Middle-East Journal of Scientific Research 19 (9): 1150-1155, 2014
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2014.19.9.1277

Joint Design of Sensing and Access Policies by Opportunistic Spectrum Access

M. Surumbar Khuzhali

Department of Electronics and Telecommunication Engineering,
Bharath University, Chennai, Tamil Nadu, India

Abstract: In today's world, spectrum scarcity increased due to tremendous growth of new users in Wireless communication system. Cognitive radio is a next generation wireless communication system that proposed as a way to reuse this underutilized spectrum in an opportunistic and non-interfering basis. The main function of cognitive radio system is the ability to reliably detect the presence of licensed primary user. Cognitive users will cooperate with each other in trying to detect licensed transmission. cooperative spectrum sensing is a promising technology in spectrum sensing with an admirable performance, further, multiple secondary users individually sense the idle channels and send their decisions to the network state and then the centre will do a final. In cooperative sensing it has multiple cooperating users which increase diversity by providing multiple measurements of the signal and thus guarantees better performance at low SNR. A design of linear-quadratic fusion strategy based on a deflection criterion is taken into account as the correlation between the nodes. We proposed a joint optimization of spectrum sensor at the physical layer and the sensing/access policies at the MAC layer, to maximize the throughput of the secondary user.

Key words: Cooperative sensing · Correlated observations · Decentralized detection · Fusion · Linear-quadratic detector

INTRODUCTION

Cognitive radio systems have been proposed as a possible solution to the [1] spectrum crisis. The idea is to detect when a specific licensed band is not used at a particular place and use the band for transmission without causing any significant interference to the transmissions of the license holder. They communicate their decisions to a fusion center that makes the final decision about the occupancy of the band by fusing the decisions made by all cooperating radios in that area that are monitoring the same frequency band. In practice, the fusion center could be some centralized controller that manages the channel assignment and scheduling for the secondary users. The system could also be one where the secondary users exchange their decisions and each secondary user performs its own fusion of all the decisions. We assume that the fusion center knows the geographic locations of all co-operating secondary users and hence can learn the correlation between their observations. However, it is unaware of the primary's location. Since the decisions made by the secondary users contain just one bit of information each and since we do not expect to have to keep track of the channel usage frequently, the data rates required for reliably (Fig. 1) communicating these decisions to the fusion center are expected to be within practical limits. The main contribution of this paper is a suboptimal fusion rule that handles correlation issues and at the same time is not heavily dependent on the model or on exact knowledge of the statistics of the signal.

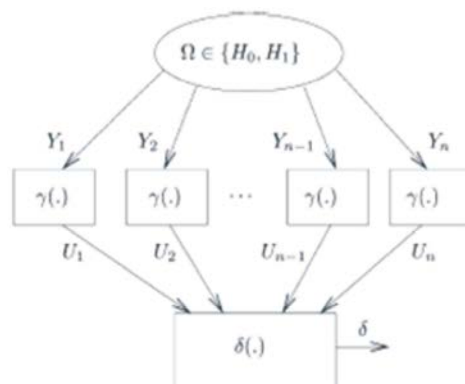

Fig. 1: Centralised detection setup

The rest of the paper is organized as follows. In Section II. System model shows the centralised

Corresponding Author: M. Surumbar Khuzhali, Department of Electronics and Telecommunication Engineering, Bharath University, Chennai, Tamil Nadu, India

detection set up, Section III. Describes the various fusion decision methods, Section IV. Optimisation of LQ detector. Section V. Shows the simulation results. Finally, the conclusions are summarized in Section VI.

Analysis Model: Secondary users may be shadowed away from the primary user's transmitter but there may be primary receivers close to the secondary users that are not shadowed from the primary transmitter. Hence, if a secondary user transmits, it may interfere with the primary receiver's reception. These issues [2] needs to be addressed in order to design practical solutions to the detection problem.

Co-operative Spectrum Sensing: An effective approach is to have users cooperating with each other to detect the primary signal. Having multiple cooperating users [3] increases diversity by providing multiple measurements of the signal and thus guarantees better performance at low SNR. Additionally, having users cooperating over a wide area also provides us with a possible solution to the hidden-terminal problem, since this problem would arise only if all the secondary users are shadowed away from the primary. If the secondary users span a distance that is larger than the correlation distance of the shadow fading, it is unlikely that all of them are under a deep shadow simultaneously. Previous works on user-cooperation for cognitive radio systems, have considered two kinds of schemes, one where some kind of joint detection is employed among all the cooperating users and another where the final decision is made based on hard decisions made by each of the cooperating users. In this paper, we focus on the more feasible system in which the individual secondary users make independent decisions about the presence of the primary signal in the frequency band that they are monitoring.

