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PERFORMANCE OF LINEAR DECISION COMBINER FOR PRIMARY USER DETECTION IN COGNITIVE RADIO

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A Thesis
Submitted in Partial Fulfillment of the Requirements for the
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The successful implementation and employment of various cognitive radio services are largely dependent on the spectrum sensing performance of the cognitive radio terminals. Previous works on detection of cognitive radio have suggested the necessity of user cooperation in order to be able to detect at low signal-to-noise ratios experienced in practical situations.

This report provides a brief overview of the impact of different fusion strategies on the spectrum hole detection performance of a fusion center in a distributed detection environment. Different decision or detection rule and fusion strategies, like single sensor scenario, counting rule, and linear decision metric, were used to analyze their influence on the spectrum sensing performance of the cognitive radio network. We consider a system of cognitive radio users who cooperate with each other in trying to detect licensed transmissions. Assuming that the cooperating nodes use identical energy detectors, we model the received signals as correlated log-normal random variables and study the problem of fusing the decisions made by the individual nodes.

The cooperating radios were assumed to be designed in such a way that they satisfy the interference probability constraint individually. The interference probability constraint was also met at the fusion center. The simulation results strongly suggests that even when the observations at the individual sensors are moderately correlated, it is important not to ignore the correlation between the nodes for fusing the local decisions made by the secondary users. The thesis mainly focuses on the performance measurement of linear decision combiner in detecting primary users in a cognitive radio network.

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CHAPTER 1

INTRODUCTION

In the last decade and half, world of communication has gone through a rampant and rapid change in wireless and personal communication. Increasing use of portable computing devices, the internet and the growth of wireless voice subscribers have inspired major inroads to emulate the leverages of existing systems. Unparallel popularity of handheld personal devices and demand for rich media contents for multimedia and entertainment services instigated the need for higher access speeds, quality of service assurance and conducive multi-user environment.

Due to rapid advance of wireless communications, a tremendous number of different communication systems exist in licensed and unlicensed bands, suitable for different demands and applications such as GSM/GPRS, IEEE 802.11, Bluetooth, UWB, 3G (CDMA series), IEEE 802.16, etc. On the other hand, radio propagation favours the use of spectrum under 3 GHz due to non-line-of-sight propagation. Consequently, many more devices, up to one trillion wireless devices by 2020, require radio spectrum allocation in order to respond to the challenges for further advances in wireless communications [1].

In the existing spectrum regulatory framework, the overall frequency spectrum is divided into frequency bands of different widths and those frequency bands are exclusively allocated to specific services. Considering the limitations of natural frequency spectrum, it is obvious that the current static frequency allocation schemes don’t have the capacity to accommodate the requirements of increasing number of higher data rate services. This significant increase in demand of spectrum is straining the effectiveness of the traditional spectrum policies. A recent survey of spectrum utilization made by FCC has indicated that the actual licensed spectrum is highly underutilized in vast temporal and geographic dimensions [2]. Moreover, the spectrum usage varies significantly with time, frequency and geographic locations.

Recent researches have demonstrated that dynamic spectrum access can be considered as a breakthrough solution to these problems of current inefficient spectrum usage. Cognitive radio has emerged as the key enabling technology which provides the ability to share the wireless channel with the licensed users in an opportunistic way. A significant improvement of spectrum utilization can be achieved by allowing a secondary user to utilize a licensed band when a licensed primary user is absent. Cognitive radio as an agile radio technology has been envisioned to promote the efficient use of the spectrum via heterogeneous wireless architectures and dynamic spectrum access techniques [3]. But at the same time, networked cognitive radios impose several challenges due to the broad range of available spectrum as well as diverse QoS requirements of applications.

1.1. Concept and Capabilities of Cognitive Radio

Cognitive radio has established itself as a tempting solution to spectral crowding problem by introducing the opportunistic usage of frequency bands that are not heavily occupied by licensed users. By sensing and adapting to the environment, a cognitive radio is able to make use of the underutilized portion of the spectrum and serve its users without causing harmful interference to the licensed users. In order to share the spectrum with licensed users without disturbing them, and also to meet the diverse QoS requirement of applications, each cognitive radio user in a cognitive radio network must be able to determine the portion of spectrum that is available (Spectrum Sensing), select the best available channel (Spectrum Decision), coordinate access to this channel with other users (Spectrum Sharing), and vacate the channel when a licensed user is detected (Spectrum Mobility).

Emphasizing the desired capabilities of the cognitive radio, Virginia Tech Cognitive Radio Working Group (VT CRWG) [4] defined cognitive radio as:

"An adaptive radio that is capable of the following:

- *i. Awareness of its environment and its own capabilities*
- *ii. Goal driven autonomous operation*
- *iii. Understanding or learning how its actions impact its goal*
- *iv. Recalling and correlating past actions, environments, and performance."*

These capabilities of cognitive radios as nodes of a cognitive radio network can be classified according to their functionalities based on the definition of cognitive radio. A cognitive radio shall sense the environment (Cognitive capabilities), analyze and learn sensed information (Self-organized capabilities), and adapt to the environment (Reconfigurable capabilities) [1]. In this thesis, the attention is primarily focused on the "Cognitive Capabilities" of cognitive radios. Some of the important cognitive capabilities of a cognitive radio include:

i. Location identification:

Location identification is the ability to determine the location of the cognitive radio itself and the location of the other transmitters, and then select the appropriate operating parameters such as power and frequency allowed in its location.

ii. Network/System Discovery:

For a cognitive radio terminal to determine the best way to communicate, it shall first discover available networks around it. These networks might be reachable either via one hoop communication or multi-hop relay nodes. Network or system discovery plays a vital role in making cognitive radio work in a more flexible way and add versatility to its operation.

iii. Service Discovery:

Service discovery usually accompanies network/system discovery. Network or system operators provide their services through their access networks. A cognitive radio terminal is expected to find appropriate services to fulfill its user's demands. It is well aware of the services available in its geographic location and also about user's demand of these available services.

iv. Spectrum Sensing:

The most important cognitive capability of a cognitive radio is its ability to perform spectrum sensing. A cognitive radio can sense and detect spectrum holes, which are frequency bands not used by licensed users or have the possibility of limited interference with the primary users, if occupied by a cognitive radio user. Spectrum sensing enables cognitive radio user to incorporate a mechanism that would facilitate sharing of the spectrum, and thus improve spectrum utilization by making use of opportunistic spectrum access method.

1.2. Spectrum sensing in Cognitive Radio

For cognitive radio to operate efficiently, secondary users should be able to measure, sense, learn, and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, radio's operative environment, user requirements, and applications. Spectrum sensing is a key element in cognitive radio communications, as it enables the cognitive radio to adapt to its environment by detecting spectrum holes, or in other words by detecting the presence or absence of the primary user of that particular frequency band.

