ADAPTIVE BOUNDARY ESTIMATION ALGORITHM FOR SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

K Deepak kumar[1], Dr. D Siva kumar[2]

[1] *Student, Information Technology, Easwari Engineering college, Tamil nadu, India*
[2] *Professor, Information Technology t, Easwari Engineering college, Tamil nadu, India*

ABSTRACT

In a cognitive radio network, a primary user (PU) shares its spectrum with secondary users (SUs) temporally and spatially, while allowing for some interference. Consider the problem of estimating the no-talk region of the PU, i.e., the region outside which SUs may utilize the PU's spectrum regardless of whether the PU is transmitting or not. And propose a adaptive boundary estimation algorithm that allows SUs to estimate the boundary of the no-talk region collaboratively through message passing between SUs, and analyze the trade-offs between estimation error, communication cost, setup complexity, throughput and robustness. This power spectrum value is compared with five methods namely Periodogram spectral estimate, Bartlett's spectral estimate, Welch spectral estimate, Blackman Tukey spectral estimate and Correlogram Spectral estimate. And simulation done using MATLAB.

Keyword : - *cognitive radio network, Periodogram, no-talk region, Blackman Tukey and Correlogram*

1. INTRODUCTION

Cognitive radio (CR) is a form of wireless communication in which a transceiver can intelligently detect which communication channels are in use and which are not, and instantly move into vacant channels while avoiding occupied ones. This optimizes the use of available radio frequency (RF) spectrum while minimizing interference to other users. In its most basic form, CR is a hybrid technology involving software defined radio (SDR) as applied to spread spectrum communications. Possible functions of cognitive radio include the ability of a transceiver to determine its geographic location, identify and authorize its user, encrypt or decrypt signals, sense neighboring wireless devices in operation, and adjust output power and modulation characteristics. The idea for CR was developed by Joseph Mitola at the Defense Advanced Research project agency (DARPA) in the United States. Full cognitive radio is sometimes known as "Mitola radio."Spectral density estimate (SDE) is to estimate the spectral density (also known as the power spectral density) of a random signal from a sequence of time samples of the signal. Intuitively speaking, the spectral density characterizes the frequency content of the signal. One purpose of estimating the spectral density is to detect any periodicities in the data, by observing peaks at the frequencies corresponding to these periodicities.

1.1 ESTIMATION OF NO-TALK REGION

In this paper, we consider the cooperative estimation of the PU's no-talk region by exploiting local communications
Amongst SUs. Our main contributions are the following:

1) We propose a distributed boundary estimation method based on the distributed learning framework of [19], and with additional smoothness constraints. Sensors outside the estimated no-talk region are allowed to transmit even if the PU is transmitting.

2) We provide approximate theoretical bounds for the communication cost incurred by our proposed method and the expected estimation error, so that the approximate optimal SU density can be inferred. This is useful for randomly allocating SUs to estimate the no-talk regions of multiple PUs transmitting over different frequency bands. We note that our theoretical performance analysis is not considered in [19], and to the best of our knowledge, is new.
3) We derive order bounds for the setup complexity of our proposed method, and expressions for the throughput achievable by the PU and SUs.
4) Simulations suggest that our proposed boundary estimation algorithm have better trade-offs in the throughput and setup communication cost than various other boundary estimation algorithms in the literature, and is more robust to SU sensing errors except when compared to the centralized least squares SVM (LS-SVM) method, which however incurs a much higher communication cost.

1.2 CRN FUNCTIONS

i. Spectrum Sensing

Detecting unused spectrum and sharing the spectrum without harmful interference to other users.

ii. Spectrum Management

Capturing the best available spectrum to meet user communication on requirements.

iii. Spectrum Mobility

Maintaining seamless communication requirement during transition to better spectrum.

iv. Spectrum Sharing

Providing the fair spectrum scheduling method among coexisting CR users.