Binary Hypothesis Testing: The basic task of the fusion center is to decide whether or not the secondary users are located inside the protected region.

- Y_i-individual sensor observation
- U_i-individual sensor decision
- $\gamma()$-identical likelihood ratio test at each sensor
- $\delta(\ )$-final decision made at the fusion center

The secondary users employ energy detectors. Since the cooperating secondary users are expected to be located close to each other and are monitoring the same frequency band, the distributions of the received powers can be modeled as identical. So the problem now becomes a binary hypothesis testing problem to decide whether or not the mean received power at their location is higher than the power expected at the edge of the protected region. When the primary is ON and the secondary users are within the protected region, the power they receive is going to be the sum of the primary signal power and the noise power. In this case, we model the received powers as being log-normally distributed. Here, we are approximating the sum of the shadowed primary signal's power and the noise power to be log-normally distributed. When the secondary users are outside the protected region, the power they receive from the primary user would be insignificant compared to the noise. This is particularly true if the primary user is far away or is switched OFF. Under this scenario, the power at the output of the energy detectors will be simply the sum of noise power and the power of any interfering signals that may be present.

It is given as,

$$\begin{aligned} &H0: y(n) = w(n) \\ &H1: y(n) = s(n) + w(n) \end{aligned} \tag{1}$$

The two hypotheses of interest are H_1, the hypothesis that the primary is present and is located close to the secondary users and H_0, the hypothesis that the primary is absent or is far away. Here, H_0 can also be viewed as the hypothesis that a spectral hole exists and hence the spectrum is free for secondary access. The cooperating secondary users subtract the estimated value of the sum of noise and interference powers (in dBm) from their received powers, to obtain their observations.

Detection Rule at the Nodes: In the system, cognitive radio is designed without expecting cooperation from other users in the detection process, with the understanding that we do not always expect a particular radio to be close enough to other radios that are also monitoring the same primary signal. Hence, we assume that the detector [4] employed at each radio meets the probability of interference constraint on its own. Since we further assume that the signals received at the cooperating users are identically distributed, the detectors used by the cooperating users will also be identical. Moreover, the optimal test used by sensor to determine its decision will be a likelihood ratio test on its observation. The optimal test used by sensor to determine its decision will be a likelihood ratio test on its observation. It is given as,

$$U_i = \Gamma_{\{\log(L(Yi))>t\}} \quad (2)$$

Where
Γ-Indicator function
L(Yi)-log likelihood ratio
t-Threshold

Indicator function, which takes on value 1 when its argument is true and 0 otherwise. For the Gaussian hypotheses, the log-likelihood ratio of the observations will be a quadratic function. Hence, node would have to compare a quadratic function of its observation to a threshold and obtain its decision in the form of bit. These bits are communicated to the fusion center where the final decision about the hypothesis is made.

Fusion of Decisions: The optimal fusion rule is to compute the joint likelihood ratio of the bits and compare it with a threshold chosen so as to meet the interference probability requirements. This solution, in general, requires the knowledge of the joint statistics of the bits under both hypotheses. The threshold to be used at the fusion center for a target interference probability will need to be estimated using simulations.

Counting Rule: One of the simplest suboptimal solutions to the data fusion problem is the Counting Rule (also referred to as the Voting Rule), which just counts the number of sensor nodes that vote in favor of H_1 and compares it with a threshold. The threshold value has to be set using simulations since the joint statistics under H_1 are not available. The special scenario where the observations are across the sensors under both hypotheses, this is the optimal rule since the joint likelihood ratio of the bits is a function of only the type of the received bit vector. Thus this would be a reasonable fusion strategy even when nothing is known about the correlation structure. Moreover, the fact that the fusion center threshold for even a simple fusion rule like the Counting Rule needs to be set using simulations.