The most effective way to detect the availability of spectrum holes is to detect the presence of primary users that are receiving data within the range of a cognitive radio. However, it is difficult for the cognitive radio to have a direct measurement of a channel between a primary transmitter and receiver. Therefore, most existing spectrum sensing algorithms focus on the detection of the primary transmitted signal based on the local observations of the cognitive radio. In the following, an overview of some of the well known spectrum sensing techniques is presented:

i. Matched Filter Detection:

In the case of available prior knowledge about the primary user signal, matched filter detection is the optimal detection method as it maximizes the SNR of the received signal in the presence of additive Gaussian noise. Matched filters are commonly used in radio communications and radar transmission. In the cognitive radio scenario, however, the use of the matched filter can be severely limited as the information of the primary user signal is hardly available at the cognitive radio. Moreover, cognitive radio requires different receivers for all signal types; thus resulting in an impractically large implementation complexity for individual sensing units.

ii. Cyclostationary Detection:

Cyclostationary feature detection uses the presence of strong periodicity in the primary user signal or in its statistics like mean and autocorrelation. This method of detection is more robust compared to other spectrum sensing techniques discussed here. If the primary user signal exhibits strong cyclostationary properties, it can be detected at very low SNR values by exploiting the information embedded in the received signal. The above approach can differentiate primary user signal from cognitive radio users signals over same frequency band provided that the cyclic features of the primary user and the cognitive radio signals differ from each other. However, cyclostationary detection is more complex to implement and requires a prior knowledge of primary user signal such as modulation format.

iii. Energy Detection:

When the primary user signal information is unknown, the energy detection method is optimal for detecting any unknown zero mean constellation signals and can be applied to cognitive radios. In the energy detection approach, the radio frequency energy or the received signal strength indication (RSSI) is measured over an observation time to determine whether the spectrum is occupied or not.

Although the energy detection approach can be implemented without prior knowledge of primary user signal, it still has some drawbacks. Some of the challenges with energy detection based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low SNR.

1.3. Organization of the report

This thesis addresses the problem of decision fusion at the fusion center of the cognitive radio network. The decisions are made at the cooperating sensors. For cognitive radio application, one has to deal with the fact that the sensors are going to observe statistically conditionally dependent data when the primary user is present. This situation could arise because of correlation in the shadowing of the signal received from the primary transmitter. The main contribution of this thesis is a suboptimal fusion rule that handles correlation issues and at the same time the rule is not heavily dependent on the model or on exact knowledge of the statistics of the signal.

The rest of the report is organized as follows. In chapter 2, cooperative spectrum sensing is discussed; mainly its advantages and challenges. Some of the prominent and recent works are discussed and attention is drawn to the assumption of independent users in those works. Chapter 3 discusses cooperative spectrum sensing for dependent users where the individual cognitive radio users receive signals from primary users under the influence of correlated shadowing. Theoretical analysis for different cases, such as single sensor scenario, counting rule, linear decision metric and linear quadratic decision metric are presented. This chapter also discusses the problem formulation and provides solution based on the theoretical analysis for all the individual cases. In chapter 4, simulation results are presented for all these individual cases and a comparison of results finishes the chapter corroborating the solution provided in the previous chapter. Chapter 5 gives the conclusion to the thesis report and introduces future opportunities in this exciting area of research.

CHAPTER 2

COOPERATIVE SPECTRUM SENSING

Traditional wireless networks have predominantly used direct point-to-point or point-to-multipoint topologies. In contrast to conventional point-to-point communications, cooperative communications and networking allows different nodes in a wireless network to share resources and to create collaboration through distributed transmission and processing [5]. In such scenarios, each user's information is sent out not only by the user itself but also by the collaborating users. Cooperative communication and networking is a new communication paradigm that promises significant capacity and multiplexing gain increase in wireless networks. It also realizes a new form of space diversity to combat the detrimental effects of severe fading [6].

The motivation behind using cooperative spectrum sensing in cognitive radio network arises from the necessity of addressing severely degraded sensing performance due to fading, shadowing or faulty sensor.

2.1 Basic Idea behind Cooperative Spectrum Sensing

Just as for any transmission sensing mechanism, such as the widely used CSMA in wireless networks, the critical challenge issue in spectrum sensing is the hidden terminal problem, which occurs when the cognitive radio is shadowed or in severe multipath fading. For a given frequency, multipath fading varies significantly with wavelength displacement. Consequently a cognitive radio suffering from multipath fading and/or shadowed by a big building or large infrastructure cannot sense the presence of primary user. Thus it is allowed to access the channel while the primary user is still in operation.

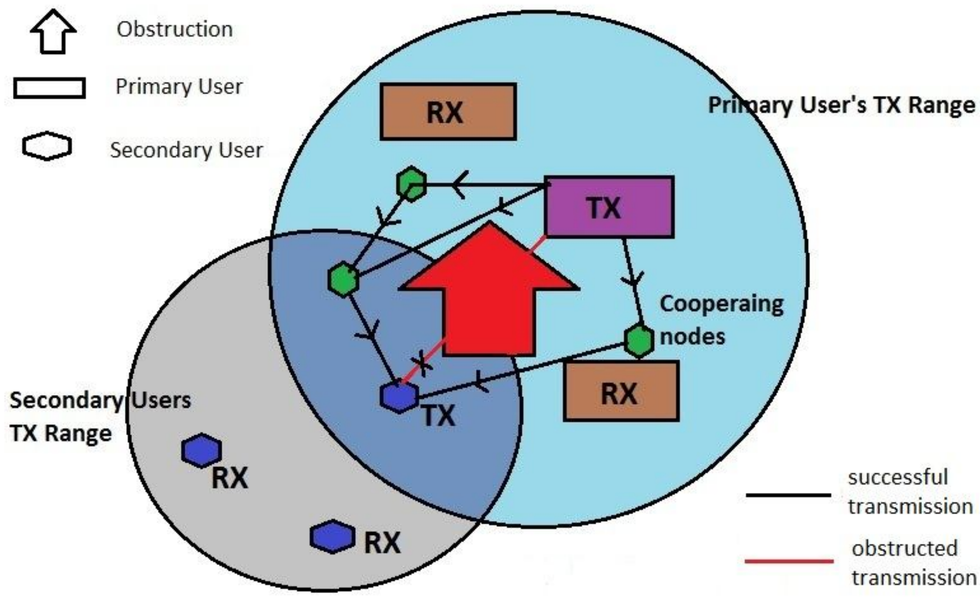

Figure: 1 Hidden Terminal Problem in Cognitive Radio Network

The cognitive radio transmitter wishes to sense the spectrum hole and to access dynamically the channel for transmission under a constrained probability of interference with the primary user. However, certain blocking resulting in shadow fading prohibits effective spectrum sensing by the cognitive radio transmitter. This is known as hidden terminal problem. Figure 1 illustrates the hidden terminal problem for spectrum sensing. The primary user system's operating transmission power range is as shown by the right big circle and the left small circle represents the cognitive radio transmission range. As shown in

Figure 1, the transmission from the primary user transmitter (the purple rectangle) is not detectable by the cognitive radio user (the blue hexagon) because of the obstruction (the red structure) between the primary transmitter and the cognitive receiver.

