Cooperative Coarse Spectrum Sensing for Cognitive Radio Sensor Networks

Ozgur Ergul   **Ozgur B. Akan**

Next-generation Wireless Communications Laboratory (NWCL)

Department of Electrical and Electronics Engineering

Koc University, 34450, Istanbul, Turkey

Email: {ozergul, akan}@ku.edu.tr

Abstract—The number of applications that use industrial, scientific and medical (ISM) radio bands increase every day, creating interference problem for the wireless sensor networks (WSN) that generally operate on these bands. Cognitive radio sensor network (CRSN) has been proposed as a promising solution to this problem. However, since sensor nodes are energy-constrained devices energy efficient spectrum sensing methods are needed for CRSN. To address this need, we propose a novel cooperative coarse sensing scheme for CRSN (CC4C). CC4C is based on sequential sensing, thus, it is simple and fast. Simulation results show that CC4C incurs less sensing delay and provides significant energy conservation compared to energy detection based coarse sensing schemes, and single stage sensing schemes where no coarse sensing is performed.

Index Terms—Cognitive radio sensor networks, spectrum sensing, opportunistic spectrum access, coarse sensing, sequential sensing

I. INTRODUCTION

In the recent years, demand for applications that use wireless communication increased exponentially. Most of the wireless traffic is generated by individuals, resulting in a highly dynamic spectrum activity that changes significantly in space and time. This trend also reflects on the ISM bands where WSNs generally operate. Since ISM bands are license-free, operating WSNs in these bands go in line with their low cost requirement. However, with the substantial increase of the interference from the surroundings, efficient utilization of conventional WSNs becomes harder every day. CRSN has been proposed as a promising solution to mitigate interference and increase spectrum utilization.

A CRSN is a distributed network of wireless cognitive radio sensor nodes, which sense an event signal and collaboratively communicate their readings over dynamically available spectrum bands in a multi-hop manner ultimately to satisfy the application-specific requirements [1]. CRSN paradigm introduces the opportunistic spectrum access (OSA) capability to the WSNs. However, OSA comes with the added burden of spectrum sensing. In the early years of WSN development, adding spectrum sensing duty to the significantly resource constrained nodes would not make sense. Nevertheless, wireless sensor nodes have gone through considerable improvements over the years. Their memory sizes increased from a few kilobytes to tens of megabytes, their processing capabilities increased from 8-bit processors operating in the lower MHz

range to 32-bit processors with dynamic clocks that can speed up to hundreds of MHZ and their power consumption is reduced through new power saving schemes [2].

Viability of CRSN has been investigated by various researchers [1], [3], [4]. A common viewpoint was that in the near future, WSNs may need cognitive radio capaiblities. As a result, recently there has been an increase in research related to CRSN [5], [6].

The most significant issue to address for the realization of CRSN is developing energy efficient spectrum sensing techniques. There is a large volume of research in the literature about spectrum sensing. However, research related to spectrum sensing for CRSN is limited. In [7], a medium access scheme that includes spectrum sensing is proposed. However, it 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 [8], 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. In [9] we proposed a narrow band fine sensing scheme, CSS, specifically designed for the CRSN. The idea was to use correlation of environmental readings of the sensors to help with decisions related to cooperative spectrum sensing. Specifically, we developed a censoring scheme that only admits nodes with low correlation in order to reduce redundancy in cooperative sensing.

An important problem in spectrum sensing is to determine the most promising channels to perform spectrum sensing on. Most of the existing solutions do not address this question. Instead they assume that the most promising channels are known or predetermined, and focus on details about the specific detection scheme. However, PU activity patterns have a significant impact on spectrum sensing [10], [11], since nodes have to perform spectrum sensing over and over in different channels until an available channel is found. In case of ordinary CRN, nodes can afford to perform sensing consecutively until a vacant channel is found. On the other hand, since CRSN nodes are energy constrained devices, it is imperative that they keep sensing time to a minimum. Therefore, a mechanism to estimate the channels that are less likely to be occupied by the PU must be devised.

