CENTRALIZED AND DECENTRALIZED COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS: A NOVEL APPROACH

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ABSTRACT

In this paper, the cooperative spectrum sensing is probabilistically modeled as a mixture of two Gaussian distributions and EM algorithm is applied for learning the parameters and classifying these two classes. Also, in order to exploit the dependencies of the states of the primary user in time, a Hidden Markov Model is used to improve the performance of the centralized spectrum sensing. Furthermore, a new decentralized cooperative spectrum sensing algorithm is proposed. In this case, the local information of secondary users are appropriately combined to guarantee a reliable communication. Our simulation results indicate the remarkable performance of the proposed cooperative sensing algorithms even in very low signal to noise ratios.

1. INTRODUCTION

Cognitive radio is the means to promote the efficient use of the spectrum by exploiting the existence of spectrum holes [1]. In fact, cognitive radio is an *intelligent* wireless communication system that is aware of its surrounding environment to *learn* from the environment and *adapt* its internal states to create highly *reliable* communications whenever and wherever needed, and utilize the radio spectrum *efficiently* [1].

Spectrum sensing (SS) plays a crucial role in the implementation of the cognitive radio technology. It provides the key ability for secondary users (SU) to detect the unused spectrum and sharing it without harmful interference with primary users (PU) [2]. Spectrum sensing approaches can be classified into two main categories [2]:

1. Local Sensing
   Each cognitive radio must independently have the capability to determine the presence or absence of the primary user in a certain spectrum. This method although is simple in terms of computation and implementation, they are sensitive to model uncertainty, fading and shadowing. There are several methods proposed for local SS such as matched filtering, Waveform-Based Sensing, Cyclostationarity-Based Sensing and Energy Detector-Based Sensing [2].
2. Cooperative Sensing
   Information from multiple cognitive radio users are appropriately incorporated for PU detection. This approach enhances the accuracy and reliability of the PU detection and it is robust to fading, shadowing and model uncertainties and, consequently, it can resolve the *hidden node problem*; also, it reduces the required sensing time. However, the complexity of this approach is higher; also, it needs a control channel and it increases the traffic overhead. Cooperative sensing can be implemented in two fashions: Centralized and Decentralized.

   In Centralized Cooperative Spectrum Sensing (CCSS) a central unit collects hard [3], [6], [7] or soft [4] sensing information from cognitive radios, identifies the available spectrum, and broadcasts this information to other cognitive radios or directly controls the cognitive radio traffic (Fig.1-(a)). For instance [5] introduces an optimal linear cooperation for SS in which the goal is to mitigate the fading effects and increase the probability of detection of the primary user.

   In Decentralized Cooperative Spectrum Sensing (DCSS) cognitive nodes share information through local communications, in-order to make their own decisions as to which part of the spectrum can be used (Fig. 1-(b)). DCSS is more advantageous in the sense that there is no need for a backbone infrastructure [2]. An incremental gossiping approach for efficient coordination within a cognitive network is explained in [8]; this simple algorithm is fast and it is robust to network changes. Moreover, [9] introduces a distributed sensing method where secondary users share their information and utilize an OR-rule to infer the presence or absence of the PU.

In this paper, Spectrum sensing is formulated as a statistical inference problem. In centralized approach, SS is formulated as a classification problem in Fusion Center (FC) and *Expectation-Maximization* (EM) algorithm is used to estimate the model parameters and detect the PU. Furthermore, a *Hidden Markov Model* (HMM) is considered to model the memory in the PU's activity. In the decentralized approach an effective message passing algorithm is proposed to distribute

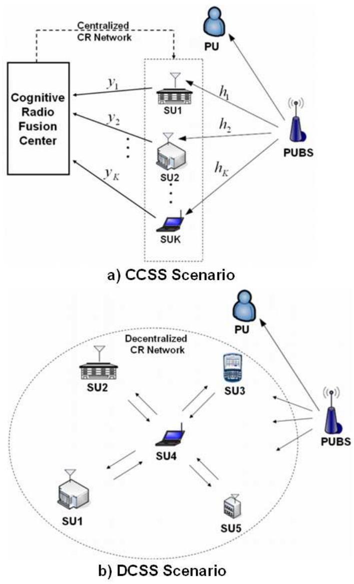

Fig. 1. (a) Centralized Cooperative Spectrum Sensing; (b) Decentralized Cooperative Spectrum Sensing.

the local decisions among SU's. Each SU, utilizes this information to improve the quality of its own decision.