The immediate solution is to adopt cooperative communication strategy into sensing by placing a set of sensors (green hexagons) scattered in different locations to detect the primary user's possible transmission and by relaying such detected information from distributed cooperative sensors to the cognitive radio transmitter.

Recent work has demonstrated that cooperative spectrum sensing can greatly increase the probability of detection in the fading channels [7], which in turn boosts the spectrum sensing performance of a cognitive radio. A brief discussion of the following two important aspects of cooperative spectrum sensing might be helpful in outlining the usefulness of cooperation in improving the spectrum sensing performance of a cognitive radio.

i. Decision Fusion Versus Data Fusion:

The Cooperative spectrum sensing approach discussed above can be considered as a *Decision Forward* protocol for cooperative networks, where each cooperative partner makes a binary decision based on local observations and then forwards one bit of decision to the fusion center. Another alternative cooperative spectrum sensing approach can be considered which is based on *Amplify and Forward* protocol for cooperative networks. In this case, instead of transmitting a one bit decision to the fusion center, each cognitive radio can send its observation value directly to the fusion center. Obviously, the one bit decision needs a low bandwidth channel. But this approach has to deal with information loss suffered while making decisions at the individual sensors.

ii. Sensing Diversity Gain:

The merit of cooperative spectrum sensing primarily depends on the achievable space diversity brought by the sensing channels: Sensing Diversity Gain. Even though one cognitive radio might fail to detect the primary user signal, there are still many chances for other cooperating cognitive radios to detect the presence of primary user. Cooperative spectrum sensing also provides mutual benefits to all the cooperative nodes, brought forward by communicating with each other to improve sensing performance. When one cognitive radio is far away from the primary user, using the cooperation of a cognitive radio that is located nearby the primary users as a relay, the presence or absence of a primary user can be detected reliably.

2.2 Advantages and Challenges of Cooperative Spectrum Sensing

Cooperative spectrum sensing in cognitive radio networks has an analogy to distributed decision in wireless sensor networks. The main difference between these two applications lies in the wireless environment that presents different context and imposes different challenges to efficient spectrum sensing. Compared to wireless sensor networks, cognitive radios and the fusion center are distributed over a larger geographic area. This difference brings out a much more challenging problem to cooperative spectrum sensing because sensing channels (from primary user to cognitive radios) and reporting channels (from cognitive radios to fusion center) are normally subject to fading and heavy shadowing.

The main advantage of cooperative spectrum sensing is that it lowers the detection sensitivity requirements. Channel impairments such as shadowing, multipath fading, and building penetration losses impose high sensitivity requirements on cognitive radios. This sensitivity requirement can be drastically reduced by making use of cooperation among the users. Cooperative spectrum sensing also improves the agility of the detection process. One of the biggest challenges in cognitive radio is reduction of the overall detection time. Cooperation among the cognitive radios can reduce detection time compared to uncoordinated detection, and thus improves agility of the detection.

On the other hand, cooperation among the cognitive radio users increases the overhead of the cognitive radio network. Cognitive radio users are usually low cost and low power devices that might not have dedicated hardware for cooperation. To deal with this obstacle, data and cooperation information is multiplexed, which cause degradation of throughput for the cognitive users. On top of that, cooperation among the cognitive radio users requires control channels to administer the overall sensing operation. The necessity of these additional channels for control purpose imposes more bandwidth demand on the cognitive radio network.

2.3 Related literature Review and Context of this Report

Use of cooperation in wireless has been studied extensively; especially with respect to achieving diversity gains and lowering outage probability via cooperation of mobile users. Researchers have demonstrated that this wonderful approach of cooperation can also be applied to the context of cognitive radio and gain benefits in terms of spectrum sensing performance and overall detection time.

The problem of spectrum sensing has been discussed in [8 - 11]. In [10], a neural network approach is proposed for cyclic spectral analysis to detect signals in unknown bands. In [9], power and frequency based sensing techniques are proposed for primary user detection in cognitive radio networks employing OFDM technology. [11] proposes a collaborative spectrum sensing approach to detect primary users. It was shown that information exchange between cognitive radios enhances the probability of detection of the primary users.

There has been significant amount of work done in the area of cooperative spectrum sensing as well. Cooperative networks achieve diversity gain by allowing the users to cooperate [10]. In [12], a possible implementation of a cooperative protocol in a CDMA system is discussed. Cooperative schemes with orthogonal transmission in a TDMA system have been proposed in [13, 14]. Previous works on user cooperation for cognitive radio systems, other than some exceptions [15, 16], have mostly studied schemes where the primary user signals received by the cognitive radio users are assumed to receive conditionally i.i.d. observations. In most of the cases, some kind of joint detection is employed among all the cooperating users. Gathering the entire received data at one place may be very difficult under practical communication constraints. Moreover, in practice, cooperation between the cognitive radio users cannot be guaranteed always, since a user can cooperate with others only when there are other users in its vicinity monitoring the same frequency band as itself.

In this thesis, a more feasible system is considered in which the individual secondary users make independent decisions about the presence of the primary signal in the frequency band that they are monitoring. The individual users 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 the 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 also could be one where the secondary users exchange their decisions and each secondary user performs its own fusion of all the decisions.

It was assumed that the fusion center knows the geographic locations of all the cooperating secondary users and hence can learn the correlation between their observations. However, it is unaware of the primary user's location. Since the decisions made by the secondary users contain just one bit of information each, and since it is not expected to keep the track of the channel usage frequently, the data rates required for reliably communicating these observations to the fusion center are expected to be within practical limits. Furthermore, the duration of data transmission is also not expected to affect the delay constraints of the spectrum sensing system.

CHAPTER 3

DECENTRALIZED PRIMARY SIGNAL DETECTION UNDER CORRELATED SHADOWING

In this thesis, we address the problem of fusing decisions that are made at the cooperating sensors. For the cognitive radio application, one has to deal with the fact that the sensors are going to observe statistically dependent data when the primary signal is present. This situation could arise because of correlation in the shadowing suffered by the signal received from the primary transmitter. Here we examine suboptimal fusion rules that handle correlation issue by using only the knowledge of lower order moments of the quantized data.