To this end, two-stage sensing methods have been proposed by various researchers. The first stage consists of a coarse sensing that is fast, but may not be very accurate. It is used to find the channels that are more likely to be available. Since coarse sensing is not accurate, a more accurate fine sensing scheme is used in the second stage for the final decision. The alternative is to keep using fine sensing on different channels, until an available channel is found. Since fine sensing requires more sensing time, and thus, more energy, the two-stage approach is generally more energy efficient.

The general approach in the literature on two-stage sensing is to use energy detection as the coarse sensing method [12], [13], [14]. There are other approaches, but they are either specific to a single PU network type, such as LTE [15], or make some unrealistic assumptions, such as predictable PU arrival process [16]. To the best of authors' knowledge, there is no coarse spectrum sensing scheme developed specifically for CRSN in the literature.

In this paper we introduce a novel coarse sensing scheme, CC4C. In the following section we give the details on CC4C operation. In Section III, we lay out the details of our performance evaluation and simulation results. Finally, in section IV, we present our concluding remarks

II. COARSE SENSING BASED ON SEQUENTIAL DETECTION

A. Motivation for Coarse Sensing

The cost of sensing increases as the probability of having PU on a channel increases. Assume that probability of a channel being available any given time is p. Let E_s denote the energy spent during sensing one channel. Then, the probability of finding a vacant band at the ith sensing is $(1-p)^{(i-1)}\ p$. Since a total of i bands are sensed, the total energy consumed is $i \cdot E_s$, thus, the expected energy consumption for sensing E_t^s can be written as $E_t^s = E_s \sum_{i=1}^{\infty}(1-p)^{(i-1)}p\ i$. The sum is the expected value of geometric distribution, thus, $E_t^s = E_s/p$.

Therefore, the expected energy consumption for sensing is inversely proportional to the probability of having an available channel. This suggests that blindly picking channels to sense may have prohibitive energy costs, especially, in crowded spectrum cases. One more issue of spectrum sensing is that CR nodes do not have any means of determining whether the detected signal is actually PU signal or not. Therefore, for example, even if the signal actually belongs to another CRN, it will be taken as PU activity. Considering this, and the expected increase in opportunistic access to spectrum in the future, it is reasonable to assume that spectrum will generally be crowded to a certain extent. Thus, CR nodes need a means to determine which channels are more likely to be available. To this end, we propose a simple coarse sensing technique, which yields approximate results for PU occupancy of the spectrum. Based on the results of this coarse sensing, nodes pick the channels which are more likely to be available and perform fine sensing on these channels.

For such a coarse sensing scheme to be viable, it should be simple, fast and energy efficient. Otherwise, just repetitive fine sensing would be more preferable. Our scheme is based on sequential probability ratio test (SPRT). It was shown in [17] that, for given false alarm (P_F) and miss probabilities (P_M), SPRT is the detector with the smallest average sample size. Thus, sequential sensing is very suitable for the purpose of a quick sensing.

B. Motivation for Sequential Detection

The core idea of our SPRT-based coarse spectrum sensing scheme is that, in SPRT, the average number of samples required to detect a PU depends on the SNR. As the SNR increases, detection of the PU can be made with smaller number of samples. So, if we were to perform detection on a group of contiguous channels instead of just one channel, as the total number of active PUs in those channels increase, the overall PU signal power increases. This means SNR increases with the number of active PUs.

Now consider a case where each node performs this coarse wideband sequential sensing in different groups of channels. Clearly, on average, the node which makes a decision with the smaller number of samples has the most crowded channel group, since on average SNR experienced by this node will be greater than the others. This is the main idea behind our coarse sensing scheme. In the following, we present the theoretical details.

C. Theoretical Background

An SPRT has two threshold values, A and B. First, the ratio of conditional probabilities of the received samples, y, is formed as $\lambda = p(y|H_1)/p(y|H_0)$. A new sample, y_k, is taken as long as λ is between the lower (A) and upper (B) threshold values. If the ratio falls below A, H_0 is decided. If it exceeds B, H_1 is decided. An alternative is to take $\eta = \ln\left(\frac{p(y|H_1)}{p(y|H_0)}\right)$, then the lower and upper limits will be $a = \ln(A)$ and $b = \ln(B)$.