The rest of the paper is as follows. First the centralized cooperative spectrum sensing is explained. In section 3 the decentralized cooperative SS is introduced. Also, simulation results illustrating the effectiveness of the algorithms are presented. Finally, section 4 concludes the paper.

2. CENTRALIZED COOPERATIVE SPECTRUM SENSING

The CCSS scenario is illustrated in Fig. 1-(a). In this case, the cognitive radio network, is provided by a fusion center or a Base Station (BS), which can be used for decision making in the spectrum sensing mode. The k-th SU senses the channel for N consecutive time period and observe a complex baseband-equivalent signal $\underline{x}_k$, $\underline{x}_k \in \mathbb{C}^N$ $(k = 1, 2, \cdots, K)$. Next, the FC collects these information through noisy channels.

The block diagram of the CCSS system is shown in Fig. 2. In this model $\underline{z}$, the baseband-equivalent signal transmitted by the PU, is propagated to the k-th SU over a noisy, flat-fading and time-invariant channel. More precisely we have:

$$\underline{x}_k = h_k \underline{z} + \underline{\omega}_k \tag{1}$$

where $\underline{\omega}_k \sim \mathcal{CN}(0, \sigma_\omega^2 \mathbf{I})$ is a Circularly Symmetric Complex Gaussian (CSCG), and h_k is a CSCG channel gain, i.e. $\underline{h}_k \sim \mathcal{CN}(0, \sigma_h^2)$ (representing Rayleigh fading between the PU and the k-th SU). Here it is assumed that $\underline{z}$, h_k and $\underline{\omega}_k$ are independent which is reasonable from a practical perspective. This model has also been used by [7].

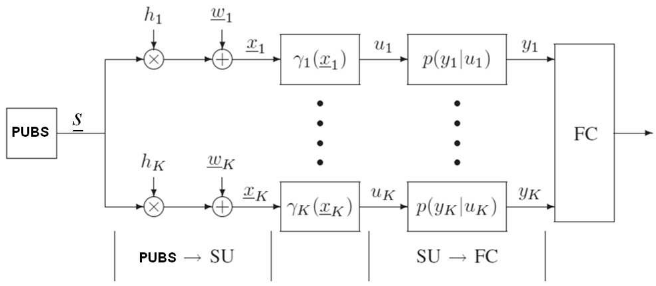

Fig. 2. CCSS: System block diagram.

At the k-th SU, an energy detector is used to make a local decision $u_k = \gamma_k(\underline{x}_k)$ which is then transmitted to the FC for the central decision making. However, two different types of cooperation can be distinguished: soft and hard. In soft decision the k-th SU sends it's energy directly to FC

$$\gamma_k(\underline{x}_k) = \frac{1}{N} \sum_{n=1}^{N} |\underline{x}_k[n]|^2$$

and in hard decision u_k is 0 unless the energy exceeds a threshold,

$$\gamma_k(\underline{x}_k) = \mathbb{I}\left\{ \frac{1}{N} \sum_{n=1}^{N} |\underline{x}_k[n]|^2 \geq \tau_k \right\}$$

where $\mathbb{I}\{.\}$ is the indicator function.

In this paper, the soft decisions are transmitted to the FC and in contrast to previous studies which SU-FC channels are assumed to be perfect control [4, 5, 6], here, an Additive White Gaussian Noise (AWGN) channel $n_k \sim \mathcal{N}(0, \sigma_{n_k}^2)$ is considered between each SU and the FC. Therefore, the received signal at the FC from k-th SU is

$$y_k = u_k + n_k \tag{2}$$

where u_k is the energy of the signal. Hence, the evidence available to the FC to make the global decision at time i is the set of SU-FC channel outputs $y_i^K = \{y_1, y_2, ..., y_K\}$.