3.1 Problem Formulation: Spectrum sensing for Primary Users

The preliminary operation of the fusion center is to make a decision: to decide whether or not the secondary users are located inside the transmission range of the primary user transmitter. It is assumed that the secondary users employ energy detectors. Because of the fact that the secondary users are expected to be located at close proximity of each other and are monitoring the same frequency band, the distributions of the received signals can be modeled as identical, but not independent. So the problem is in fact a binary hypothesis testing problem to decide whether or not the mean received power at the location of a secondary user is higher than the power expected at the edge of the transmission range of the primary user transmitter.

When the primary transmission is ‘ON’ and the cognitive radio users are within the transmission range of the primary user, the power received by the individual sensors will be the sum of the power received from the primary user and the noise power. In this case, the received power is modeled as being log-normally distributed. It is also assumed that the correlation between the powers in dB received at two different sensors decays exponentially with distance between them.

When the secondary users move outside of the transmission region of the primary user transmitter, the power received from the primary would be insignificant compared to the noise. This is practically true if the primary user is very far away from the sensing nodes or is switched ‘OFF’. Under this scenario, the output of the energy detectors will be the net energy in the noise signal, which will be proportional to the noise power or variance. In most of the cases, perfect knowledge of the noise power is not feasible in practice due to the uncertain interfering signals in the environment. This uncertainty is modeled by considering the received signal as being log-normal distributed with some known variance. Furthermore, it is assumed that the uncertainties are i.i.d. across the sensors.

The two hypothesis 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 user 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 $\{Y_i\}_1^n$. Hence, the statistical model for the vector $\underline{Y}$ of observations at the *n* cooperating secondary users under the two hypotheses,

$$H_0 : \underline{Y} \sim \mathcal{N}(\underline{0}, \sigma_0^2 I)$$

$$H_1 : \underline{Y} \sim \mathcal{N}\left(\theta\, \underline{1}, \Sigma\right) \; with \; \theta \geq \mu_1 \text{.................................(1)}$$

where $\mathcal{N}(\underline{v}, M)$ denotes a Gaussian vector distribution with mean $\underline{v}$ and covariance matrix M. Here θ is a variable parameter representing the mean of the distributions observed under H_1, while μ_1 is the mean total power in dBm received at the edge of the transmission region minus the noise power in dBm. σ_0^2 represents the uncertainties in the noise power, Σ is the matrix with elements $\Sigma_{ij} = \sigma_1^2 \rho^{d_{ij}}$, where d_{ij} is the distance between nodes indexed by i and j, ρ is a measure of the correlation coefficient between nodes separated by unit distance, and σ_1^2 is the net variance under H_1. The parameter ρ is related to the correlation distance, D_C, by the relation $\rho = \exp\left(\frac{-1}{D_C}\right)$ [15].

The system must guarantee that the probability of interfering with the primary transmission is less than some pre-specified limit, p_I. It is assumed that the secondary users use the spectrum for transmission whenever they detect a spectrum hole. Hence, the probability of interfering with the primary user would be equal to the probability of making an erroneous decision under hypothesis H_1.

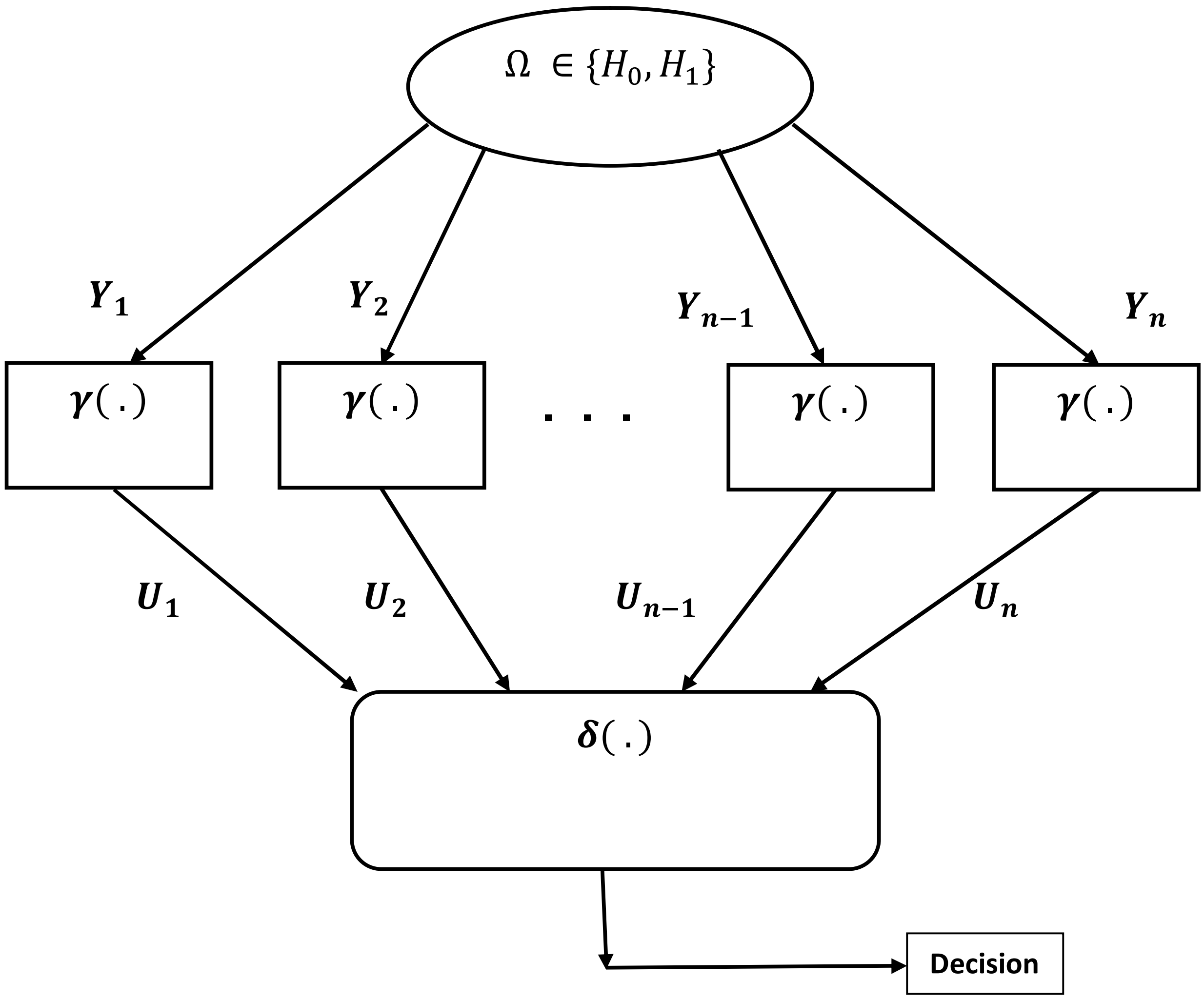

Figure: 2 Decentralized detection setup

So the system should guarantee that the probability of making an erroneous decision under H_1 should be lower than the constraint on the probability on interference. Moreover, this constraint should be met for all values of θ greater than or equal to μ_1. This is a composite binary Neyman-Pearson hypothesis testing problem. As no prior information about the distribution of the mean powers is available, the system is to be designed in such a way that it meets the interference probability constraint with equality for the least favorable value of θ, which is equal to μ_1.