Linear Quadratic Detector (LQ): The main contribution of this paper is a general suboptimal solution to the fusion problem that uses partial statistical knowledge and gives better performance [5] than the one obtained by ignoring the correlation information completely. This solution makes use of the second-order statistics of the local decisions under H_1 and the fourth-order statistics under H_0 in the form of moments. Since the observations are independent under H_0, the moments under H_0 are easily calculated or estimated. The second-order moments under H_1 can be obtained by calculating or estimating just the pair wise statistics under H_1. The information about these moments is in general a lot easier than obtaining the entire joint statistics of the signals especially when there are a large number of cooperating nodes. The fusion rules is the class of LQ detector [6] that compares a linear-quadratic function of (vector of decision made by all the users) with a threshold. Since we are including quadratic terms as well while computing our detection metric, we expect to see improved performance over the Counting Rule that is purely linear. Moreover, since we are using only moment information, this detector is quite general and can be used for all classes of distributions of the signals. We seek to optimize over the class of LQ detectors using the generalized signal-to-noise ratio or deflection criterion. Although deflection cannot be related directly to the error-probability for non-Gaussian observations, a detector with a higher value of deflection is expected to have better error-probability performance than one with a lower value of deflection. We show using simulations that the optimal deflection-based LQ detector that we derive in this section gives improved error performance over the Counting Rule in correlated environments.

Optimization of LQ Detector: The deflection of a detector that makes a decision by comparing a function to a threshold is defined as,

$$D_T = \frac{\left[E_1\left(T(X)\right) - E_o\left(T(X)\right)\right]^2}{VAR_o\left(T(X)\right)} \quad (3)$$

D_T-Deflection of detector
T(X)-decision metric
VAR-Variance
E_0 and E_1-Expectations under H_0 and H_1

Although deflection [7] cannot be related directly to the error-probability for non-Gaussian observations, a detector with a higher value of deflection is expected to have better error-probability performance than one with a lower value of deflection. In this case, the detection metric can be viewed as a linear quadratic function of the log-likelihood ratios of the individual random variables. This observation suggests that an intelligent choice of values to be assigned to the quantized observations in our problem would be the log-likelihood ratios of the bits themselves.

The decision metric is,

$$T(X) = h^T X + X^T M \quad (4)$$

X-Vector of log-likelihood ratio of received signal
h-Vector of length
M-square matrix

The components of X are given by,

$$X_i = \log\left(\frac{q_1(U_i)}{q_o(U_i)}\right) - E_o\left[\log\frac{q_1(U_i)}{q_o(U_i)}\right] \quad (5)$$

U_i-decision made at the individual sensor
q-distribution of U_i under binary hypothesis

The new decision metric is,

$$S(Z)=X^T Z \quad (6)$$

The optimised decision metric is,

$$S_{opt}(Z) = \mu_a^T \Lambda_a^{-1} Z_a \quad (7)$$

Λ_a-diagonal matrix
μ_a-fn of first and second order moments under H1
Z_a-vector

RESULTS AND DISCUSSION

The performance of a detector can be illustrated by plotting the probability of detecting spectrum holes against the probability of interference obtained with the detector. we simulated for a network of nine cooperating nodes uniformly placed inside a unit square with the distance between nearest neighbors kept at 0.5.This effectively amounts to assuming that the length of the side of the square is around half the correlation distance. Assuming a mean received SNR of 0 dB at the edge of the guard band, a shadowing standard deviation of 4 dB and a noise uncertainty dB, we get the value of the mean total power at the edge of the guard band, to be 3.4 dB and the effective standard deviation of the received power as 2.1 dB.

Sensor Threshold Fixed: We simulated the two rules for probability of interference values in the range 0.001 to 0.01. The sensors use identical likelihood ratio tests for obtaining their decision variables. The performance comparison is also shown on the (Fig. 2) same graph.

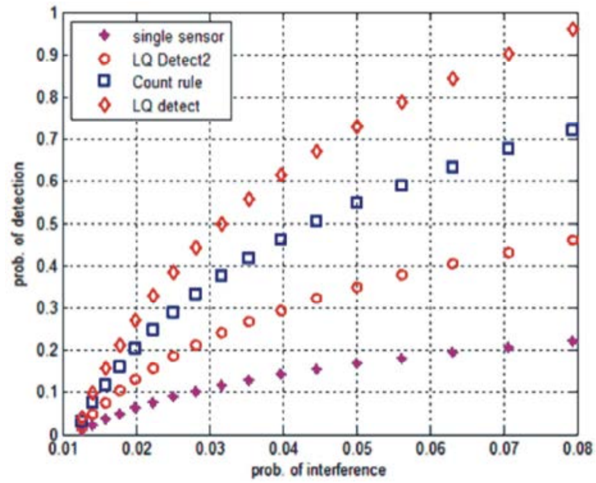

Fig. 2: Comparison based on detection probabilities

As expected, the performances of the detectors that make use of the information from all the sensors are better than the one that uses decisions made at a single sensor. In particular, the LQ detector is seen to give around two to three times the detection probability as that of the single sensor detector for the interference probability values considered even though the observations are highly correlated. It can also be inferred that the LQ detector yields a substantial gain over the Counting Rule, especially at low values of interference probability, which would be the region of interest for the cognitive radio application.