We first consider the following scenario. The received signal under the two hypotheses are,

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

where $n(t)$ is zero mean, additive white Gaussian noise with variance σ_n^2. $s(t)$ is the combination of all PU signals residing on the entire wide band that we are attempting to sense. 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 all PU signals are 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 are made on various previous work in the literature (e.g., [18])

The first step in forming a SPRT is to calculate the thresholds for the desired $P_F = \alpha$ and $P_M = \beta$ values [19], $A \approx \frac{\beta}{(1-\alpha)}$ and $B \approx \frac{(1-\beta)}{\alpha}$.

One property of sequential tests is that the performance criteria, i.e., P_F and P_M requirements, can always be met if sufficient amount of samples are taken. However, the actual

amount of samples needed to meet the criteria in any given time depends on the instantaneous SNR of the signal since, P_M at a given time instant depends on instantaneous SNR. The expected number of samples to make a decision, also called expected run length (ERL), under H_0 and H_1 for a given $P_F = \alpha$ and $P_M = \beta$ are given as [19],

$$E\{N|H_0\} \approx \frac{1}{\sigma_0^2}\left[(1-\alpha)\left(\ln\frac{\beta}{1-\alpha}\right)^2 + \alpha\left(\ln\frac{1-\beta}{\alpha}\right)^2\right] \quad (2)$$

$$E\{N|H_1\} \approx \frac{1}{\sigma_1^2}\left[\beta\left(\ln\frac{\beta}{1-\alpha}\right)^2 + (1-\beta)\left(\ln\frac{1-\beta}{\alpha}\right)^2\right] \quad (3)$$

where σ_0^2 and σ_1^2 are the variances for a single sample under respective hypotheses. Without loss of generality, we take the first sample, i.e., $\sigma_0^2 = Var(\eta(y_1)|H_0)$ and $\sigma_1^2 = Var(\eta(y_1)|H_1)$.

$$\begin{aligned}\sigma_k^2 &= Var(\eta(y_1)|H_k) = E\left[\left(\ln\left(\frac{p(y_1|H_1)}{p(y_1|H_0)}\right)\right)^2|H_k\right]\\ &= \ln(\sigma_n^2/\sigma_j^2)\frac{\sigma_j^2-\sigma_n^2}{2\sigma_j^2\sigma_n^2}Var\left(y_1^2|H_k\right)\end{aligned} \quad (4)$$

where $\sigma_j^2 = \sum_{k=1}^j \sigma_{s_k}^2 + \sigma_n^2$, and $\sigma_{s_k}^2$ is the received signal power of PU k and j is the number of active PUs within the group of bands that we perform coarse sensing on. Finally, y_1^2 is chi-square distributed with

$$var(y_1^2) = 2\,var(y_1|H_k) = \begin{cases} 2\sigma_n^2, & \text{under } H_0 \\ 2\sigma_j^2, & \text{under } H_1 \end{cases} \quad (5)$$

As a result, when the number of active PUs in the sensed wide band region is j, ERLs under respective hypotheses are,

$$E\{N|H_0\} \approx \frac{1}{K_0}\left[(1-\alpha)a^2 + \alpha b^2\right] \quad (6)$$

$$E\{N|H_1\} \approx \frac{1}{K_1}\left[\beta_j a^2 + (1-\beta_j)b^2\right] \quad (7)$$

where $K_0 = \frac{\sigma_j^2-\sigma_n^2}{\sigma_j^2}\ln(\sigma_n^2/\sigma_j^2)$ and $\frac{\sigma_j^2-\sigma_n^2}{\sigma_n^2}\ln(\sigma_n^2/\sigma_j^2)$, β_j denotes the P_M value when there are a total of j active PUs on the sensed group of channels, a and b are as defined at the beginning of this section.

Eqn. 7 indicates that ERL under H_1 depends on β_j, which depends on the number of active PUs, j. We calculate β_j as follows.