Here the decision process at the fusion center is defined as,

$$\delta(\underline{u}) = \begin{cases} 1 & \text{if fused decision is } H_1 \\ 0 & \text{if fused decision is } H_0 \end{cases} \quad \text{.............................(2)}$$

To summarize, the detection problem is reduced to a simple Neyman-Pearson hypothesis testing problem between the two modified hypotheses

$$H_0 : \underline{Y} \sim \mathcal{N}(\underline{0}, \sigma_0^2 I)$$

$$H_1 : \underline{Y} \sim \mathcal{N}(\mu_1 \underline{1}, \Sigma) \quad \text{....................................(3)}$$

The fusion center has access to the binary valued decisions made by the sensors based on their individual observations and makes the final decision about the hypotheses using the individual sensor decisions. $\{U_i\}_1^n$ represents the decisions made by the individual sensors and $\underline{U}$ represents the vector of decisions made by all sensors.

3.2 Detection Rule at the Individual Nodes

In most practical scenarios, all the cooperating cognitive radios cannot always expect cooperation from other users in the detection process. Considering this limitation, the cognitive radios considered in this thesis report are assumed to employ detector that would meet the interference probability constraint individually. Since the distributions of the signals received at every sensor are assumed to be identical, the energy detectors they use are also assumed to be identical. Individual nodes will try their best to make a correct decision and will use optimal likelihood ratio test on its observations. In this report, it is assumed that the observations made by the individual nodes obey Gaussian distribution. In fact the distribution is the corresponding marginal distribution obtained from (3).

The likelihood ratio in the case of identically distributed Gaussian observations takes the form:

$$L = \frac{(2\pi\sigma_1^2)^{-\frac{1}{2}} \,.\, \exp\left\{-\frac{1}{2\sigma_1^2}(y-\mu_1)^2\right\}}{(2\pi\sigma_0^2)^{-\frac{1}{2}} \,.\, \exp\left\{-\frac{1}{2\sigma_0^2}(y-\mu_0)^2\right\}}$$

or,

$$L = \frac{\sigma_0}{\sigma_1} \,.\exp\left\{\left(\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2}\right)y^2 + \left(\frac{\mu_1}{\sigma_1^2} - \frac{\mu_0}{\sigma_0^2}\right)y + \left(\frac{\mu_0^2}{\sigma_0^2} - \frac{\mu_1^2}{\sigma_1^2}\right)\right\} \quad \ldots\ldots\ldots\ldots(4)$$

The likelihood ratio test at the individual nodes will compare this likelihood ratio with an appropriate threshold. It is assumed that all the individual nodes employ the same threshold in a likelihood ratio test. The threshold is chosen so that the probability of making an incorrect decision under the hypothesis H_1 meets the constraint on the interference probability. For the assumption of Gaussian distribution, the likelihood ratio test becomes:

$$\frac{\sigma_0}{\sigma_1} \,.\exp\left\{\left(\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2}\right)y^2 + \left(\frac{\mu_1}{\sigma_1^2} - \frac{\mu_0}{\sigma_0^2}\right)y + \left(\frac{\mu_0^2}{\sigma_0^2} - \frac{\mu_1^2}{\sigma_1^2}\right)\right\} \underset{H_0}{\overset{H_1}{\lesseqgtr}} t_1$$

Straight forward simplification yields $$a y^2 + by \underset{H_0}{\overset{H_1}{\lesseqgtr}} t_3 \qquad (5)$$

where, $a = \left(\frac{1}{2\sigma_0^2} - \frac{1}{2\sigma_1^2}\right)$ and $b = \left(\frac{\mu_1}{\sigma_1^2} - \frac{\mu_0}{\sigma_0^2}\right)$

The likelihood ratio test simplifies to a comparison of a quadratic form of observations with a threshold "*t*":

$$a y^2 + by \underset{H_0}{\overset{H_1}{\lesseqgtr}} t_3 = t$$

$$or, \qquad y \underset{H_0}{\overset{H_1}{\lesseqgtr}} -\frac{b}{2a} \pm \psi, \qquad where \quad \psi = \sqrt{\frac{t}{a} + \frac{b^2}{4a^2}}$$

So an individual node uses a likelihood ratio test and decides in favor of the hypothesis H_0 if,

$$-\frac{b}{2a} - \psi < y < -\frac{b}{2a} + \psi$$

and in favor of the hypothesis H_1 if,

$$-\frac{b}{2a} - \psi \geq y \geq -\frac{b}{2a} + \psi \qquad (6)$$

The testing threshold is chosen so that the constraint on interference probability is satisfied and the same threshold is used to measure the spectrum hole detection performance for the nodes. This ensures that the individual nodes can satisfy the interference constraint on their own. So in situations where an individual node finds itself operating without any cooperating neighbors, it can still operate within the desired interference level. The probability of interference and the probability of detecting spectrum hole have the following expressions:

$$p_I = Q\left(\frac{-\frac{b}{2a} - \psi - \mu_1}{\sigma_1}\right) - Q\left(\frac{-\frac{b}{2a} + \psi - \mu_1}{\sigma_1}\right)$$

$$p_{sh} = Q\left(\frac{-\frac{b}{2a} - \psi - \mu_0}{\sigma_0}\right) - Q\left(\frac{-\frac{b}{2a} + \psi - \mu_0}{\sigma_0}\right)\text{..................}(7)$$

3.3 Decision Making at the Fusion Center

All the decisions made at the individual nodes are communicated to the fusion center. The optimal fusion rule computes the joint likelihood ratio of the decisions and compares it with a threshold chosen such that the interference probability constraint is satisfied. But this optimal fusion rule in general requires the knowledge of the joint statistics of the decisions under both the hypotheses.