Sensor Thresholds Varied: We allow the users to choose their thresholds from a set of values close to the original predetermined threshold. We still restrict them to use the same threshold. The algorithm performs a limited search in a finite set of sensor thresholds and chooses the one that gives the best error performance at the fusion center. This choice would depend on both the configuration of the cooperating users as well as the target interference probability. The detection probabilities for the LQ detector obtained by allowing the users to vary their thresholds is also listed in clearly, the values indicate that additional gains in detection probability can be obtained, as expected. This, however, would require additional communication overheads between the fusion center and the individual users. Moreover, there is no simple criterion to optimally choose the threshold to be used at the individual users for a given interference probability and known correlation information. Searching over the entire real number line for possible threshold values is clearly not a feasible solution.

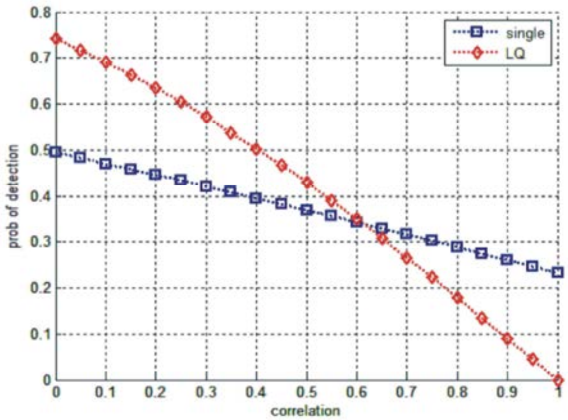

Fig. 3: Comparison based on correlation

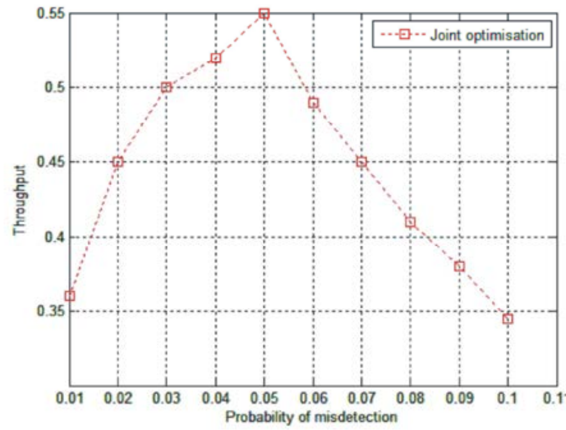

Fig. 4: The impact of spectrum sensor operating point on the throughput of the secondary user

Comparison of Performances as a Function of Correlation: In this simulation, we compare the performances of the LQ detector and the Counting Rule detector (Fig. 3) for different values of the correlation parameter [8]. The interference probability is kept fixed at 0.001 and the detection probability obtained with the detectors is plotted as a function of correlation. The sensors use identical quantizes with threshold chosen such that the probability of making a wrong sensor decision under equals the constraint in the probability of interference. The LQ detector outperforms the Counting Rule detector for all values of greater than 0.6. For low values of correlation, the observations at the sensors are nearly independent under both hypotheses. For values of the correlation greater than 0.6, the performance of the Counting Rule detector steadily decreases and converges to that obtained with a single sensor [9], while the performance of the LQ detector starts increasing for higher correlation values. The non monotonic behavior of the performance of the LQ detector as a function of correlation is due to the fact that the value of the correlation parameter affects the detection problem in two different ways. The ability to distinguish between the two hypotheses based on this feature clearly increases as increases.

Hence, in detectors that try to exploit both these features, we expect to see a non monotonicity in performance as a function of correlation.Our results clearly suggests that even when the observations at the sensors are moderately correlated, it is important not to ignore the correlation between the nodes for fusing the local decisions made at the secondary users.

Optimal Strategy for Opportunistic Spectrum Access: This strategy develops optimal opportunistic spectrum access (OSA) by integrating the design of spectrum sensor at the physical layer with that of spectrum sensing and access policies [11] at the medium access control (MAC) layer. The design objective is to maximize the throughput of secondary users while limiting their probability of colliding with primary users. By exploiting the rich structures of the problem, we establish a separation principle: the design of spectrum sensor and access policy can be decoupled from that of sensing policy without losing optimality.