Let Z_0 be the region of samples for which H_0 is decided,

$$Z_0 = \{y \in \mathbb{R}^\infty | \eta_N(y_1,\cdots,y_N) \le a\} = \cup_{n=1}^\infty Z_{0n} \quad (8)$$

where N is the number of samples taken to make the decision, η is the log-likelihood ratio test, and

$$Z_{0n} = \{y \in \mathbb{R}^n | N = n \text{ and } \eta_n(y_1,\cdots,y_n) \le a\} \quad (9)$$

Therefore, Z_{0n} is the region of samples for which H_0 is decided with n samples, i.e.,

$$\begin{aligned}\eta_n &= \sum_{i=1}^n\left(\ln\frac{p(y|H_1)}{p(y|H_0)}\right)\\ &= \ln(\sigma_n/\sigma_j)^n\left(\frac{(\sigma_j^2-\sigma_n^2)}{2\sigma_j^2\sigma_n^2}(y_1^2+\cdots+y_n^2)\right) \le a\end{aligned} \quad (10)$$
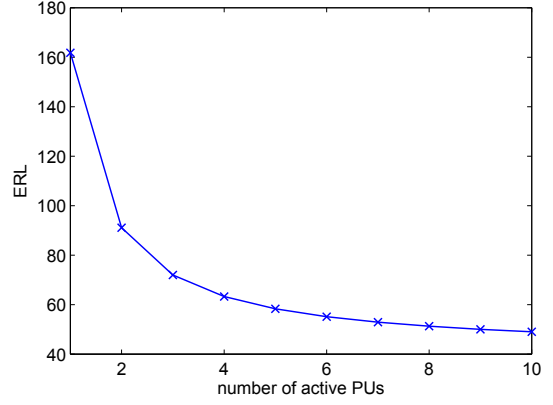

Fig. 1. Expected run length for various number of active PUs.

Then,

$$Z_{0n} = \left\{y \in \mathbb{R}^n | \sum_{k=1}^n y_k^2 \le r^2\right\} \quad (11)$$

where

$$r^2 = \frac{2\sigma_j^2\sigma_n^2}{(\sigma_j^2-\sigma_n^2)}\ln\left(a\left(\frac{\sigma_j}{\sigma_n}\right)^n\right) \quad (12)$$

We see that Z_{0n} is the region inside of a hypersphere of n-dimensions. Z_{0n} can also be represented in n-dimensional spherical coordinate system with coordinates

$$r = \sqrt{y_1^2 + y_2^2 + \cdots y_n^2} \quad (13)$$

$$\theta_1 = \text{arccot}\left(\frac{y_1}{\sqrt{y_n^2 + y_{n-1}^2 + \cdots + y_2^2}}\right) \quad (14)$$

$$\cdots$$

$$\theta_{n-2} = \text{arccot}\left(\frac{y_{n-2}}{\sqrt{y_n^2 + y_{n-1}^2}}\right) \quad (15)$$

$$\phi = 2\,\text{arccot}\left(\frac{\sqrt{y_n^2 + y_{n-1}^2} + y_{n-1}}{y_n}\right) \quad (16)$$

Z_{0n} and Z_{0m} are mutually exclusive sets for $n \ne m$, therefore, α and β can be written as

$$\beta = \int_{Z_0} p(\bar{y}|H_1)d\bar{y} \quad (17)$$

$$= \sum_{n=1}^\infty \int_{Z_{0n}} \prod_{k=1}^n p(y_k|H_1)dy_k \quad (18)$$

Similarly,

$$\alpha = \sum_{n=1}^\infty \int_{Z_{1n}} \prod_{k=1}^n p(y_k|H_0)dy_k \quad (19)$$

where Z_1 and Z_{1n} are defined similar to Z_0 and Z_{0n}, i.e., $Z_1 = \{y \in \mathbb{R}^\infty | \lambda_N \ge B\} = \cup_{n=1}^\infty Z_{1n}$ and $Z_{1n} = \{y \in \mathbb{R}^n | N = n \text{ and } \lambda_n \ge B\}$
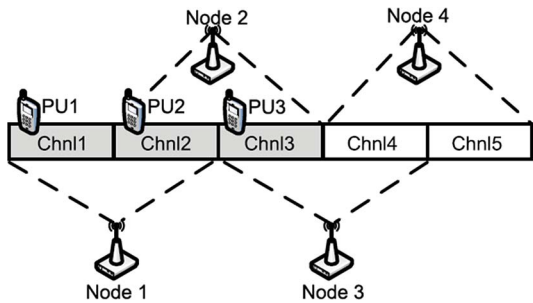
Fig. 2. A sample scenario depicting overlapped sensing idea to overcome near-PU problem.