For the system under consideration, the U_is are binary quantized versions of correlated Gaussian variables under the hypothesis H_1. So gathering information about their joint statistics is difficult and time consuming especially for large values of *n* (*n* is number of cooperating nodes as in Figure 2). Therefore, by avoiding computationally difficult joint statistics, some simple suboptimal fusion strategies are considered in this report. While selecting the suboptimal strategies, emphasis is given to those fusion rules for which only partial statistical information about the quantized observations is required. In the absence of the joint statistics, the fusion center threshold is estimated using simulations. In the following, three suboptimal fusion strategies: Counting rule, Linear decision metric, and Linear quadratic decision metric are discussed and for each case the fusion center threshold is determined using a simulation study.

i. Counting Rule

The first suboptimal fusion rule to be discussed is Counting Rule. It is also known as the Voting Rule. Counting Rule is one of the simplest suboptimal data fusion strategies. The fusion center counts the number of sensor decisions which is taken in favor of the hypothesis H_1. So in essence, the counting rule tries to determine how many cooperating nodes decided in favor of the presence of a primary user and compares it with a threshold that satisfies the interference probability constraint. The threshold value is determined using simulations since the joint statistics under H_1 are not easily computable.

Since the counting rule produces discrete values of probability of interference and probability of spectrum hole detection, randomization technique is used to make sure that the threshold is chosen in such a way that it satisfies the exact probability of interference. The randomization is done as follows:

P_{I_1}: Probability of interference that is (closest to and smaller) or equal to the target interference probability, P_I, and achieved by setting the threshold at $t = t_1$

P_{I_2}: Probability of interference that is (closest to and larger) or equal to the target interference probability,P_I, and achieved by setting the threshold at $t = t_2$

Then the randomization factor, ε, can be determined to achieve the constrained probability of interference as follows,

$$P_I = \varepsilon \,.\, P_{I_2} + (1 - \varepsilon) \,.\, P_{I_1}$$

Simplifying for ε produces, $\varepsilon = \frac{P_I - P_{I_1}}{P_{I_2} - P_{I_1}}$

Now let,

P_{sh_1}: Probability of detecting spectrum hole achieved by setting the threshold at $t = t_1$

P_{sh_2}: Probability of detecting spectrum hole achieved by setting the threshold at $t = t_2$

Then the performance of the fusion center using the randomization factor, ε, in accordance to the counting rule is:

$$P_{sh} = \varepsilon \,.\, P_{sh_2} + (1 - \varepsilon) \,.\, P_{sh_1}$$

The unavailability of joint statistics of decisions under both hypotheses dictates the fusion center to adopt the suboptimal strategies like the counting rule. As a natural consequence of suboptimal strategy, the resulting Receiver

Operation Characteristics (ROC) curve (a plot of P_{sh} *vs* P_I) does not have the desired *'concave'* shape. The performance of the detector under suboptimal fusion strategy can be reasonably improved by using the hidden concavity of the apparently non-concave ROC.

The idea of concavification of ROC is very similar to the randomization technique used in Neyman-Pearson hypothesis testing when the observation space is discrete. In the standard version of the NP test with discrete valued observations, there are a finite number of achievable points on the ROC. Once the randomization is allowed, the adjacent points on the ROC are essentially joined by a straight line. The reason behind this linear estimation is that the probability of errors of the new rule is a convex combination of the probabilities of error of the two original rules that are being randomized. The resultant randomized ROC will be concave. This is always the case when a likelihood ratio test is under consideration.

While considering the suboptimal cases, the detectors under consideration are not the optimal likelihood ratio detector and hence if the randomization operation is performed (i.e. joining adjacent points by straight lines, or equivalently, randomizing between adjacent rules), in general it yields a non-concave curve. However, if the randomization is allowed between arbitrary points on the ROC, which are not adjacent to each other, the resulting curve yields the concave hull of the ROC. So by making use of the hidden concavity of the ROC, the performance of the suboptimal detectors can be improved more significantly compared to the improvement achieved with traditional randomization only.

Figure 3 demonstrates that, by allowing randomization between points which are not necessarily adjacent, the performance can be enhanced by making use of the convex hull of the ROC.

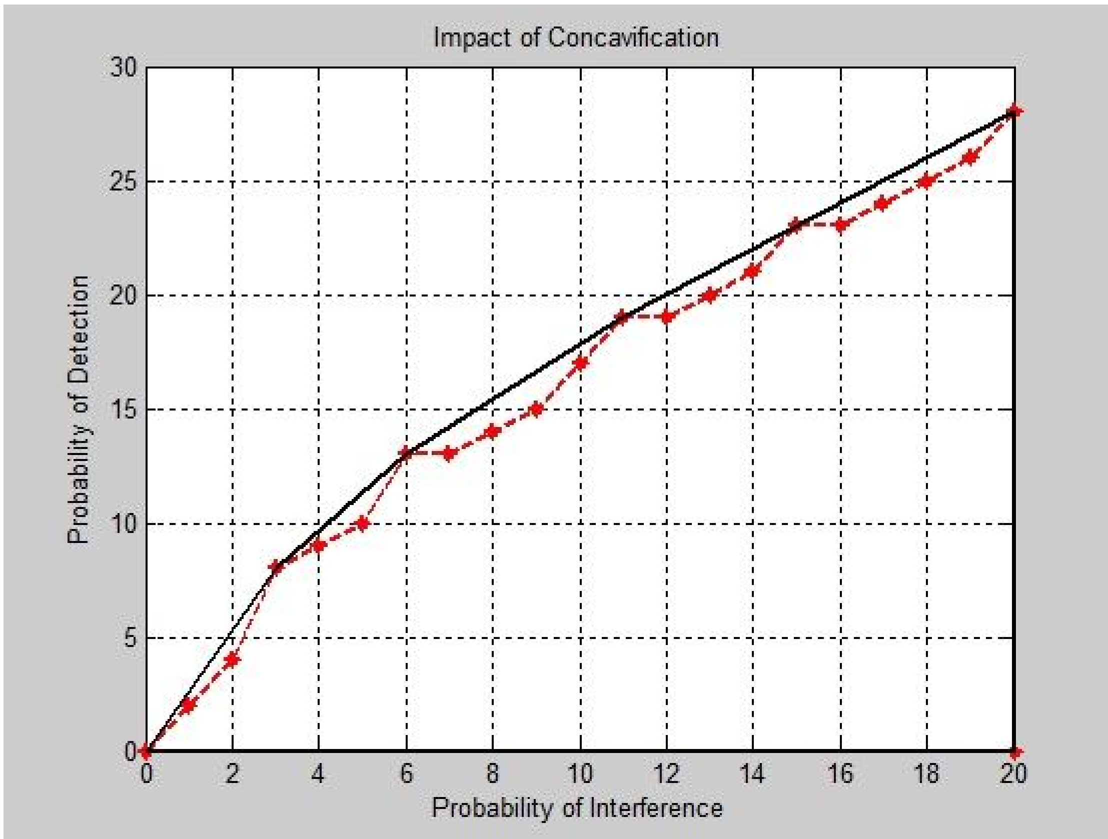

Figure 3: Improvement in performance due to concavification

ii. Linear Decision Metric

In this section, a class of linear detector is considered. Linear detectors compare a linear function of decisions with a threshold. Since the linear suboptimal strategy uses only moment information about the decision vector, this detector can be used for all classes of distributions of the signals. The optimization over the class of linear detector is done using the generalized signal-to-noise ratio or deflection criterion [20, 21]. Let $\underline{X}$ be the observations in some detection problem. The deflection of a detector that makes a decision by comparing a function $T(\underline{X})$ to a threshold is defined as

$$D_T = \frac{\{E_1[T(\underline{X})] - E_0[T(\underline{X})]\}^2}{Var_0(T(\underline{X}))} \quad \text{.........................(8)}$$