The ROC curve of the energy detector is given by,

$$1-\delta = 1-\gamma\left(\frac{M}{2},\eta\frac{\sigma_o^2}{\sigma_1^2}\right) \tag{8}$$

Where,
η-Threshold
γ-Gamma function
δ-Sensor operating point
It can be modified as,

$$\in = 1-\gamma\left(\frac{M}{2},\eta\right)$$

This separation principle enables us to obtain closed form optimal sensor Operating characteristic and access policy, leading to significant complexity reduction [10]. It also allows us to study the inherent interaction between spectrum sensor and access policy and the trade-off between false alarm and misdetection in opportunity identification**.**The impact of sensor operating point δ on the throughput and the optimal access policy of the secondary user. The figure (Fig. 4) plots the maximum throughput of the secondary user for each given sensor operating point δ.Inaccurate transition probabilities can cause performance loss.

CONCLUSION

In such scenarios, the LQ detector provides a simple fusion rule that yields significant performance gains over the Counting Rule while still using only partial statistical knowledge about the correlated decision variables. The Counting Rule is useful in a system where the correlation between the observations at the users is small. We extend this level to jointly optimizing the spectrum sensor at the physical layer and the sensing/access policies at the MAC layer, to maximize the throughput of the secondary user under a constraint on the collision probability perceived by the primary network [11-13].

REFERENCES

1. Broderson, R.W., A. Wolisz, D. Cabric, S.M. Mishra and D. Willkomm, 2004. CORVUS: A Cognitive Radio Approach for Usage of Virtual Unlicensed Spectrum. Berkeley, CA: Univ. California Berkeley Whitepaper.
2. Sahai, A., N. Hoven and R. Tandra, 2004. Some fundamental limits on cognitive radio, in Proc. 42nd Allerton Conf. Communication, Control, and Computing, Oct.
3. Mishra, S.M., A. Sahai and R.W. Brodersen, Cooperative sensing among cognitive radios, in Proc. IEEE Int. Conf. Communications, pp: 1658-1663.
4. Veeravalli, V.V., J.F. Chamberland, A. Swami and Ed. *et al.,* 2007. Detection in sensor networks, in Wireless Sensor Networks. Signal Processing and Communications Perspectives. New York: Wiley.
5. Picinbono, B. and P. Duvaut, 1988. Optimal linear-quadratic systems for detection and estimation, IEEE Trans. Inform. Theory, 34(2): 304-311.
6. Picinbono, B., 1995. On deflection as a performance criterion in detection, IEEE Trans. Aerosp. Electron. Syst., 31(3): 1072-1081.
7. Drakopoulos, E. and C.C. Lee, 1991. Optimum multisensor fusion of correlated local decisions, IEEE Trans. Aerosp. Electron. Syst., 27(4): 5-14.
8. Kam, M., Q. Zhu and W.S. Gray, 1992. Optimal data fusion of correlated local decisions in multiple sensor detection systems, IEEE Trans. Aerosp. Electron. Syst., 28(3): 916-920.
9. Zhao, Q., L. Tong, A. Swami and Y. Chen, 2007. Decentralized cognitive MAC for opportunistic spectrum access in ad hoc networks: A POMDP framework, IEEE J. Select. Areas Commun., 25(3): 589-600.
10. Chen, Y., Q. Zhao and A. Swami, 2006. Joint design and separation principle for opportunistic spectrum access, in Proc. Asilomar Conf. Signals, Systems and Computers, pp: 696-700.
11. Unnikrishnan, J. and V. Veeravalli, 2008. Cooperative sensing for primary detection in cognitive radio, IEEE J. Sel. Topics Signal Process., 2(1): 18-27.
12. Tatyana Aleksandrovna Skalozubova and Valentina Olegovna, 2013. Reshetova Leaves of Common Nettle (Urtica dioica L.) As a Source of Ascorbic Acid (Vitamin C), World Applied Sciences Journal, 28(2): 250-253.
13. Rassoulinejad-Mousavi, S.M., M. Jamil and M. Layeghi, 2013. Experimental Study of a Combined Three Bucket H-Rotor with Savonius Wind Turbine, World Applied Sciences Journal, 28(2): 205-211.
14. Vladimir G. Andronov, 2013. Approximation of Physical Models of Space Scanner Systems World Applied Sciences Journal, 28(4): 528-531.