An Overview of Cooperative Spectrum Sensing in Cognitive Radios

Christopher Baumler, *Student Member, IEEE*

***Abstract*—Cognitive radios are considered a viable solution to the spectrum scarcity problem. However, they are subject to problems such as path loss, shadowing, and the hidden primary user dilemma. In this paper, an overview of a potential solution, cooperative cognitive radio sensing networks, is given. To maintain generality energy detector based sensing is considered. A variety of decision combination schemes are considered including soft, hard, and hybrid schemes. Also, some problems experienced by cooperative networks are discussed, and cluster-based networks are considered as a further improvement.**

I. Introduction

COGNITIVE radio (CR) has been defined as a wireless communication system built around the concepts of constant interpretation of the surrounding environment and intelligent actions in response to changes. More specifically, CR is an innovative technique designed to make more efficient use of the increasingly saturated radio frequency spectrum. As wireless data transmission rates escalate, efficient use of available radio resources becomes paramount. The problem is revealed more clearly by the findings of the Federal Communications Commission, a government body which discovered that many licensed frequency bands in the United States are underutilized by their primary users. This lack of use of a frequency channel has been termed a spectrum hole and is more rigorously defined as a section of the frequency spectrum that is allotted to a primary user but is not seeing use at a certain time and geographic location [1].

One promising method for increasing spectral efficiency is to allow secondary users who are not licensed to use the frequency bands in question to take advantage of spectral holes. CRs are designed specifically for this purpose, having the ability to perform spectrum sensing to detect when frequency channels are available and modify their operating parameters to transmit over the newly vacant frequency band. However, for CRs to be useful, they must be able to quickly and accurately detect the presence of primary users on licensed channels and cease transmission so as to avoid causing interference.

There are several methods for implementing spectrum sensing including energy detector based sensing, waveform-based sensing, cyclostationarity-based sensing, radio identification based sensing, and matched filtering [2]. These sensing strategies vary greatly in complexity and quality, yet each faces a set of common challenges that give rise to the need for cooperative spectrum sensing. Foremost among the problems are issues such as path loss, shadowing, and hidden primary users. Path loss refers to the decrease in signal power as the distance between transmitter and receiver increases. Shadowing or fading is fluctuation of signal power from the predicted attenuation due to path loss [1]. The hidden primary user problem results when shadowing obscures a primary user from detection by a CR [2]. While these issues can result in considerable difficulties with individual CR spectrum sensing, their effects can be significantly mitigated when networks of CRs work cooperatively, sharing sensing information.

In Section II we introduce the general structure of a CR network and discuss energy detector based spectrum sensing. Section III provides a comparison of different decision making approaches used in determining whether a primary user is present. Cluster-based sensing, a further improvement on the CR network, is reviewed in Section IV. Finally, we provide concluding remarks in section V.

II. Cooperative Sensing Networks

An example of a commonly used structure for cognitive radio based networks is depicted in Fig. 1. The network consists of a number of cognitive radios positioned around a central base station. The figure also depicts a primary user transmitter/receiver pair. Generally, the distance between individual CRs is considered to be much smaller than the distance between the CRs and the primary user transmitter. The dashed lines represent spectrum sensing by the CRs, and the solid lines show the transmissions taking place. When present, the primary user transmitter communicates information to the primary user receiver. In addition, the CRs report the results of their individual spectrum sensing efforts to a base station. This station combines all of the gathered decision data and makes the final sensing decision. It also manages the network, assigning open communication channels to the CRs [3]. The methods used by the base station to determine the availability of a channel fall into three general categories, which will be discussed in section III. The strategies used by the base station to determine which CR is allowed to use a particular channel are not discussed in this paper.