2.1. CCSS: Gaussian Mixture Model

The CCSS can be formulated as a binary hypothesis testing problem with the null and alternative hypothesis:

$$\begin{array}{ll} H_0: & \text{Primary user is not active } (s_i = 0) \\ H_1: & \text{Primary user is active } (s_i = 1) \end{array}$$

.

In this case the hidden variable at time i, is the status of the channel s_i and the observations at FC are y_i^K. Since $\underline{\omega}_k$ and h_k are CSCG, we have,

$$x_k \sim \begin{cases} \mathcal{CN}(0, \sigma_{\omega_k}^2 \mathbf{I}) : H_0 \; (\underline{z} = 0) \\ \mathcal{CN}(0, (P\sigma_{h_k}^2 + \sigma_{\omega_k}^2)\mathbf{I}) : H_1 \; (\underline{z} \neq 0) \end{cases}$$

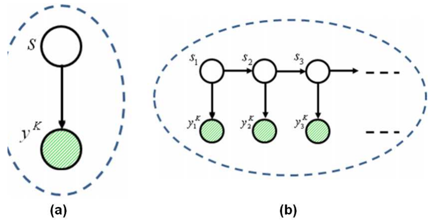

Fig. 3. a) Graphical Representation of the Gaussian mixture model; b) Hidden Markov Model in spectrum sensing.

where $P = \mathbb{E}[|z|^2]$ is the energy of the primary user. For a large number of sensing samples, N, Central Limit Theorem (CLT) states that $u_k = \frac{1}{N}||\underline{x}_k||^2$ is asymptotically normally distributed under either H_0 or H_1, so roughly speaking, we have:

$$u_k \sim \begin{cases} \mathcal{N}(\sigma^2_{\omega_k}, \frac{2}{N}\sigma^4_{\omega_k}) : H_0 \\ \mathcal{N}(P\sigma^2_{h_k} + \sigma^2_{\omega_k}, \frac{2}{N}(P\sigma^2_{h_k} + \sigma^2_{\omega_k})^2) : H_1 \end{cases}$$

Now for simplicity assume that the noise and channel statistics are the same, then,

$$u^K \sim \begin{cases} \mathcal{N}(\sigma^2_{\omega}.\mathbf{1}_K, \frac{2}{N}\sigma^4_{\omega}.\mathbf{I}_K) : H_0 \\ \mathcal{N}((P\sigma^2_{h} + \sigma^2_{\omega}).\mathbf{1}_K, \frac{2}{N}(P\sigma^2_{h} + \sigma^2_{\omega})^2.\mathbf{I}_K) : H_1 \end{cases}$$

where $u^K = \{u_1, ..., u_K\}$, and finally y^K can be modeled as normal distribution $\mathcal{N}(\mu_0, \Sigma_0)$ (under H_0) and $\mathcal{N}(\mu_1, \Sigma_1)$ (under H_1) as defined by:

$$y^K \sim \begin{cases} \mathcal{N}(\sigma^2_{\omega}.\mathbf{1}_K, (\frac{2}{N}\sigma^4_{\omega} + \sigma^2_n).\mathbf{I}_K) : H_0 \\ \mathcal{N}((P\sigma^2_{h} + \sigma^2_{\omega}).\mathbf{1}_K, (\frac{2}{N}(P\sigma^2_{h} + \sigma^2_{\omega})^2 + \sigma^2_n).\mathbf{I}_K) : H_1 \end{cases} \quad (3)$$

Therefore, y^K is a mixture of two Gaussians (Fig. 3-(a)), which means

$$p(y^K) = \pi_0\mathcal{N}(y^K|\mu_0, \Sigma_0) + \pi_1\mathcal{N}(y^K|\mu_1, \Sigma_1)$$

where π_0 and π_1 are prior probabilities.

