Energy-efficient Cooperative Spectrum Sensing for Cognitive Radio Sensor Networks

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***Abstract*—Cognitive radio sensor network (CRSN) is an emerging sensor networking paradigm that aims to incorporate opportunistic spectrum access capability to the wireless sensor networks. Since sensor nodes are energy-constrained devices, design of efficient spectrum sensing schemes is imperative for the implementation of CRSNs. In order to address this need, a cooperative spectrum sensing scheme (CSS), specifically designed for CRSNs, is presented in this paper. CSS aims to minimize power consumption and delay during spectrum sensing, while meeting the performance requirements in terms of accuracy with minimal complexity. Simulation results indicate that significant power savings can be achieved with the proposed solution.**

***Index Terms*—Cognitive radio sensor networks, cooperative spectrum sensing, correlation based sensing**

I. Introduction

Wireless sensor networks (WSN) provide the capability to capture and relay information to be used in an increasing number of areas of interest. Wireless sensor nodes have gone through considerable improvements in the recent years with reduced size, increased memory and processing capabilities as well as reduced power consumption through developed power saving schemes Although increased capabilities of sensor nodes render some of the concerns such as limits of computational complexity and memory size less critical, new problems arise with the evolving technology. WSNs almost exclusively operate in unlicensed ISM bands. While a few years ago, especially the higher frequency regions of the ISM bands were not as crowded, today, there is significant amount of increase in the applications that use these bands, causing the coexistence problem[1]. Clearly, WSNs need additional capabilities to combat the interference they receive from other applications which use these bands.

A promising solution is to use the Cognitive Radio (CR) technology to equip the sensor nodes with opportunistic spectrum access (OSA) capability. Cognitive radios can sense the spectrum and identify the vacant bands, providing them with the opportunity to communicate in licensed bands without hindering primary user (PU) communication. Towards this end, CRSN is a recently emerging paradigm. [1]. With their increased memory and processing capabilities as well as more efficient power management facilities, depending on the application type, sensor nodes can meet the additional requirements of cognitive radio to obtain the OSA capability. Viability of CRSN has been investigated by various researchers (e.g. [2], [1]) A common viewpoint was that in the near future, WSNs may need cognitive radio capabilities. As a result, recently there has been an increase in research related to CRSN (e.g. [9], [4])

There is a large volume of research in the literature about cooperative spectrum sensing. On the other hand, there are only a few solutions specific to CRSN. In [5], authors propose a medium access scheme which includes spectrum sensing. However, the proposed scheme does not utilize multiple channels. If the channel is sensed busy, sensors wait for the next opportunity. Furthermore, the sensing scheme is simplistic and assumes high SNR values. In [6], a spectrum sensing scheme which aims to minimize energy consumption due to spectrum sensing is proposed. However, the proposed scheme is not practical since it requires the nodes to solve complex optimization problems to obtain the optimal threshold values for sensing.

A Cooperative sensing for OFDM based on energy detection in MIMO CRSN is proposed in [7]. The solution assumes that PUs use OFDM. Furthermore, it requires multiple antennas on sensor nodes, thus, it is not a realistic solution. Also it requires all nodes to participate in sensing, therefore, it is wasteful of resources. Another cooperative sensing is proposed in [8]. The solution is based on the spatial spectral estimation. It assumes all SUs use spread spectrum. There is no PU detection. Rather, amount of interference to PUs are controlled. It requires very complex calculations since it is based on direction of arrival estimation. In [9], a distributed wideband sensing scheme for CRSN is presented. Its major problem is that since it is based on compressive sensing, it assumes sparse use of spectrum, which is contrary to the current status of wireless spectrum. Therefore, it performs poorly in crowded bands. Moreover, it requires all nodes to participate.

All of the previously proposed solutions approach CRSN spectrum sensing problem as if it the underlying network was a generic cognitive radio network. None of them make use of the inherent advantages of the sensors. The novelty of our scheme is the idea of exploiting the actual sensing data of the sensors to develop a more efficient spectrum sensing mechanism as follows:

An important consideration for cooperative sensing is which nodes to include in the sensing. It was shown in [10] that, although sensing performance increases with the increasing

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number of cooperating nodes, this increase has diminishing returns, and the contribution of highly correlated nodes is very limited . However, having every node send its spectrum sensing data to each other node to calculate correlations is clearly a very demanding task in terms of resource consumption. It will also increase the delay caused by spectrum sensing considerably. Instead, we propose that nodes use actual sensing data of their neighbors that they overhear. Here we emphasize the difference between spectrum sensing data and the data of actual sensing performed by the nodes, such as heat, humidity, etc.