Higher value of deflection is expected to have better error probability performance than the one with a lower value of deflection. The linear decision metric can be viewed as a linear function of the log - likelihood ratios of the individual random variables. The decision metric can be expressed as:

$$T(\underline{X}) = \underline{h}^T . \underline{X} \quad \text{.......................................(9)}$$

here $\underline{h}$ is a vector of length *n* and $\underline{X}$ is the vector of log – likelihood ratios of the received decisions with means under H_0 subtracted. This is a special case of linear quadratic decision metric used in [15]. The components of $\underline{X}$ are given by,

$$X_i = \log\left\{\frac{P(U_i|H_1)}{P(U_i|H_0)}\right\} - E_0\left[\log\left\{\frac{P(U_i|H_1)}{P(U_i|H_0)}\right\}\right] \quad \text{..................(10)}$$

It is obvious from the expression of X_i that the expected value of X_i under H_0 is zero. So the expression of the deflection of the detector simplifies to:

$$D_T = \frac{\{E_1[\underline{h}^T . \underline{X}]\}^2}{E_0[\{\underline{h}^T . \underline{X}\}^2]} = \frac{\{\underline{h}^T . E_1[\,\underline{X}\,]\}^2}{\underline{h}^T . E_0[\underline{X} . \underline{X}^T] . \underline{h}} = \frac{\{\underline{h}^T . \underline{\mu}\}^2}{\underline{h}^T . \mathbb{K} . \underline{h}}$$

where, $\underline{\mu} = E_1[\,\underline{X}\,]$ and $\mathbb{K} = E_0[\underline{X} . \underline{X}^T]$

So the problem now reduces to finding the $\underline{h}$ vector that maximizes the deflection, D_T, of the detector. Using the result from [23], the weight vector that maximizes the deflection and the supremum value of the deflection is given by,

$$\sup D_T = \underline{\mu} \,.\, \mathbb{K}^{-1} \,.\, \underline{\mu}^T$$

the supremum is attained at

$$\underline{h}_{opt} = \mathbb{K}^{-1} \,.\, \underline{\mu}^T \quad \text{.................................(11)}$$

So the optimal linear decision metric has the form,

$$T_{opt}(\underline{X}) = \underline{h}_{opt}{}^T \,.\, \underline{X}$$

equivalently, $$T_{opt}(\underline{X}) = (\mathbb{K}^{-1} \,.\, \underline{\mu}^T) \,.\, \underline{X} \quad \text{..............................(12)}$$

So the deflection optimal linear detector will compare this decision metric to a threshold chosen such that the interference probability constraint is satisfied. This threshold would have to be set using simulations since the statistics of the decision metric are not available. Randomization may also be required to achieve the interference probability constraint as the decision metric is discrete valued. In the simulations, both concavification of ROC and randomization techniques are used to achieve improved performance of this suboptimal detector.

iii. Linear Quadratic Decision Metric

In this section, a general suboptimal solution to the fusion problem from [15] is presented. Linear quadratic detectors compare a linear-quadratic function of decisions with a threshold. The optimization over the class of linear-quadratic detectors is done using the generalized signal-to-noise ratio or deflection criterion [20, 21]. Let $\underline{X}$ be the observations in some detection problem. The deflection of a detector that makes a decision by comparing a function $T(\underline{X})$ to a threshold is defined as in (8). Higher value of deflection is expected to have better error probability performance than one with a lower value of deflection. The decision metric can be viewed as a linear-quadratic function of the log - likelihood ratios of the individual random variables. The decision metric can be expressed as:

$$T(\underline{X}) = \underline{h}^T . \underline{X} + \underline{X}^T . \mathbb{M} . \underline{X} \text{.............................} (13)$$

here $\underline{h}$ is a vector of length *n*, $\mathbb{M}$ is a $(n \times n)$ square matrix and $\underline{X}$ is the vector of log – likelihood ratios of the received decisions with means under H_0 subtracted. The components of $\underline{X}$ are given by,

$$X_i = \log\left\{\frac{P(U_i|H_1)}{P(U_i|H_0)}\right\} - E_0\left[\log\left\{\frac{P(U_i|H_1)}{P(U_i|H_0)}\right\}\right] \text{..................} (14)$$

It is obvious from the expression of X_i that the expected value of X_i under H_0 is zero. We need to find the optimal LQ metric of the form (13) that maximizes the deflection given by (8). The decision metric in (13) can be modified to the form:

$$S(\underline{Z}) = \underline{x}^T . \underline{Z} \text{...} (15)$$

where, $C = E[\underline{X}.\underline{X}^T]$, $\underline{x} = [\underline{h}^T \quad matrix2vector(\mathbb{M})]$

and, $\underline{Z} = \begin{bmatrix} X_1 \dots X_n X_1^2 - C_{11} \dots X_1 X_n - C_{nn} X_2 X_1 - C_{21} \dots X_2 X_n - C_{2n} \\ \dots X_n X_1 - C_{n1} \dots X_n^2 - C_{nn} \end{bmatrix}$

So the expression of the deflection of the detector simplifies to:

$$D_S = \frac{\{E_1[\underline{x}^T . \underline{Z}]\}^2}{E_0[\{\underline{x}^T . \underline{Z}\}^2]} = \frac{\{\underline{x}^T . E_1[\ \underline{Z}\ ]\}^2}{\underline{x}^T . E_0[\underline{Z} . \underline{Z}^T] . \underline{x}} = \frac{\{\underline{x}^T . \underline{\mu}\}^2}{\underline{x}^T . \mathbb{K} . \underline{x}}$$

where, $\underline{\mu} = E_1[\ \underline{Z}\ ]$ and $\mathbb{K} = E_0[\underline{Z} . \underline{Z}^T]$