Probability of miss detection when there are j active PUs β_j can be written as

$$\beta_j = \sum_{n=1}^{\infty} \int_{Z_{0n}} (2\pi\sigma_j^2)^{-n/2} \exp\left(-\frac{1}{2\sigma_j^2}\sum_{k=1}^{n} y_k^2\right) dV_n \quad (20)$$

where $dV_n = dy_1 dy_2 \cdots dy_n$ is the differential volume element. In spherical coordinates dV_n can be written as

$$dV_n = r^{n-1} \prod_{m=1}^{n-2} (sin\theta_m)^m d\theta_m d\phi dr$$

As established in (11), the integral limits constitute the volume of a hypersphere, therefore, the integral in (20) can be written as

$$I(n) = \int_0^R \int_0^{2\pi} \int_0^{\pi} \cdots \int_0^{\pi}$$
$$(2\pi\sigma_j^2)^{-n/2} \exp\left(-\frac{1}{2\sigma_j^2}r^2\right) r^{n-1} \prod_{m=1}^{n-2} (sin\theta_m)^m d\theta_m d\phi dr$$
$$= (2\pi\sigma_j^2)^{-n/2} \int_0^R \exp\left(-\frac{1}{2\sigma_j^2}r^2\right) r^{n-1} dr \frac{2\pi^{n/2}}{\Gamma(n/2)} \quad (21)$$

$\Gamma(\cdot)$ is the gamma function given as $\Gamma(x) = \int_0^{\infty} t^{x-1}e^{-t}dt$. Evaluating the final integral, we have,

$$I(n) = 1 - \frac{\Gamma\left(\frac{n}{2}, \frac{r^2}{2\sigma_j^2}\right)}{\Gamma\left(\frac{n}{2}\right)} \quad (22)$$

where $\Gamma(a, x) = \int_x^{\infty} t^{a-1}e^{-t}dt$ is the upper incomplete gamma function. Thus,

$$\beta_j = \sum_{n=1}^{\infty} I(n) = \sum_{n=1}^{\infty} 1 - \frac{\Gamma\left(\frac{n}{2}, \frac{r^2}{2\sigma_j^2}\right)}{\Gamma\left(\frac{n}{2}\right)} \quad (23)$$

By placing β_j in Eqn 7 we can obtain the ERL for j active PUs. The relation between expected run length and the number of active PUs is shown in Fig. 1, for $P_F = 0.01, P_M = 0.01, \sigma_n = 1$ and $\sigma_s = 1$, i.e., normalized noise power and an SNR of 0 dB. As clearly seen here, the number of samples taken before the decision is made, gives us an approximate idea about how many of the channels within the sensed wideband are occupied.

D. The Near-PU Problem

CC4C has one weak point. Since it depends on overall SNR to be an indication of the number of active PUs, if one of the PUs is too close to the secondary network, CC4C may yield undesired results. For example, if a PU in one group of channels has twice the received power of another PU in another group of channels, when only these two are active in their respective channel groups, on average CC4C concludes that the group with the higher PU power has twice the number of PUs in that group., where, in fact there is only one PU active in each group.

One way to overcome this problem is to use averaging methods. We propose two averaging method. One is to pick two nodes that are furthest away from each other to perform CC4C on the same channel group, then take the average of ERLs reported by them. With nodes chosen this way, a PU that is close to one will be further away from the other, and averaging results of such two nodes will *smooth* the effect of near PU problem.

Another averaging method is to use the previous method along with choosing channel groups in an overlapping manner. The idea is illustrated in a simplistic case in Fig. 2. There are a total of five channels in the entire spectrum. Four nodes perform CC4C coarse sensing, each covering two channels, with one channel overlapping. The ERL at each channel is determined by averaging the ERLs of nodes that performed coarse sensing for that channel. For the presented example case, if PU2 presents the near PU problem for node 2, node 1 will smooth that effect, since it is further from the PU and ERL of channel 2 is determined by averaging.