There are a number of justifications for using actual sensing data instead of spectrum sensing data. First, the sensor nodes will send their sensing results regardless of spectrum sensing operation. Therefore, it is logical to make use of this information instead of having nodes additionally transmit their spectrum sensing samples. Second, building a moving average of this correlation gives a good idea about the attenuation introduced by the current obstacles between nodes. Thus, it is viable to use this correlation within the spectrum sensing mechanism to overcome the adverse effects of shadowing. Simulation results given in section IV also support our claim.

The details of our scheme is given in section II. The theoretical background for correlation based node selection is given in section III. In section IV a performance evaluation based on simulation results is given. Finally, in section V we present our concluding remarks

II. System Model

CSS is based on energy detection, since it is the most suitable detection type for sensor nodes due to its simplicity. We first consider the following scenario. The received signal under the two hypotheses are,

$$\begin{aligned} H_0 &: y(t) = n(t) \\ H_1 &: y(t) = s(t) + n(t) \end{aligned} \tag{1}$$

where $y(t)$ is bandlimited to the spectrum channel that is being sensed, $n(t)$ is zero mean, additive white Gaussian noise with variance σ_n^2, and $s(t)$ is the PU signal. We do not assume a specific PU signal type, since the sensing scheme has to meet the detection criteria regardless of the PU signal specifics. Therefore, we analyze a general case where the PU signal is assumed to be Gaussian random process with zero mean and variance σ_s^2. In practical cases, most of the digital modulation types have zero mean with a certain signal power as variance. Thus, our assumption is meaningful. Similar assumptions were made in various previous work in the literature (e.g., [11]).

For energy detection, the following statistic is formed using the N observations obtained by each node

$$r_j(r) = \sum_{k=1}^{N} y_k^2 = \sum_{k=1}^{N} \left(y_{k(i)}^2 + y_{k(q)}^2 \right) \tag{2}$$

where $y_{k(i)}$ and $y_{k(q)}$ indicate the in-phase and quadrature components of the k^{th} sample of the bandpass signal y_k. $r_j(r)$ is the summation of chi-square distributed random variables for the j^{th} node [12]. Central limit theorem indicates that for large N, $r_j(r)$ approaches a Gaussian distribution.

III. Analysis of Correlation Based Node Selection

Detection performance is maximum when observations (i.e. spectrum sensing data) of the nodes are independent. However, independence assumption is not realistic. There is almost always a certain degree of correlation among the nodes. CSS aims to choose nodes with the least correlation to minimize the adverse effects of correlation in sensing. To illustrate the idea, consider the following two cases. In the first case, we have two independent observations. In the second case we consider observations which are correlated with a correlation coefficient of ρ. The general expression for sufficient statistic for two correlated readings can be expressed as

$$l(\vec{r}) = \frac{1}{2}(\vec{r}^T - \vec{m_0}^T)Q_0(\vec{r} - \vec{m_0}) - \frac{1}{2}(\vec{r}^T - \vec{m_1}^T)Q_1(\vec{r} - \vec{m_1}) \tag{3}$$

where Q_j indicates the inverse of the covariance matrix $K_j = E[(\vec{r} - \vec{m}_j)(\vec{r}^T - \vec{m}_j^T)]$ under hypothesis j, and $\vec{m_1}$ and $\vec{m_0}$ indicate the mean values under respective hypotheses.

For normalized noise power and assuming noise samples are independent we have,

$$l_{uncor} = \frac{1}{2}(r_1^2 + r_2^2)\frac{\gamma}{1+\gamma} \tag{4}$$

and,

$$\begin{aligned} l_{cor} = \frac{1}{2}(r_1^2 + r_2^2)\left[1 - \frac{1+\gamma}{(1+\gamma)^2 - \rho^2}\right] + \\ r_1 r_2 \left[1 + \frac{\rho}{(1+\gamma)^2 - \rho^2}\right] \end{aligned} \tag{5}$$

where, l_{cor} and l_{uncor} are the sufficient statistic for the correlated and two uncorrelated cases, respectively. Here, $\gamma = \sigma_s^2/\sigma_n^2$ is the SNR and ρ is the correlation coefficient between r_1 and r_2.