Before examining the sensing strategies used in cooperative CR networks, we must consider the case of an individual CR node. To maintain generality we assume that all nodes utilize energy detector based sensing, as this is the most generic detection method and does not require knowledge of the primary user's transmitted signal. Energy detection has low computational and implementation complexity, but it performs

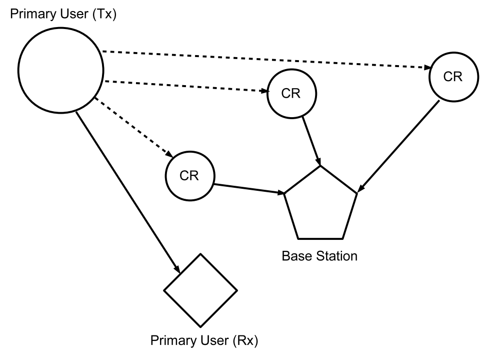

Fig. 1. Cognitive radio network.

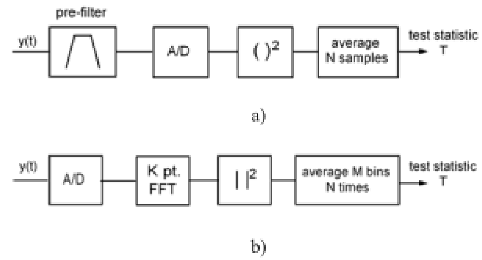

Fig. 2. Energy detector implementations courtesy of [4].

poorly when signal-to-noise (SNR) ratio is low [2]. The SNR value below which detection cannot take place is known as the SNR wall and is derived experimentally in [4].

Energy detection locates signals by comparing received energy to a threshold value determined by the noise present in the environment. Consider the received signal

$$y(n) = hs(t) + n(t) \tag{1}$$

where $s(t)$ is the signal transmitted by the primary user, $n(t)$ is additive white Gaussian noise (AWGN) present in the channel, and h is the complex gain of the channel. The received energy becomes the test statistic and is given by

$$E = \sum_{i=0}^{N} |y(n)|^2 \tag{2}$$

where N is the number of samples used for one observation. This test statistic, which has a chi-square distribution, is compared to a threshold λ to decide between the following two hypotheses:

$$\begin{aligned} H_0 : Y(t) &= n(t) \\ H_1 : Y(t) &= hs(t) + n(t). \end{aligned} \tag{3}$$

H_0 predicts the absence of a primary user ($s(t) = 0$), and H_1 predicts the presence of a primary user. Intuitively, we see that choosing a decision threshold that is too high, the CR will be less likely to detect a primary user when one is present. This is known as the probability of missed detection P_m which is equivalent to $1 - P_d$ where P_d is the probability of detection given as

$$\begin{aligned} P_d &= P(E > \lambda | H_1) \\ &= \frac{\Gamma(N, \frac{\lambda}{2})}{\Gamma(N)} \end{aligned} \tag{4}$$

where $\Gamma(a, x)$ is the gamma function. Likewise, we see that if a decision threshold is chosen that is too low, the CR will be more likely to detect a primary user when none is present. The probability of false alarm is defined as

$$\begin{aligned} P_f &= P(E > \lambda | H_0) \\ &= Q_N(\sqrt{2\gamma}, \sqrt{\lambda}) \end{aligned} \tag{5}$$

where $Q_u(a, x)$ is the generalized Marcum Q-Function, and γ is the instantaneous SNR [3]. From these equations we see that choosing an optimal threshold is vital, as a high P_m increases the interference seen by the primary user, and a high P_f is synonymous with poor spectrum utilization [5].

In practice an energy detector is usually implemented in one of two ways. The first method uses a pre-filter matched to the bandwidth for which detection is occuring. This stage is followed by an analog to digital converter which takes N samples for a given observation period. Each sample is squared, and the average of all of the samples is taken. This method is depicted in Fig. 2.a). A more common implementation is shown in Fig. 2.b). This method is similar to the first; however, it uses a periodogram to estimate spectral energy in the frequency domain rather than the time domain. This is accomplished by squaring the magnitude of the FFT and averaging [4].