Hence, EM algorithm can be used to estimate the unknown parameters of this model, namely (π_0, μ_0, Σ_0) and (π_1, μ_1, Σ_1) [10] (chapters 10 and 11). Accordingly, FC utilizes the Quadratic Discriminative Analysis (QDA) which is basically Log-likelihood function

$$\begin{aligned} r(y^K) \;\; = \;\; & \log(\frac{\pi_1}{\pi_0}) + \frac{1}{2}\log(\frac{|\Sigma_0|}{|\Sigma_1|}) \\ & + \frac{1}{2}(y^K - \mu_0)^T\Sigma_0^{-1}(y^K - \mu_0) \\ & - \frac{1}{2}(y^K - \mu_1)^T\Sigma_1^{-1}(y^K - \mu_1) \end{aligned}$$

to classify and assign the new observation vector y^K to the one of the two classes, H_0 or H_1.

Fig. 4 illustrates the performance of the EM algorithm in CCSS. In this case, different number of SUs were considered and the probability of error (more precisely probability of wrong decision) was measured at different SNR's. In our simulations, the PU transmits a Binary Phase Shift Key (BPSK) sequence with power P and all channels and noises are assumed to have the same statistics ($\mathcal{CN}(0, 1)$) therefore nodes are operating at the same SNR. It is clear that using the CCSS, the detection of the PU is possible even at very low SNR's. In addition, by increasing the number of SUs the p_e was decreased. This is expected, because having more SUs provides more information at FC and accordingly, more reliable decisions can be made.

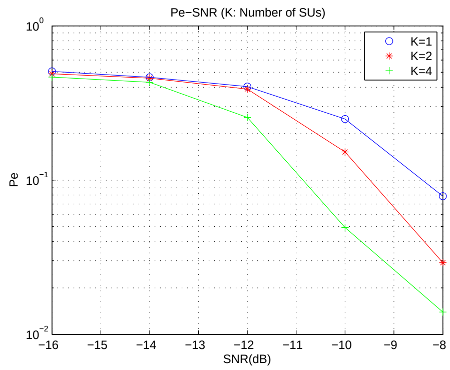

Fig. 4. EM based Spectrum Sensing performance. In this figure, error probability verses SNR is plotted for different number of SUs. The performance is obviously improved by the increase the number of SU (K).

2.2. CCSS: Hidden Markov Model

In section 2.1 we implicitly assumed that the PU's statuses, $s_i(i = 1, 2, \cdots)$, are independent. This essentially means that there is no memory in the system and PU's activity is independent from time to time. However, it is quite natural to assume that whenever the PU is active, it is more likely to be active next time and vice versa; in other words, the system is not memoryless. One way to capture this effect is to assume that $s_i(i = 1, 2, \cdots)$ is evolving according to a Markov chain and at each time, based on the channel status s_i, we have an observation (y_i^K) at the FC (see (Fig. 3-(b))). In this case, like the problem that was discussed in section 2.1 the observed data has a mixture model (equation 3). The only difference is that the classes are not independent and evolving according to a transition matrix which should be estimated along with the other parameters of the Gaussian mixture model. The inference problem for HMMs involves taking as input the observed data and yielding as output a probability distribution on the underlying states. This problem can be solved recursively in a neat way and in the mean time EM algorithm can be used to derive the mixture components [10].

Figure 5 illustrates the performance of the HMM in the CCSS and compares it with the Gaussian mixture model when $K = 2$. It is clear that, by modeling the dependencies in the PU's activity with a HMM, the performance is significantly

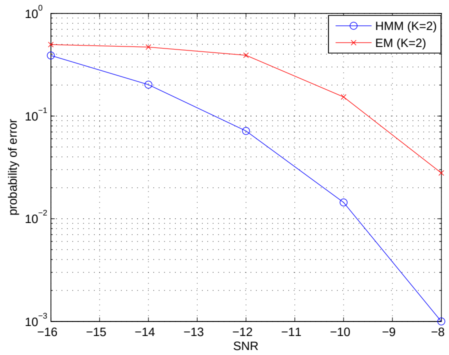

Fig. 5. HMM and EM based spectrum sensing performances for $K = 2$ SUs. As you can see HMM by utilizing the time dependency in the PU activity has a lower error probability for the same SNR.

improved.

3. DECENTRALIZED COOPERATIVE SPECTRUM SENSING (DCSS)

In DCSS as it was explained in section 1, there is no FC to collect all the information and make a unanimous decision. However, some of the SU's can share their information with each other to make the decision processing more reliable (see Fig.1-(b)). In this section, a DCSS algorithm is proposed which improves the reliability of decisions made by the SU's.