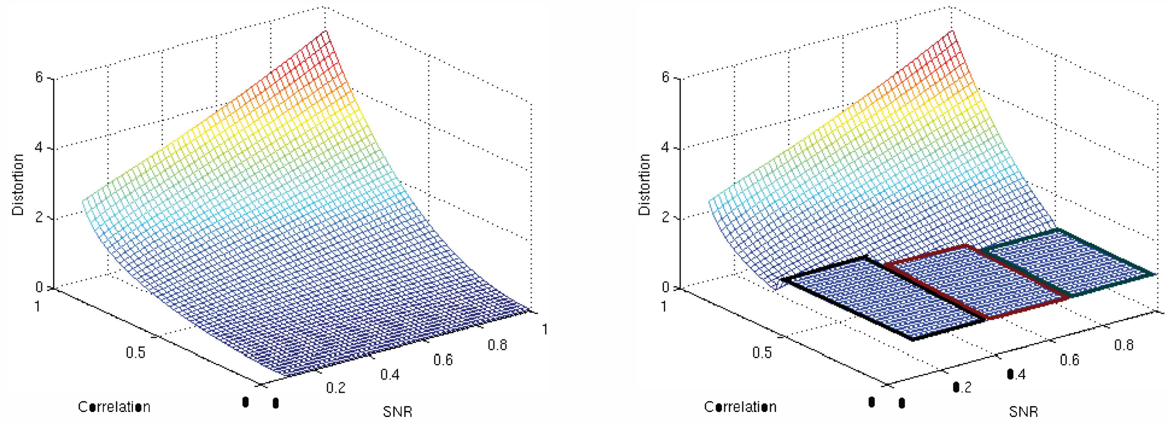
The larger the correlation, the greater the different between two sufficient statistic. Since l_{uncor} represents the ideal case, we want to choose nodes with the least correlation so that the suficient statistic, l_{cor}, is as close to the ideal as possible.

In our solution we propose the following method to choose the nodes which will take part in cooperative sensing. We define a distortion metric, D, that indicates the difference in contribution between two uncorrelated nodes and two nodes with correlation ρ. We take D to be the MMSE error between the sufficient statistics of these two cases, i.e.,

$$D = E\left[(l_{uncor} - l_{cor})^2\right] \tag{6}$$

Placing Eqn. (4) and Eqn. (5) in Eqn. (6), expanding the expectation and making algebraic manipulations, D can be expressed as

$$D = (1+\gamma)^2 P^2 + \rho^2 (1+\gamma)^2 Q^2 - 2\rho^2 (1+\gamma)^4 PQ \tag{7}$$



(a) (b)

Fig. 1. Distortion in sufficient statistics and corresponding admittance regions

where

$$P = \frac{\gamma}{1+\gamma} - 1 + \frac{1+\gamma}{(1+\gamma)^2 - \rho^2} \tag{8}$$

and

$$Q = 1 + \frac{\rho}{(1+\gamma)^2) - \rho^2} \tag{9}$$

As mentioned in Section I, it is unrealistic to calculate the correlation coefficient of spectrum sensing data. In a wireless sensor network, sensor nodes overhear their neighbors' reported sensing data all the time. Since this data is readily available, we propose to calculate correlations using these actual sensor data. As justified in Section I, and supported by the results in Section IV this is a perfectly exploitable aspect of wireless sensor operation, and it is unique to CRSNs.

The distortion, D, for various SNR and correlation values is shown in Fig. 1(a). We see that in low SNR regions the distortion due to correlation is lower. In addition, more cooperating nodes are needed to obtain the required sensing performance in low SNR regions. Thus, the number of nodes to take part in cooperated sensing can be determined by SNR and correlation parameters as explained below.