III. Decision Making Approaches

The primary defining characteristic of a cooperative sensing CR network is the decision fusion that takes place at the base station. Rather than making spectrum sensing decisions independently, individual nodes send their detection results to the base station, which combines the data and makes an overall decision for the network. The information sent can be soft, hard, or a hybrid combination of the two [2].

A. Soft Decisions

Soft decisions occur when the base station has full access to the individual measurements taken by CR nodes. This means the continuous valued energy measured by each CR must be quantized with sufficient bits to retain accuracy before transmission to the base station. While soft decisions are generally more optimal than hard decisions, the added communication overhead is highly undesireable [5].

Several different soft combination schemes exist with varying levels of performance and complexity. Among the simpler methods are Equal-Gain Combining (EGC) and Maximal-Ratio Combining (MRC) [5]. The optimal soft combination scheme is the Neyman-Pearson criterion or, equivalently, the likelihood ratio test (LRT). In this scheme a threshold λ is chosen to give a predetermined false alarm probability, and the decision is made using the measured energies of each CR,

$$E = \sum_{j=1}^{K} \frac{\gamma_j}{1+\gamma_j} Y_j. \tag{6}$$

K is the number of CRs reporting data, Y_j is the energy of the jth CR, γ_j is the instantaneous SNR, and $\frac{\gamma_j}{1+\gamma_j}$ is the weight given to the jth CR. In the case where $\gamma_j >> 1$, (6) reduces to the EGC scheme, and when $\gamma_j << 1$, it reduces to the MRC scheme. This suggests that in high SNR regions, EGC is nearly optimal, and in low SNR regions, MRC is nearly optimal [6].

While the likelihood ratio test scheme is the optimal soft detection method, it requires knowledge of the channel gain of each CR, which adds complexity to the system. Thus, a simpler soft detection scheme such as EGC may be desirable. As alluded to previously, in this scheme the test statistic E is given by

$$E = \sum_{j=1}^{K} Y_j. \tag{7}$$

This equation yields a chi-square random variable with degree of freedom equivalent to the sum of the degrees of freedom of the K individual test statistics. Likewise, the non-centrality parameter is equal to the sum of the non-centrality parameters of the K individual statistics. Using this information, and conditioning on the SNR of fading channels, we write the probabilities of detection and false alarm for the base station as

$$\begin{aligned} Q_d &= P(E > \lambda | H_1, \gamma_1 = l_1 ..., \gamma_K = l_K) \\ &= Q_{KN}\left(\sqrt{2N \textstyle\sum_{j=1}^{K} l_j}, \sqrt{\lambda} \right) \end{aligned} \tag{8}$$

$$\begin{aligned} Q_f &= P(E > \lambda | H_0) \\ &= \frac{\Gamma(KN, \lambda/2}{\Gamma(KN)} \end{aligned} \tag{9}$$

where N denotes the time bandwidth product, or the number of samples used by the energy detector for one observation. The average probability of detection can be determined by unconditioning (8) with respect to the γ_j's and is given by [5]

$$Q_d^* = \int_{\gamma_0} Q_{KN}\left(\sqrt{2Nx}, \sqrt{\lambda} \right) f_{\gamma_0}(x) dx \tag{10}$$

where γ_0 is the sum of the K i.i.d. instantaneous SNRs for each CR channel. This parameter follows a Gamma distribution given as

$$f_{\gamma_0}(x) = \frac{x^{K-1} e^{-x/\bar{\gamma}}}{(n-1)! \gamma^{-K}}. \tag{11}$$

Fig. 3. is a plot of average channel SNR in dB versus probability of detection. It shows simulation results comparing the optimal soft combination (OC) scheme, MRC, EGC, and a one-bit hard combination scheme. The results verify the assertion that the likelihood ratio test is indeed optimal. We also see that the EGC soft combination, while performing suboptimally, still achieves significantly better results than the hard combination scheme. Thus, EGC may be considered as a middle ground between performance and complexity/communication overhead [6].