2. SYSTEM MODEL

Suppose that there is one PU and N SUs in a bounded region $A \subset \mathrm{R}d$.1 We say that the PU is active if it is transmitting in its licensed spectrum. Suppose that the PU is located at $x0$. We assume that all wireless channels are symmetric, and define the no-talk region [4] of the PU to be the set $R = \{x \in \mathrm{R}d : P0 - L(x, x0) > \theta 0\}$, where $P0$ is the transmit power of the PU, $L(x, x0)$ is the average propagation loss function between the PU and a SU located at x, and $\theta 0$ is a fixed threshold. The average propagation loss can be modeled as $L(x, x0) = l(\_x - x0\_) + S(x, x0) + F(x, x0)$,2 where $l(\_x - x0\_)$ is the power attenuation due to the distance $\_x - x0\_$ between a SU at location x and the PU at location $x0$, $S(x, x0)$ represents the average shadowing effect, and $F(x, x0)$ is the average power loss due to multipath fading. We suppose that the PU can tolerate an average interference below the fixed threshold $\theta 0$ so that SUs outside of R can utilize the PU spectrum regardless of whether it is active or not. SUs within the no-talk region R are required to refrain from using the PU spectrum if the PU is transmitting. Note that the threshold $\theta 0$ is chosen to include a safety margin or budget for the propagation loss due to shadowing and fading, and other parameters like the average density of SUs. The reader is referred to [4] for a detailed discussion of the different considerations involved in defining the no-talk region of a PU.

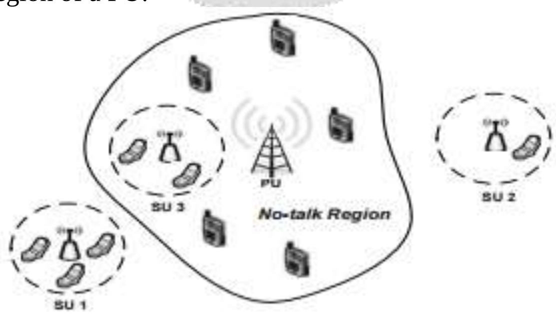

Fig -1 Spatial spectrum sharing between PU and multiple SUs. SU 1 and 2can use the licensed spectrum of the PU without spectrum sensing. SU 3 canonly utilize the spectrum when the PU is inactive.

In this paper, we aim to estimate the no-talk region *R*, or equivalently the boundary of *R*, in order to facilitate spatial spectrum sharing between the PU and SUs. The average propagation loss $L(x, x0)$ for a SU at position x depends on various factors including the terrain, the type and number of reflectors and attenuators between the PU and SU, and other ambient environmental factors. The propagation loss function is thus difficult to determine to good accuracy in practice, and therefore we assume that $L(x, x0)$ is unknown, and adopt a learning approach to estimate the region *R* solely based on the received power at the SUs. We make the following assumptions.

Assumption 1:

(a) Communications by SUs are over relatively shorter distances than the PU, and hence the transmit power of each SU is at most *P*0. Multiple SUs can share the PU's spectrum spatially

(b) The region *R* is compact, and has a smooth4 boundary.

(c) Time can be discretized into intervals and the PU is active in each interval with known probability $\pi \in [0, 1]$, independently across intervals.

2.1 BOUNDARY ESTIMATION

In this section, we propose a distributed boundary estimation algorithm that determines the boundary of the set *R* based on message passing between SUs. The SUs are grouped into clusters, and most communications are over relatively short ranges within clusters. Each cluster has a SU that serves as the cluster head. The cluster head communicates with SUs inside its cluster, performs most of the necessary computations required for distributed estimation of the boundary, and communicates with other cluster heads. Cluster heads thus expend more energy than typical SUs inside the cluster. Incentives can be designed to compensate cluster heads; an example being given higher priority to access the spectrum. Such incentive mechanisms are out of the scope of our current work, and will not be discussed here. Our distributed boundary estimation procedure consists of the following steps.

(i) *Formation of clusters.* Each SU independently nominates itself to be a cluster head with probability p_h. A cluster head broadcasts a message over a control channel to all SUs within a distance δ to inform them of their inclusion into the cluster. To avoid collisions amongst cluster heads, a carrier sense multiple access protocol is used. Note thata cluster head can also belong to another cluster, and a SU can belong to multiple clusters.

(ii) *Boundary cluster identification.* We design a metric to identify those clusters that lie close to the boundary of the set *R*. We call these the boundary clusters.