Assume $G = (V, E)$ is a graph on the SU's where each node is a SU, also $(i, j) \in E$ if and only if there is a communication link between node i and j. We assume that these links are independent Binary Symmetric Channels (BSC) with cross probability α which means if u is the input and y is the output then $p(y \neq u \mid u) = \alpha$. Note that interference form primary user is modeled as noise.

The proposed DCSS is as follows. At the first iteration of the algorithm (nodes are assumed to be synchronized), every node senses the channel and based on the received energy makes a hard decision (see section 2). Let the jth node decision be $u_j^{(1)}$ $(j = 0, 1, \cdots, K-1)$. Then every node sends it's decision $(u_j^{(1)})$to its neighbors, assume the output of the BSCs be $y_{jt}^{(1)}$ where $t \in N(j)$ $(N(j) = \{t \in V : (j,t) \in E\})$ this completes the first iteration. In the second iteration, every node makes a new decision $(u_j^{(2)})$ based on the data that it had, $(u_j^{(1)})$, and the data that it received from the neighbors, $(y_{\mathrm{N}(j)j}^{(1)})$. At this point SU_j's decision is based on its own information and the 1-neighbor [1] information. This process is being continued till the point that every node has the whole information (the number of iterations would be the graph diameter).

[1] t is a k-neighbor of j if and only if the shortest path from j to t is of length k

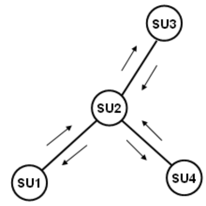

Fig. 6. A typical graph of SU's. Every edge in this graph is a BSC.

The jth decision reliability at iteration i can be determined by two numbers, probability of false alarm, $p_{fj}^{(i)} = P(u_j^{(i)} = 1 \mid H_0)$ and probability of detection, $p_{dj}^{(i)} = P(u_j^{(i)} = 1 \mid H_1)$. Without loss of generality assume the neighbors of SU_0 are SU_j $j = 1, 2, \cdots d$. As it was explained, SU_0 receives $y_j^{(i)}$ $(j = 1, 2, \cdots d)$ from it's neighbors. one can find:

$$\tilde{p}_{fj}^{(i)} := P(y_j^{(i)} = 1 \mid H_0) = p_{fj}^{(i)}(1-\alpha) + (1 - p_{fj}^{(i)})\alpha$$

$$\tilde{p}_{dj}^{(i)} := P(y_j^{(i)} = 1 \mid H_1) = p_{dj}^{(i)}(1-\alpha) + (1 - p_{dj}^{(i)})\alpha$$

Consequently the log-likelihood at SU_0 can be written

$$\begin{aligned} r_0^{(i+1)} &= \sum_{j=0}^{d} \log \frac{P(y_j^{(i)} \mid H_1)}{P(y_j^{(i)} \mid H_0)} \\ &= \sum_{j=0}^{d} \log \frac{\mathbb{I}\left\{y_j^{(i)} = 0\right\}(1 - \tilde{p}_{dj}^{(i)}) + \mathbb{I}\left\{y_j^{(i)} = 1\right\}\tilde{p}_{dj}^{(i)}}{\mathbb{I}\left\{y_j^{(i)} = 0\right\}(1 - \tilde{p}_{fj}^{(i)}) + \mathbb{I}\left\{y_j^{(i)} = 1\right\}\tilde{p}_{fj}^{(i)}} \end{aligned}$$

where $y_0^{(i)} = u_0^{(i)}$, $\tilde{p}_{f0}^{(i)} = p_{f0}^{(i)}$ and $\tilde{p}_{d0}^{(i)} = p_{d0}^{(i)}$. In other words, $u_0^{(i)}$ has passed a noise less channel with $\alpha = 0$.

The Maximum Likelihood (ML) detection at time $i+1$ is determined based on $r_0^{(i+1)}$, so we have

$$u_0^{(i+1)} = \mathbb{I}\left\{r_0^{(i+1)} > 0\right\}$$

$$p_{f0}^{(i+1)} = P(r_0^{(i+1)} > 0 \mid H_0) \quad (4)$$

$$p_{d0}^{(i+1)} = P(r_0^{(i+1)} > 0 \mid H_1) \quad (5)$$

This process is conducted for every node each time.