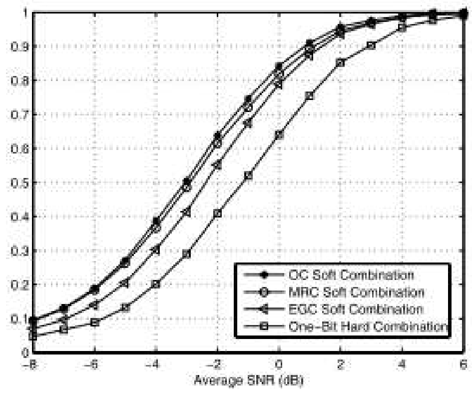

Fig. 3. Comparison of combination schemes courtesy of [6] $(K = 8, N = 6)$

B. Hard Decisions

In a hard decision scheme, individual CRs only send their final 1-bit decisions, representing H_0 or H_1, to the base station, which then uses a fusion algorithm to make an overall decision. Such a method has significantly lower communication overhead than a soft decision scheme but also suffers from decreased probability of detection and increased probability of false alarm [5]. The general form of the hard decision combination scheme follows the following logic rule

$$Z = \sum_{i=1}^{K} D_i \begin{cases} \geq n, & H_1 \\ < n, & H_0 \end{cases} \tag{12}$$

where $D_i \in \{0, 1\}$ is the binary decision of the ith CR and K is the number of CRs reporting their hypotheses. Also, in this equation H_0 and H_1 refer to the hypotheses of the base station, not the individual nodes. Thus, we see that the base station chooses H_1 when n or more CRs individually report H_1. By choosing $n = 1$, the logical rule becomes the OR rule, where detection of a primary user by one CR is sufficient for the base station to infer the presence of a primary user. Likewise, by choosing $n = K$, the AND rule is encountered. Here a single CR detecting an open channel is sufficient to guarantee that the base station decides no primary user is present [3].

If we make the reasonable assumption that the distance between any two CRs is small compared to the distance from any CR to the primary transmitter, then we can also assume a model with independent and identically distributed (i.i.d) Rayleigh fading. Further, the instantaneous SNRs $\gamma_1 ... \gamma_K$ will be i.i.d exponentially distributed random variables, all having mean $\bar{\gamma}$. By also choosing the threshold λ to be the same for all CRs, the probabilities of false alarm P_f and the probabilities of detection P_d for each CR become independent of each other. Thus, we can write the probability of false alarm for the cooperative network as

$$\begin{aligned} Q_f &= P\{H_1|H_0\} \\ &= \sum_{l=n}^{K} \left(\begin{array}{c} K \\ l \end{array} \right) P_f^l (1-P_f)^{K-l}. \end{aligned} \quad (13)$$

The probability of missed detection becomes

$$\begin{aligned} Q_m &= P\{H_0|H_1\} \\ &= 1-\sum_{l=n}^{K} \left(\begin{array}{c} K \\ l \end{array} \right) P_d^l (1-P_d)^{K-l}. \end{aligned} \quad (14)$$

By minimizing the total error probability $Q_f + Q_m$ for the cooperative network, we see that the optimal value of n is $K/2$. This is known as the half-voting rule. However, if a very small threshold is chosen, the AND rule becomes optimal. Similarly, if a very large threshold is chosen, the OR rule becomes optimal. In equation form

$$n \approx \left\lceil \frac{K}{1+\alpha} \right\rceil \quad (15)$$

where

$$\alpha = \frac{ln\frac{P_f}{1-P_m}}{ln\frac{P_m}{1-P_f}} \quad (16)$$

In a similar fashion, an optimal threshold λ can be determined numerically for a given K, n, and SNR [3]. However, experimental observations of variations in interference and noise from one CR to another in the same network, suggest that chosing a single fixed threshold is suboptimal for practical situations. A proposed alternative to a fixed threshold system is to allow each CR to independently estimate a threshold based on local noise and interference measurements. This individual threshold system has been experimentally compared to the fixed threshold system, and performance increases of 15% to 20% have been observed [4].