(iii) *Distributed boundary estimation.* Messages are exchanged between members of a boundary cluster and its cluster head. In addition, messages are exchanged between cluster heads of neighboring boundary clusters to collaboratively estimate the boundary of *R*.

2.2 ALGORITHM

Initialization:
- $\bar{z}_i = u_i$, for $i = 1, \ldots, N$.
- $f^0_{C_j} = 0$, $m_{j,k} = 0$ and $\bar{\epsilon}_{j,k} = 0$, for all $C_j \in B$, $k \in \mathcal{N}(C_j)$.
- t_{max} = maximum number of iterations

for each $C \in B$ **do**
    for each $i \in C$ **do**
        Compute $K(x_i, x_j)$ by measuring $\|x_i - x_j\|$ for all $j \in C$. Send computed values to the cluster head.
    end for
end for
for $t = 1, \ldots, t_{max}$ **do**
    for $j = 1, \ldots, M$ **do**
        Solve (7) by setting $f_{C_j}(x) = \sum_{i \in C_j} \beta_{j,i} K(x, x_i)$, and minimizing over $(\{\beta_{j,i} : i \in C_j\}, \epsilon_{j,k})$. Let $f^t_{C_j}$ be the optimal solution for f_{C_j}.
        Update
- $\bar{z}_i = f^t_{C_j}(x_i)$, and send $\bar{z}_i$ to all $k \in \mathcal{N}(C_j)$.
- $\bar{\epsilon}_{j,k} = \epsilon_{j,k}$.
- $m_{j,k} = \frac{1}{|C_j|} \sum_{i \in C_j} f^t_{C_j}(x_i)$, and send $m_{j,k}$ to all $k \in \mathcal{N}(C_j)$.

    end for
end for

3. PERFORMANCE ANALYSIS

In this section, we first analyze the trade-off between communication cost and estimation error in the DBE algorithm. Then, we propose a two-step approach to spatial spectrum sensing based on the DBE algorithm, and compare its setup complexity and throughput with that of the traditional fusion center (FC) approach.

3.1 Communication Cost and Estimation Error

We let the SU locations be distributed as a homogeneous Poisson point process Π in R^d with rate λ, and assume that the region of interest A has unit d-dimensional volume. Since we do not have any prior knowledge of the SU locations, it is reasonable to assume that SUs are located independently and randomly. The homogeneous Poisson point process captures this assumption and has been widely adopted in the literature to model the distribution of ad hoc communicating devices. The Poisson point process also makes the mathematical analysis tractable, which provides insights into the system performance in practical scenarios. In Section V-C, we present simulation results for a specific case when SUs are not distributed according to a homogeneous Poisson point process. We consider the trade-off between communication cost and the estimation error resulting from the boundary estimation as the rate λ varies, and we determine an approximate optimal density for the SUs that minimizes a weighted sum of the communication cost and estimation error. Finding the optimal density is useful in the case where there are multiple PUs, and random subsets of SUs may be chosen to estimate the boundary of each PU. Intuitively, as SUs become more dense, the expected communication cost increasesbecause the number of SUs in each cluster and the number of boundary clusters increase, but the expected estimation error decreases due to the availability of more training examples. In the following, because of technical difficulties, we present*heuristic* approximations to both the expected communication cost and estimation error, and determine the optimal density by minimizing a weighted sum of these approximations. We present simulation results in Section V to verify that the approximate optimal density found is close to the true optimal one. For simplicity, we assume that the boundary cluster heads all come from a fixed region D with volume $b > 0$, that this region contains the boundary of R, and that it is sufficiently small so that certain approximations, which we describe below, hold. In finding the optimal density, we will see that the region D need not be known in advance. We summarize some of the notations introduced in this section in Table II for ease of reference.

