-based architecture, a RCC is used to coordinate the spectrum access of all the UE in the system. Before any radio transmission takes place, each UE and BTS announces its intentions over the RCC. All UE and BTSs monitor the RCC to ensure that all intended new communication links will not interfere with them. In the case that a new session will create harmful interference, objections are raised over the RCC to signal that the new session may not use the resources it intends to [17], [18].

It should be noted that, as opposed to conventional cognitive radio systems, this new architecture has a central entity responsible for spectrum allocation and management. Therefore, we believe that such an approach could, at least partially, address existing concerns on the possible interference between cognitive (secondary) and primary systems (compared, for example, to ad-hoc cognitive radio networks). As an additional interference protection layer, we envision that spectral sensing can be incorporated into the original concept of ARM-based systems as a method that would allow for (1) validation of the data transmitted through the RCC, and (2) gathering of spectrum usage information from systems that are not connected to the ARM (for example, other unlicensed systems). In this configuration, the ARM could serve as the entity responsible for spectrum sensing data fusion.

VI. Conclusions

Cognitive radio is a new and exciting technology that, among other applications, has the potential to unlock the spectrum necessary for the deployment of next generation high data rate systems. However, for this concept to become a practical technology, research into the processing, transmission, and fusion of spectrum sensing information is still necessary. In this paper, different aspects of a distributed approach to spectrum sensing were addressed and preliminary results were presented. The use of cyclic feature-based methods for signal detection and classification was discussed, and it was shown that such methods provide reliable detection/classification even at low signal-to-noise ratio scenarios.

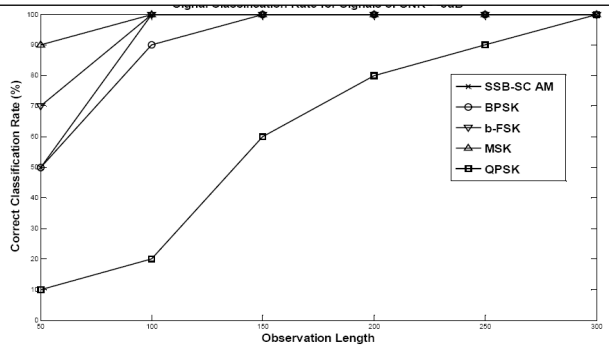

Fig. 7. Probability of correct classification using a cyclic feature algorithm described in [16].

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(Continued from above.) If (as SkyTel Plans for its networks) the Network knew all authorized users, and they were all using this form of CR on the Network, then, after said Resolution/ Accuracy was sufficiently developed by the increasingly knowledgable Network, it would be able to instruct each radio at each place and time what spectrum it may use without interference to and from other users-- based upon past experiences. This should subtantially (1) shorten the time of these determinations, and (2) decrease the resources (power and distributed-mesh radio reporting as described in this paper) needed by each mobile radio, for the determinations, (3) provide an alternative, historical source of this detemination to the real-time spectrum-use sensing of the radio, etc. (4) It would be able to track all radios precisely and perform a "traffic cop" role as the radios move around the Network, and their authorized services and priorities change. Thus, HALO may play a vital role in "Cogintive Radio Networks."