Ideally, each node would check to see if it will yield a distortion larger than the required minimum for its instantaneous SNR value, and refrain from participating in sensing if that is the case. This would correspond to any SNR-correlation pair in Fig. 1(a), for which, the distortion is higher than the required minimum. However, it is not realistic to expect resource constrained nodes to perform the involved calculations each time. Instead, we propose forming predetermined *admittance regions* for which corresponding SNR and correlation ranges are below the distortion threshold. If node SNR and correlation is within these regions they will participate in the cooperative sensing. The idea of admittance regions is illustrated in Fig. 1(b) with relation to Fig. 1(a). The flattened three regions are the so called admittance regions for which D is below a certain threshold (1 in this case). Each of these regions can be defined by two snr-correlation pairs, each defining one of the upper corners of the region. These pairs are precalculated and hardcoded into the nodes. Each node checks to see if its SNR and correlation values are within one of these regions. If not, it concludes that its distortion value is too high, does not participate in spectrum sensing and goes to sleep. Otherwise, it participates in sensing. This considerably reduces the number of nodes that perform sensing while still meeting the spectrum sensing performance constraints as supported by the simulations given in the next section.

IV. CSS Performance Evaluation

In order to make an assessment about the proposed scheme, we performed extensive simulations. We ran each simulation 5000 times. Results presented in the figures are the average numbers of these 5000 trials. In each run, a random topology is created. First, a large number of events at random locations are generated. In a real life scenario, sensor nodes gather this data over the time of their normal operation. Then, correlations between nodes for these sensing data are computed. The channel is AWGN with log-normal shadowing. A path loss exponent of 3.7 and a shadowing variance of 3.65 dB is used since these are typical values. Thresholds were calculated for $P_{FA} = 0.1$.

To the best of our knowledge there is no generic (i.e. that works without assumptions about PU signal) and non-complex (e.g requiring multiple antennas, etc.) cooperative spectrum sensing method developed for CRSN to compare CSS with. Therefore, we choose a cooperative scheme that is designed for CR networks [13]. This scheme is chosen because, like CSS, it also employs a kind of censoring strategy to choose nodes. In this scheme, nodes which have sufficient statistic that is close to the threshold value are not included in the sensing, i.e. only nodes that have very high or very low SNR are chosen. The idea is to include nodes that are more "sure" about their decision. Since threshold is calculated assuming a noise floor, this method performs poorly in noise fluctuations. We call this method the SNR-based censoring method. When

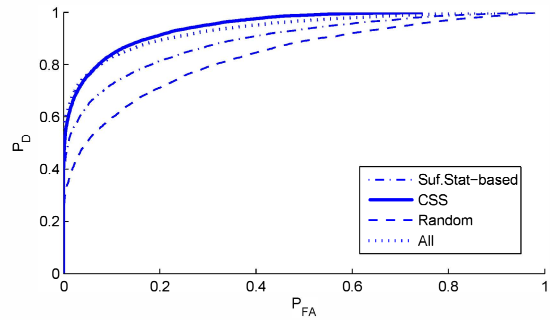


Fig. 2. P_D vs P_F for varying threshold values.

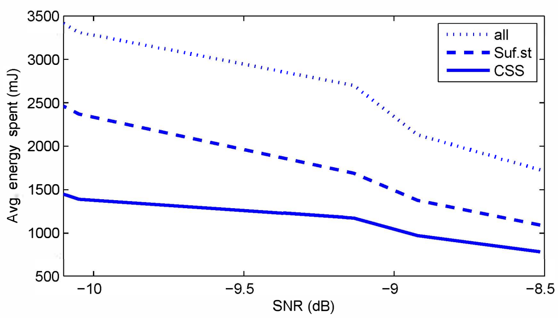


Fig. 3. Energy spent under various SNR

deciding which nodes to censor, our method also uses the correlation between nodes. Therefore, we expect CSS to yield better performance.