1) Communication Cost: Suppose that the cost of sending a message from a SU at position x to another at position x_ is given by a non-negative function g(_x − x__) with $g(0) = 0$. In many wireless applications, this cost is modeled by the power required to achieve a given signal to noise ratio at the receiver, and $g(r)$ is a function of the form cr^{ζ}, where $c > 0$ and $\zeta \in [2, 5]$. Let a disk of radius δ centered at x be denoted as $B_x(\delta)$, and let v_d be the volume of a unit disk in R^d. The expected communication cost can be found by considering the intra-cluster communication cost and the intercluster communication cost separately. The intra-cluster cost

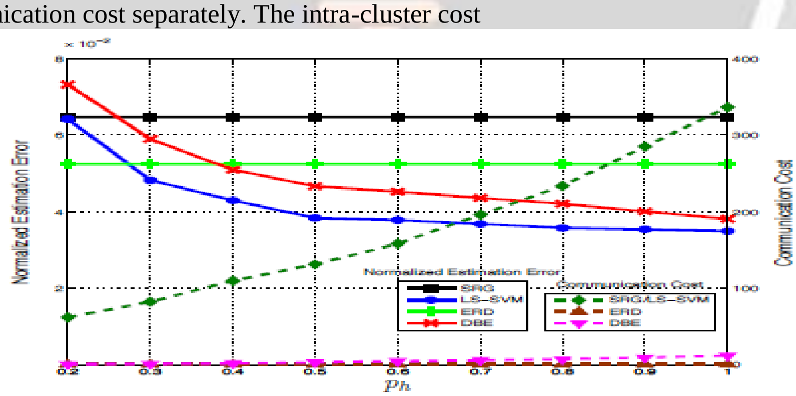

Fig-2 Normalized estimation errors and total communication costs for different values

4. SIMULATION RESULT

In this section, we present simulation results to verify the performance of the DBE algorithm and the DBE-SS method. In each simulation run, 1000 sensors are uniformly distributed in a region A of size 5×5 km2, with the PU (e.g., a TV transmitter) located at the center of the region. We use the standard CCIR model [37] for the path loss. For each datapoint, we perform 1000 simulation runs using the parametersin Table III.

A. *Estimation Error and Communication Cost*

We compare the communication cost incurred and the estimation performance of the DBE algorithm with that of various benchmark algorithms, including the following:

1) Centralized boundary estimation algorithm based on LSSVM a global classifier is trained based on information from all SUs in the boundary clusters.

2) Centralized image processing based seeded region growing (SRG) algorithm [38]: we regard the decision *ui* of each SU *i* as a pixel gray level in a binary image and segment the image by growing a region from a seed pointusing an intensity mean measure.

3) Distributed Bayesian event region detection (ERD) algorithm a threshold decision scheme is appliedto correct the errors of local SU decisions. We refer the reader to for details.

The estimation performance is evaluated according to , normalized by four times the area of *R*. Since the estimation function *f* takes values close to 1 or −1, the normalized estimation error is approximately the area in which misclassification occurs, expressed as a fraction of the area of *R*. The communication cost is computed by assuming that each message passed between two SUs a distance *r* apart incurs a cost of *g*(*r*) based on *r*2. Figure 2 shows the normalized estimation error and communication cost for each algorithm when choosing different values for *ph*, which is the probability that each SU independently nominates itself to be a cluster head. The threshold γ in the boundary cluster decision rule in Section III-A is set to be 0.6. As *ph* increases, the performance of the SR Gand ERD algorithms remain constant as these algorithms do not use clustering.