The remaining problem is how to determine the nodes that are furthest away from each other. A good approximation of this would be to use correlations of spectrum sensing samples of the nodes. Since the probability of having more shadowing objects between two nodes increases as the distance increases, correlations of spectrum sensing samples for the furthest away node pairs is more likely to be closer to zero. However, exchanging thousands of samples with multiple nodes every time spectrum sensing is performed to calculate this correlation is not realistic. The data is huge, the number of transmissions is n^2, if number of total nodes is $n + 1$, moreover, available channel(s) to transmit this information is not yet known since spectrum sensing is yet to be performed. However, in a CRSN we can instead use the idea that we proposed in [9]. It is to use correlations of environmental sensing data instead of sharing spectrum sensing data. Sensors' environmental reading are already regularly sent to the sink node as the normal operation of the CRSN. All of the neighbors overhear it these reports. Therefore, in a CRSN, nodes can continuously keep track of their correlation with their neighbors, which can be used as an estimate to determine the nodes that are far away from each other. This is what makes CC4C a very suitable coarse sensing scheme for CRSN.
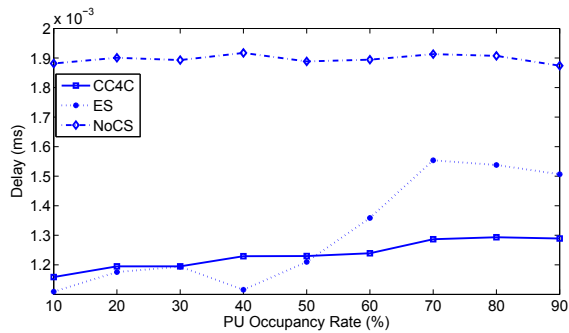
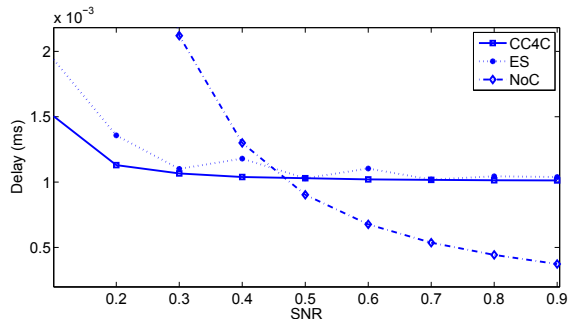Fig. 3.   Average delay vs PUs occupancy rate

Fig. 4.   Average delay vs SNR

III. CC4C PERFORMANCE EVALUATION

In this section, we present our result on the performance of CC4C with comparison to the energy sensing (ES) based coarse sensing schemes. We do not include schemes that are specific to a certain PU type since those schemes would have the additional information and be specifically tailored to that PU, the comparison would not be fair. In the simulations we use a two-stage sensing for both cases. For coarse sensing, we determined the threshold (and the number of samples for the ES case) for desired parameters of probability of false alarm, $P_{FA} = 0.1$, and probability of detection, $P_D = 0.9$. The performance of fine sensing is not the focus of this paper, therefore, the chosen method is not very important as long as same fine sensing method is used in both compared schemes. For both methods, we used energy detection with much tighter desired parameters, i.e. $P_{FA} = 0.01$ and $P_D = 0.99$. We also include the case where no coarse sensing is performed and available channel is found by repetitive fine sensing in different channels until an available channel is found. We label this case as NoCS in the figures.

For both CC4C and ES cases, if an available channel was not found at the end of the fine sensing stage, we assume that the node which has data to transmit has to wait till the next round of sensing. We assume that one round of sensing is performed at each 1 ms interval (for example, LTE has a scheduling interval of 1ms). We take the delay due to spectrum sensing to be the interval between the beginning of coarse sensing and the time when the node finds a channel to transmit.

We use the parameters given in [20] for energy consumption. Namely, we take consumed energy for spectrum sensing

to be $E_s = I_r V t_s$, where $I_r = 19.7 mA$ is the receive mode current, $V = 3V$ is the supply voltage and t_s is the total amount of time spent in spectrum sensing including both stages.

We assumed the whole usable band to have 40 channels. CC4C divides the spectrum into equal size chunks and performs coarse sensing on these chunks concurrently. To present a fair delay comparison, we assumed that in the ES case, multiple nodes perform coarse sending concurrently on different portions of the band with equal size. For both methods we assumed 8 nodes performing coarse sensing concurrently on 5 channels each. In each simulation, we used an interval of 100 spectrum sensing rounds. We ran the simulations 1000 times and present the average of the results of these runs.