In addition to optimal values of λ and n, we can determine the optimal number of CRs k^* to include in the network. If the number of CRs in a network is large, the time necessary to communicate all data to the base station may become prohibitively large. Thus, determining the smallest number of CRs in a network to guarantee a desired error performance ϵ becomes essential. This has been done in [3]. First, we define

$$F(k, n_k^{opt}) = Q_f + Q_m - \epsilon \quad (17)$$

where k is the number of cooperative CRs, and

$$n_k^{opt} = min\left(k, \left\lceil \frac{k}{1+\alpha} \right\rceil\right) \quad (18)$$

is the optimal value of n. Evaluating

$$F(k^*, n_{k^*}^{opt}) = Q_f + Q_m - \epsilon \leq 0, \quad (19)$$

we get $k^* = \lceil k_0 \rceil$ where k_0 is the first zero-crossing point of $F(k, n_k^{opt})$ in terms of k. Using k^* CRs reduces the time required for communicating sensing data while ensuring an error bound of ϵ [3].

C. Hybrid Decisions

In an attempt to combine the optimal performance of soft decision schemes with the low communication overhead of hard decision schemes, hybrid schemes have been proposed such as a softened two-bit hard combination. In such a scheme, three thresholds λ_1, λ_2, and λ_3 are used to divide a CR's range of observed energy into 4 regions rather than just one as in hard decision schemes. This requires each CR to relay two bits back to the base station to communicate the region in which the detected energy falls. The base station weights the regions r_i such that $r_0 = 0$, $r_1 = 1$, $r_2 = L$, and $r_3 = L^2$. The weighted sum is then given by

$$N_c = \sum_{i=0}^{3} r_i N_i \quad (20)$$

where N_i is the number of reported CR energies in region i. If $N_c \geq L^2$, the primary signal is detected. The thresholds, λ_1, λ_2, and λ_3 are chosen to meet a desired false alarm probability and to optimize detection performance. These thresholds and L are obtained through an exhaustive, computationally complex search. However, since the calculations need not be done in real time on the hardware system, no implementation difficulties present themselves [6].

Simulation results in [6] show that the softened two-bit hard combination scheme demonstrates superior performance to conventional one-bit schemes and is even comparable to the EGC soft combination scheme. The hybrid method's improved performance and reduced communication overhead make it a viable decision fusion strategy.

IV. Cluster-Based Sensing

So far in our consideration of cooperative cognitive radio networks, we have implicitly assumed a number of ideal conditions. For instance, we have assumed that each CR is located far enough from its neighbor so as to be unaffected by correlated shadowing. This problem results when two CRs in close proximity experience similar signal degradation due to shadowing. It is significant, because it skews the results of the base station's decision scheme [5]. Another nonideal condition that has so far been ignored is fading of the reporting channel between the CRs and the base station. A promising strategy to counter this occurence is to use cluster-based spectrum sensing networks. In such a network, CRs are divided into small groups according to a distributed clustering algorithm. Then, the node with the best reporting channel SNR collects sensing data from the other nodes in the cluster and makes a sensing decision. Subsequently, it forwards this information on to the base station [7].

We have already shown the probabilities of missed detection and false alarm for a traditional CR network. To derive these probabilities for a network that experiences reporting channel fading, let $P'_{f,i}$ be the probability that the base station receives H_1 when the ith CR node sends H_0, and let $P^{'}_{m,i}$ be the probability that the base station receives H_0 when the ith CR node sends H_1. We can then define Q_f and Q_m as

$$Q_f = 1 - \prod_{i=1}^{K}[(1-P'_{f,i})(1-P'_{f,i}) + P'_{f,i}P'_{m,i}], \quad (21)$$

$$Q_m = \prod_{i=1}^{K}[P'_{m,i}(1-P'_{f,i}) + (1-P'_{m,i})P'_{m,i}] \quad (22)$$

where K is again the number of CR users in the network. From this we see that $P'_{m,i} = P'_{f,i}$, and we can write the reporting error probability as

$$P_{e,i} = P'_{m,i} = P'_{f,i}. \quad (23)$$

Further, we observe that Q_m is increased by the imperfect reporting channel, and Q_f is bounded by $P_{e,i}$.