In the simulations AWGN channel model with log-normal shadowing. A path loss exponent of 3.7 and a shadowing variance of 3.65 dB is used. First simulation is performed to compare the performance of CSS with other methods by means of receiver operating characteristic (i.e. ROC) curves. In the figures, the solid line represents CSS. The dotted line is for the case where all nodes participate in the sensing, the dot-dash line is the sufficient statistic-based censoring method designed for CRNs. The threshold offset values of sufficient statistic based method and D value of CSS are chosen such that average number of nodes that participate in the cooperation are equal. For ROC simulations, we also added the case of random node selection. This is represented by the dashed line. Random node selection has the same number of average nodes. This case was included to make comparisons about the effect of intelligent node selection on performance. As seen in Fig. 2, CSS has the best performance except for a very narrow region where threshold is very high. Here CSS has slightly lower P_D than the case where all nodes are included in sensing.

In the second simulation we compare the energy spent in different sensing cases. Transmission power values of the PUs are 50 mW. Their locations are picked randomly with a mean distance that corresponds to the desired average SNR for each case.

We calculate energy consumption as

$$E_s = n_s t_s I_r V \tag{10}$$

TABLE I
VALUES USED IN THE SIMULATIONS FOR ENERGY CONSUMPTION

l_p	100
t_s	4 μs
t_b	32 μs
I_r	19.7 mA
I_t	17.4 mA
V	3 V

and

$$E_t = l_p t_b I_t V \tag{11}$$

where E_s and E_t are energy spent in sensing and energy spent for transmission of sensing results for one node, respectively. n_s is the number of samples takes for sensing, t_s is the time it takes to obtain one sample, t_b is byte transmission time, l_p is the packet length in bytes, I_r and I_t are the transmit and receive mode currents, and V is the supply voltage of the sensor nodes. Since the sensing data reported by the nodes is a single measurement (i.e. 1 or 2 bytes), packet size is small. We assume a packet length of 100 bytes including the protocol headers for spectrum sensing result reports. Note that this is not a limit on ordinary communication packets of the sensor network, but rather only an estimate for packets that are used to report sensing results. Furthermore, with regard to comparisons among the sensing methods presented below, the determining factor is the number of packets transmitted in each method, and not so much the size of these packets.

For the rest of the parameters typical values [14] given in Table I is used .

The results given in Fig. 3 focus on the low-SNR region where cooperative sensing is used to increase detection performance. CSS provides more than 100 % energy saving compared to the cases where all nodes participate up to about -9.5 dB SNR. It is also considerably more energy efficient than the sufficient statistic-based method, which only makes use of SNR. The performance difference between these two cases clearly demonstrate the importance of using correlation in node selection.

Finally, we investigate the delay incurred by sensing for different sensing methods. Presented delay in Fig. 4 includes the delay during spectrum sensing as well as the delay due to packet exchange of the spectrum sensing results. The typical values used in the second simulation are also used here (i.e values in Table I). As the number of participating nodes increase, the number of required samples to meet the sensing accuracy decreases, however, with diminishing returns. On the other hand, the number of packet exchanges increase. The overall delay for different SNR values is given in Fig. 4. As SNR increases, the required number of samples to meet sensing performance decreases. The delay in CSS is less than half of the case where all nodes participate. CSS also causes 15% to 18% less delay compared to the sufficient statistic based method.

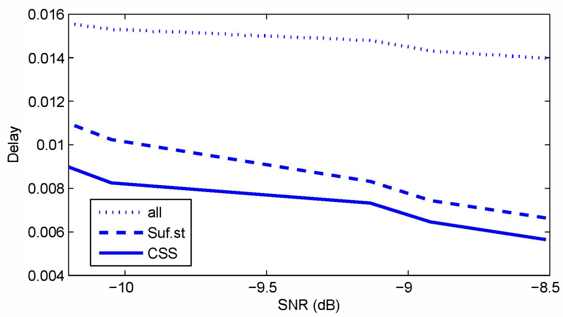


Fig. 4. Delay incurred by sensing under various SNR

V. Conclusions

An energy-efficient, cooperative spectrum sensing scheme for CRSN is presented. Energy efficiency is obtained by using the correlations of sensing data to reduce the number of nodes that participate in the sensing. Since rest of the nodes can switch to sleep mode, significant amount of energy conservation is obtained. With the reduced number of nodes that have to share their results, the latency incurred by spectrum sensing is also reduced. We have performed extensive simulations to compare the accuracy (i.e. ROC curves), the energy consumption and sensing delay of the proposed solution with various other cases. Simulation results verify that CSS has better detection performance, imposes less energy consumption and less delay.

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