In Fig. 3, we present the delay incurred by the sensing schemes as the spectrum gets more crowded. We see the advantage that two-stage sensing schemes provide clearly. The single stage scheme causes up to 69.7% delay compared to CC4C. CC4C and ES have similar performances under low PU occupancy, but CC4C has lower delay as the occupancy rate increases up to a 20.75% improvement.

In Fig. 4, delay comparison for increasing SNR values is given. Single stage sensing scheme performs extremely poorly in low SNR regions, so much so that we had to zoom the plot to see the difference between CC4C and ES. However, as the SNR increases, single stage scheme performs better and actually proves to be more advantageous for SNR values greater than 0.5, i.e., -3 dB. This is expected because the number of required samples to meet detection criterion rapidly drops as SNR increases. At about -3 dB, the required number of samples for fine sensing becomes so low that repetitive fine sensing incurs less delay. However, keep in mind that obtaining desired results in high SNR regions is easy. In real life scenarios CRs generally operate in low SNR regions and the real challenge is to meet sensing requirements at SNR values as low as -20dB. In this low SNR region, CC4C causes less delay compared to other schemes with up to 10.3% less delay compared to ES.

Energy consumption comparison as PU occupancy rate increases is given in Fig. 5. Here also, there is a large difference between two-stage schemes and the single stage scheme. Single stage scheme consumes 119.4% more energy compared to CC4C. ES also consumes more energy than CC4C, difference up to 49.89% difference between the two schemes.

In Fig. 6, we present energy consumption as the SNR increases. Once again, the single stage scheme performs very poorly in low SNR regions. CC4C performs better than the other schemes, enabling up to 85.95% conservation compared to ES.

IV. CONCLUSIONS

A coarse spectrum sensing scheme to be used in a two-stage spectrum sensing method for CRSN, CC4C, is presented. CC4C matches our previous proposal on fine sensing for CRSN perfectly to form a two-stage sensing scheme, since
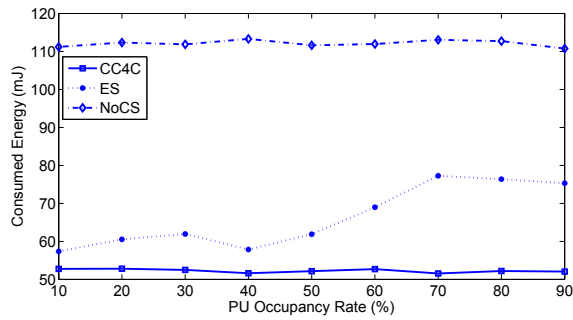
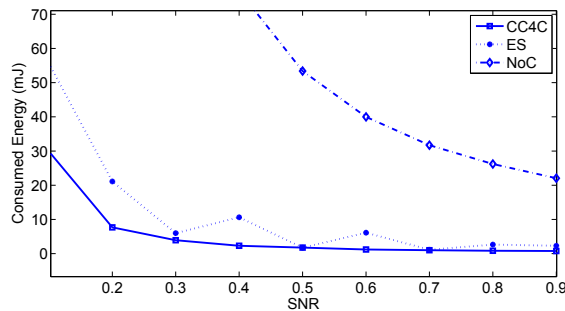Fig. 5.   Average energy consumption vs PUs occupancy rate

Fig. 6.   Average energy consumption vs SNR

both methods make use of correlations of environmental readings of the sensor nodes and once they are calculated for one, they can be used by the other one. Simulation results show that CC4C is considerably more energy efficient compared to the other schemes. Comparing delay incurred by spectrum sensing, we see that CC4C yields the best results in the low SNR region, where delivering sensing requirements is the hardest.