An interesting point about equations 4 and 5 is that $p_{f0}^{(i+1)}$ and $p_{d0}^{(i+1)}$ are just functions of d (degree of SU_0), α (noise parameter)and the reliability of it's neighbors ($p_{fj}^{(i)}$ and $p_{dj}^{(i)}$ for $j = 0, 1, \cdots d$). In other words, if every node knows the whole graph $G = (V, E)$, $p_{f0}^{(i+1)}$ and $p_{d0}^{(i+1)}$ can be computed recursively. Notice that initial points are $p_{fj}^{(1)} = Q(\frac{\tau - \sigma_\omega^2}{\sqrt{\frac{2}{N}}\sigma_\omega^2})$ and $p_{dj}^{(1)} = Q(\frac{\tau - (P\sigma_h^2 + \sigma_\omega^2)}{\sqrt{\frac{2}{N}}(P\sigma_h^2 + \sigma_\omega^2)})$ for all j. In these equations τ is the hard decision threshold and $Q(.)$ is the standard gaussian Q-function.

In order to demonstrate the effectiveness of this algorithm a simulation were conducted on the graph shown in figure 6. The probability of error verses SNR for SU_1 and SU_2 are illustrated in Fig. 7. As you can see the performance is improved by increasing the number of iterations for SU_1. However in SU_2 the performance is improved in the second iteration and decreased a bit for high SNRs in the third iteration. The reason is, SU_2, has gathered all the relevant information in the second iteration and the third is just adding more randomness in the decision which reduces the performance. Therefore it is natural that nodes run the algorithm not more than it is necessary to gather all the information.

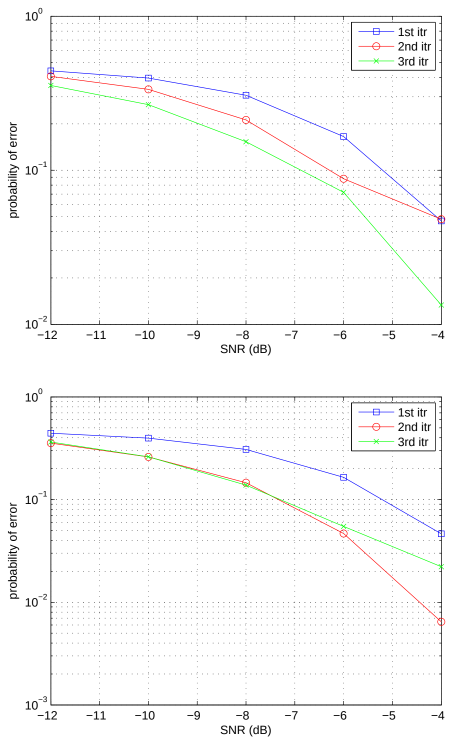

Fig. 7. DCSS performance for SU_1(up) and SU_2 (down).

4. CONCLUSION

Cooperative spectrum sensing methods are of great importance in cognitive radios because: 1) they are robust against impairments in wireless communication systems, and 2) they improve the coordination and cooperation between SUs. Consequently, cooperative sensing techniques enhance the accuracy and reliability of the SS in cognitive radios. In this paper, effective solutions for centralized and decentralized cooperative spectrum sensing in cognitive radios were proposed.

Our simulation results showed that the robust and reliable detection of PU is possible even at very low SNR's which is of crucial importance in cognitive radios. A comparison between the performance of the EM and the HMM models in CCSS clearly indicates that capturing the dependencies in the PU's activities at different times (using HMM) can significantly improve the performance of the system. We also showed how the flexibility and the lack of need of the centralized fusion center in DCSS can be compromised with the reliability and accuracy of spectrum sensing in CCSS. However, in both case (CCSS, DCSS), the performance is improved by the increase of the number of SUs. Therefore, careful considerations must be made in the design of cognitive radios by making an appropriate trade off between available resources and goals.

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