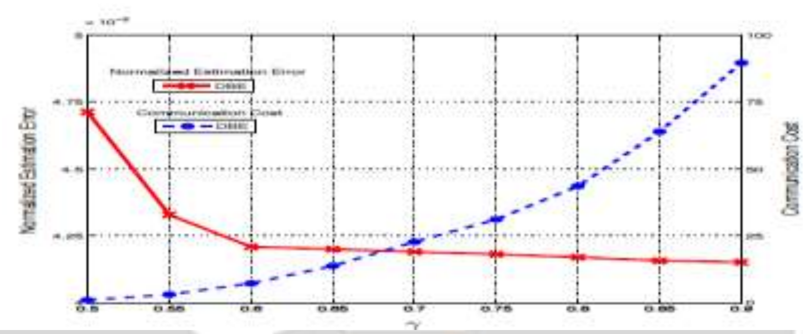

Fig-3 Normalized estimation errors and total communication costs

B. Throughput

In this subsection, we present numerical results for the ROCs and throughputs of the FC and DBE-SS methods after boundary estimation with p_h = 0.8 and γ = 0.6. Recall that the fusion center has no knowledge of the ROC of individual SUs, and a simple *k*-out-of-*N* fusion rule is utilized in place of optimal fusion. Figure 6 shows the ROC curves of the two methods. It is seen that the DBE-SS method has a higher detection probability for each false alarm probability because only information from SUs in *R* are utilized, leading to less errors. , we vary the detection probability and plot the PU throughput versus the throughput per SU for both DBESS and FC methods. The throughput per SU for the DBESS method is relatively flat over all PU throughputs as SUs outside $\hat{R}$ can transmit regardless of whether the PU is present or not. We also see that the SU throughput is higher than that for the FC method. Figure 8 shows the average SU throughput when the PU throughput is fixed at 4 bits/sec/Hz, and the volume of *A* is decreased. We see that the DBE-SS method should only be used if *A* is more than 10% larger than *R*.

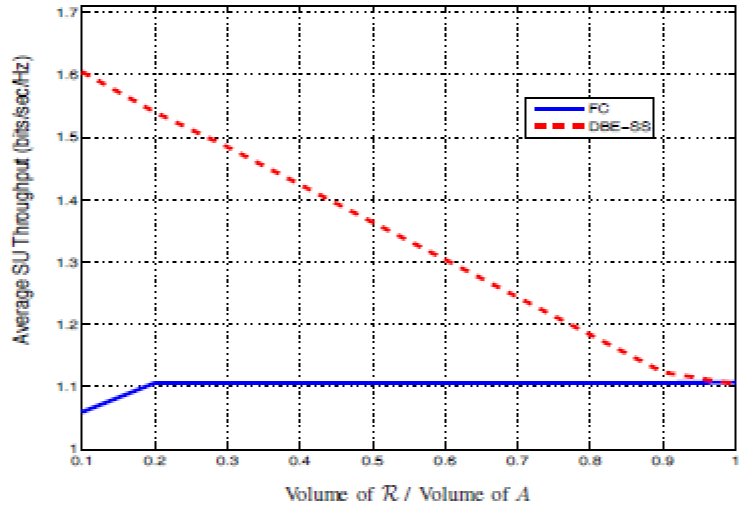

Fig-4 Average throughput per SU as volume of *A* changes

C. Robustness

We now compare the robustness of the various boundary estimation algorithms. We fix p_h = 0.8 and γ = 0.6. To simulate SU sensing errors, a boundary cluster is randomly chosen with probability ς, and then a random subset of the SU sensing decisions in the chosen cluster is changed from −1 to 1, while an equal number of SU sensing decisions is changed from 1 to −1. We plot the average normalized estimation error shows that our proposed DBE algorithm is more robust than the other benchmark boundary estimation methods, except for the centralized LSSVM method. We also compare with a modified version of the DBE algorithm in which we set η_j = 0 for all j = 1, . . . , M so that the smoothness constraint (6) no longer applies. We see that including the smoothing constraint improves the robustness of our algorithm as neighboring boundary clusters moderate their local classifiers to avoid an abrupt change in the average classification function value within their clusters. Next, we compare the estimation error of the DBE algorithm with and without the smoothness constraint (6) when the SUs are no longer distributed as a homogeneous Poisson point process. With probability ω, a boundary cluster is independently populated with 20 SUs uniformly distributed inside the cluster. With probability $1-\omega$, a boundary cluster is divided into four quadrants, and a quadrant is chosen randomly. The chosen quadrant is then populated with 20 SUs uniformly. we see that the smoothing constraint results in a lower estimation error shows a portion of the estimated boundaries.