ACKNOWLEDGMENT

REFERENCES

[1] O. B. Akan, O. B. Karli, O. Ergul, "Cognitive Radio Sensor Networks," *IEEE Network Magazine,* vol. 23, no. 4, pp. 34-40, Jul-Aug. 2009

[2] L. Nachman, J. Huang, J. Shahabdeen, R. Adler, R. Kling, "IMOTE2: Serious Computation at the Edge," *International Wireless Communications and Mobile Computing Conference (IWCMC),* pp.1118,1123, Aug. 2008

[3] H. G. Gog, K. H. Kwong, C. Shen, C. Michie, I. Andonovic, "CogSeNet: A Concept of Cognitive Wireless Sensor Network," *IEEE Consumer Communications and Networking Conference (CCNC),* pp.1-2, Jan. 2010

[4] G. Vijay, E. Bdira, M Ibnkahla "Cognitive approaches in Wireless Sensor Networks: A survey," *25th Biennial Symposium on Communications (QBSC),* pp.177-180, May 2010

[5] B. Gulbahar, O.B. Akan, "Information Theoretical Optimization Gains in Energy Adaptive Data Gathering and Relaying in Cognitive Radio Sensor Networks," *IEEE Transactons on Wireless Communications,* vol.11, no.5, pp.1788-1796, May 2012

[6] H. Zhang, Z. Zhang, X. Chen, R Yin, "Energy Efficient Joint Source and Channel Sensing in Cognitive Radio Sensor Networks," *IEEE International Conference on Communications (ICC), 2011,* pp.1-6, 5-9 June 2011

[7] L. Stabellini, M. U. Javed, "Energy-Aware Spectrum Sensing in Cognitive Wireless Sensor Networks: A Cross Layer Approach," *Wireless Communications and Networking Conference (WCNC), 2010 IEEE,* pp. 1-6, 2010

[8] S. Maleki, A.Pandharipande, G. Leus, "Energy-Efficient Distributed Spectrum Sensing for Cognitive Sensor Networks," *IEEE Sensors Journal,* vol.11, no.3, pp.565-573, Mar. 2011

[9] O. Ergul, O. B. Akan, "Energy-efficient Cooperative Spectrum Sensing for Cognitive Radio Sensor Networks," *to appear in Proc. IEEE Symposium on Computers and Communications (ISCC),*, Jul. 2013

[10] J. Riihijarvi, J. Nasreddine, P. Mahonen, "Impact of Primary User Activity Patterns on Spatial Spectrum Reuse Opportunities," *Wireless Conference (EW), 2010 European,* pp.962-968, 2010

[11] K. W. Sung, S. L. Kim, J. Zander, "Temporal Spectrum Sharing Based on Primary User Activity Prediction," *IEEE Transactions on Wireless Communications,* vol. 9, no.12, pp.3848-3855, December 2010

[12] S. Maleki,A. Pandharipande, G. Leus, "Two-stage spectrum sensing for cognitive radios," *IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP),* pp.2946,2949, March 2010

[13] L. Ling, N. M. Neihart, S. Roy, D. J. Allstot, "A two-stage sensing technique for dynamic spectrum access," *IEEE Transactions on Wireless Communications,* vol.8, no.6, pp.3028,3037, June 2009

[14] Z. Li, H. Wang, J. Kuang, "A two-step spectrum sensing scheme for cognitive radio networks," *International Conference on Information Science and Technology (ICIST),* pp.694,698, 26-28 March 2011

[15] M, Abdelmonem, M. H. Ismail, M. S. El-Soudani, M. Nafie, "Coarse spectrum sensing for LTE systems," *IEEE International Conference on Telecommunications (ICT),* pp.116,121, 4-7 April 2010

[16] S.C. Chen, C.J Chang, R.H. Gau, "A two-phase and two-period spectrum sensing scheme using high-layer information for cognitive radio networks," *Computing, Communications and Applications Conference (ComComAp),* pp.250,255, 11-13 Jan. 2012

[17] A. Wald, J. Wolfowitz, "Optimum character of the sequential probability ratio test," *Ann. Math. Statist.,* no. 19, pp. 326-339.

[18] Y. C. Liang, Y. Zheng, E. C. Y. Peh, A. T. Hoang, "Sensing-Throughput Tradeoff for Cognitive Radio Networks," *IEEE Transactions on Wireless Communications,* vol.7, no.4, Apr. 2008.

[19] H. V. Poor, "An Introduction to Signal Detection and Estimation," *SpringerVerlag,* 2nd Ed., 1994.

[20] R. Jurdak, A. G. Ruzelli, and G. M. P. O'Hare, "Radio Sleep Mode Optimization in Wireless Sensor Networks," *IEEE Transactions on Mobile Computing,* vol.9, no.7, pp. 995-968, Jul. 2010.