Cluster-based sensing networks can be utilized to reduce $P_{e,i}$. Let j be the number of CR clusters reporting decisions and let N_j be the jth cluster channel. Since each cluster decision is sent through the CR with the highest quality channel, a diversity gain of N_j is obtained when assuming Rayleigh fading [7].

Next, the reporting error probablity $Q_{e,i}$ of an individual cluster i will be determined to show the previously stated diversity gain. First, let

$$\rho_{max,i} = max(\rho_{i,1}, \rho_{i,2}, ..., \rho_{i,Ni}) \quad (24)$$

be the channel SNR of the CR node chosen to report to the base station. Here $\rho_{i,j}$ is the SNR of the jth CR in cluster i. Choosing binary phase shift keying (BPSK) as the modulation scheme, the error probability for cluster i becomes

$$Q_{e,i|\rho_{max,i}} = Q(\sqrt{2\rho_{max,i}}). \quad (25)$$

In addition, the average error probability over all j channels is found through integration to be

$$\begin{aligned} Q_{e,i} &= \sum_{m=0}^{N_i-1} \binom{N_i-1}{m} (-1)^{N_i-m-1} \frac{N_i}{2(N_i-m)} \\ &\times \quad (1 - \sqrt{\frac{\bar{\rho}_i}{N_i - m + \bar{\rho}_i}}). \end{aligned} \quad (26)$$

In [7] cluster-based sensing is examined for different numbers of CR users in cluster i. The results, depicted in Fig. 4., demonstrate the diversity gain. For a constant SNR, increasing the number of CRs in the cluster decreases the reporting error. Additionally, cluster-based sensing is simulated for both decision fusion and energy fusion strategies. The results show that cluster-based sensing offers a significant improvement over conventional sensing.

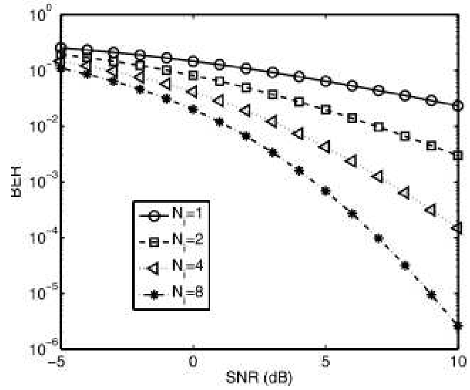

Fig. 4. Reporting BER versus average SNR for $N_j = 1, 2, 4, 8$ CRs courtesy of [7]

V. Conclusion

Cognitive radios offer a viable solution to the spectrum scarcity problem. However, when operating individually, their ability to detect spectrum use is susceptible to problems such as path loss, shadowing, and the hidden primary user dilemma. One solution to these issues is to use cooperative cognitive radio networks where a collection of CRs each perform individual sensing and send their results to a base station. The base station uses a soft, hard, or hybrid combination scheme to derive an overall hypothesis regarding the presence of a primary user. Cooperative networks have been analytically and experimentally shown to have better detection qualities than individual CRs. However, they experience some problems as well. Correlated shadowing is an issue that results when CRs are located in close proximity and experience similar channel degradation due to shadowing. CR networks must also cope with reporting channel fading where the channels used to send decision data to the base station experience degradation. This problem is countered using cluster-based sensing where CRs are grouped into clusters, and the CR with the best channel quality in the cluster is elected to combine detection decisions for the group and forward the information to the base station. The enhanced spectrum detection performance offered by cluster-based sensing and cooperative spectrum sensing in general has been shown to drastically improve the quality of cognitive radios, allowing them to be considered as a primary method to alleviate underutilization of frequency spectra.

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