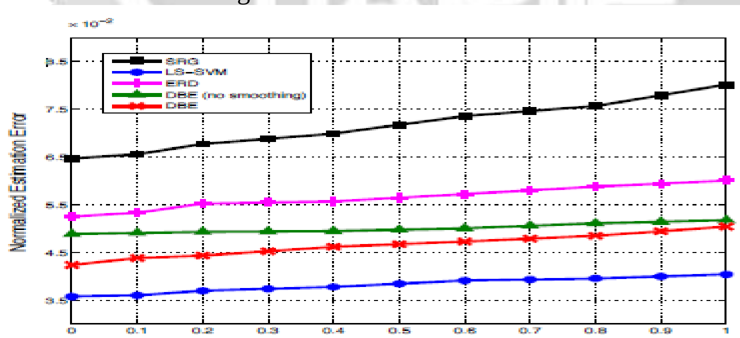

Fig-5 Robustness comparison of boundary estimation algorithms

5. CONCLUSION

This work is done to estimate spectrum using adaptive boundary estimation algorithm for estimating boundary and no-talk region of primary users. And literature survey had been done and method used for execution is discussed above. And also this estimation technique is more effective than all the other available spectrum estimation methods. And there is no estimation of boundary in the existing spectrum estimation models and my method will be also used for estimating boundary region. And the simulation of this adaptive boundary estimation algorithm for spectrum sensing in cognitive radio networks is done using MATLAB.

6. REFERENCES

1. Ant´onio Furtado, Lu´ısIrio, Rodolfo Oliveira, Lu´ıs Bernardo, and RuiDinis (2015)'Spectrum Sensing Performance in Cognitive Radio Networks with Multiple Primary Users'. IEEE Transactions on Vehicular Technology, Vol .2, No. 4, pp.1-11.

2. Athar Ali Khan, Mubashir Husain Rehmani, and Martin Reisslein, (2015) 'Cognitive Radio for Smart Grids:Survey of Architectures, Spectrum Sensing Mechanisms, and Networking Protocols, IEEE Communications Surveys & Tutorials, Vol .2, pp.1-41.

3. Anurag Bansal, Ms. Rita Mahajan, (2011) 'Building Cognitive Radio System Using Mat lab', International Journal of Electronics and Computer Science Engineering, Vol .1, pp. 1-5.1

4. B. Suseela, D.Sivakumar (2014) 'Power Spectrum Estimation and PAPRAnalysis for Cognitive Radio Networks'. International Conference on Communication and Signal Processing, Vol .5, pp. 1686-1691.

5. Chung-Kai Yu, Kwang-Cheng Chen, Fellow, and Shin-Ming Cheng, (2010) 'Cognitive Radio Network Tomography', IEEE Transactions on vehicular Technology, Vol. 59, NO. 4, pp. 1980-1997.

6. Jayakrishnan Unnikrishnan, Venugopal V. Veeravalli, (2008) 'Cooperative Sensing for Primary Detection in Cognitive Radio', IEEE Journal of selected topics in signal processing, Vol. 2, NO. 1, pp. 18-27.

7. Kandasamy Illanko, Muhammad Naeem, Alagan Anpalagan, and Dimitrios Androutsos (2016) 'Energy-Efficient Frequency and Power Allocationfor Cognitive Radios in Television Systems', Vol.10, No.1, pp. 313-324.

8. Simon Haykin, David J. Thomson and Jeffrey H.Reed, (2009) 'Spectrum Sensing for Cognitive Radio'.Proceedings of the IEEE, Vol. 97, No.5, pp. 849-877.

9. Xiang-Yang Li, Panlong Yang, Yubo Yan, (2015) 'SPA: Almost Optimal Accessing of Nonstochastic Channels in Cognitive Radio Networks', IEEE Transactions on Mobile Computing, pp. 1-14.

10. Yuan Lu, Alexandra Duel-Hallen (2015) 'Channel-Aware Spectrum Sensing and Access for Mobile Cognitive Radio Ad Hoc Networks' , IEEE Transactions on Vehicular Technology, Vol .2, pp. 1-9.

11. Yasmina El Morabit, Fatiha Mrabti (2015) 'Spectrum Allocation Using Genetic Algorithm in Cognitive Radio Networks' IEEE Transactions on vehicular Technology, Vol.5, pp.90-93.

12. Zhi Quan, Shuguang Cui, Ali H. Sayed, (2008) 'Optimal Linear Cooperation for Spectrum Sensing in Cognitive Radio Networks' , IEEE Journal of selected topics in signal, Vol. 2, NO. 1, pp. 28-40.

13. Zhuo Qiu, Yongqiang Hei, (2014) "Efficient Taguchi Algorithm for Cognitive Radio Spectrum Allocation" IEEE Journal of selected topics in signal, Vol. 2, NO. 1, pp. 07-13