So the problem now reduces to finding the $\underline{x}$vector (in other words, $\underline{h}$vector and $\mathbb{M}$matrix) that maximizes the deflection, D_S, of the detector. This problem of optimizing the weights of LQ decision metric has been discussed in [20, 21]. Using the results from [20, 21], the weight vector that maximizes the deflection and the corresponding supremum value of the deflection is given by,

$$\sup D_S = \underline{\widetilde{\mu_a}}^T . \Lambda_a^{-1} . \underline{\widetilde{\mu_a}}$$

the supremum is attained at, $\underline{\widetilde{x_a}}_{opt} = \Lambda_a^{-1} . \underline{\widetilde{\mu_a}}$……………………….(16)

and the optimal linear decision metric has the form,

$$S_{opt}(\underline{Z}) = \underline{x}_{opt}{}^T . \underline{Z} = \underline{\widetilde{x_a}}_{opt} . \underline{Z}$$

equivalently, $S_{opt}(\underline{Z}) = \underline{\widetilde{\mu_a}}^T . \Lambda_a^{-1} . \underline{\widetilde{Z_a}}$………………………….(17)

here,

i. Λ_a, is the diagonal matrix containing only the nonzero diagonal elements of $\Lambda$and $\underline{\widetilde{x_a}}$ and $\underline{\widetilde{\mu_a}}$ are the vectors composed of the corresponding elements of $\underline{\tilde{x}}$ and $\underline{\tilde{\mu}}$, where,

$$\mathbb{K} = V^T \,.\, \Lambda^{-1} \,.\, V$$

$$\underline{\tilde{x}} = V^T \,.\, \underline{x} \qquad \textit{and} \qquad \underline{\tilde{\mu}} = V^T \,.\, \underline{\mu}$$

$V: a\ unitary\ matrix \qquad and \qquad \Lambda$: a diagonal matrix with nonnegetive entries

ii. $\underline{\widetilde{Z_a}}$, is obtained by keeping only the terms of $\underline{\tilde{Z}}$, corresponding to those of $\underline{\tilde{\mu}}$ that appears in $\underline{\widetilde{\mu_a}}$, where, $\underline{\tilde{Z}} = V^T \,.\, \underline{Z}$

So the deflection optimal linear quadratic detector will compare this decision metric to a threshold chosen such that the interference probability constraint is satisfied. This threshold would have to be set using simulations since the statistics of the decision metric are not available. Randomization may also be required to achieve the interference probability constraint as the decision metric is discrete valued. It is interesting to notice that the linear decision metric discussed in the previous subsection is a special case of the linear-quadratic decision metric with $\mathbb{M} = 0$.

CHAPTER 4

SIMULATION RESULTS AND DISCUSSION

Simulations were run under several scenarios in order to determine the performance of the detectors under the above discussed suboptimal fusion strategies since analytical expressions for the error probabilities of these detectors cannot be obtained. For the detection problem under consideration, the performance metrics of interest are the probability of successfully detecting the presence of a spectrum hole and the probability of interference of the cognitive radio users with the primary users under H_1. The probability of detecting the presence of a spectrum hole is same as the probability of correct decision under H_0, which is given by, $P\left(\delta\left(\underline{U}\right) = 0 \middle| H_0\right)$. The probability of interference under H_1 is same as the probability of erroneous decision under H_1, which is given by, $P\left(\delta\left(\underline{U}\right) = 0 \middle| H_1\right)$.

In order to observe the performance of the fusion center satisfying the interference probability constraint, a network of nine cooperating nodes is considered. The nodes are assumed to be uniformly placed inside a unit square with the distance between nearest neighbors kept at 0.5 unit. The correlation coefficient, ρ, is taken to be 0.6. This effectively amounts to assuming the side of the square is around half the correlation distance. The mean and variance under H_0 is kept fixed at 0 dB (μ_0) and 1 dB (σ_0^2), and under H_1 is assumed to be 2.1 dB (μ_1) and 3.4 dB (σ_1^2). Any solution to a decentralized detection problem has two decision making parts; the first step is to choose the best decision or detection rule at the individual nodes and the second part addresses the problem of selecting the best fusion rule to be used at the fusion center. In the following two subsections, simulation results obtained for both the decision making steps are presented.

4.1 Results for Detection Rules at the Individual Nodes

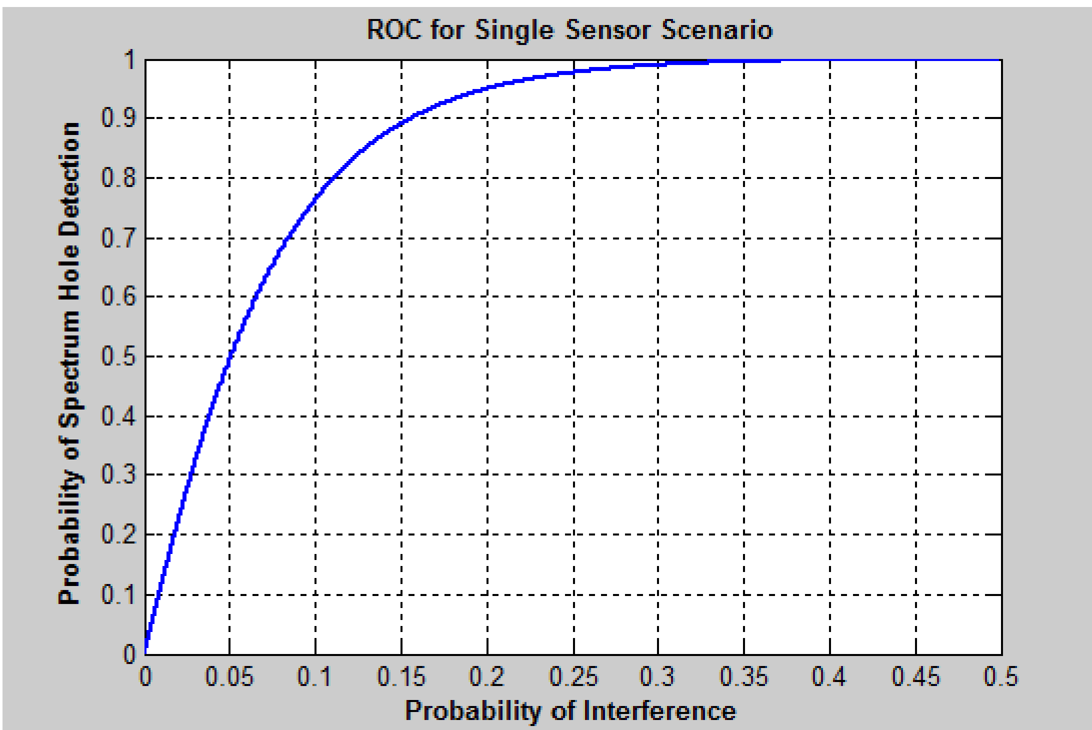

Figure 4: Performance of the Individual Sensors

In this section, the performance of individual sensor nodes are presented and analyzed. Individual sensors, while detecting the existence of any spectrum hole, do their best and use the optimal *Likelihood Ratio Test* to make decisions about the presence or absence of the primary user in the frequency band of interest.

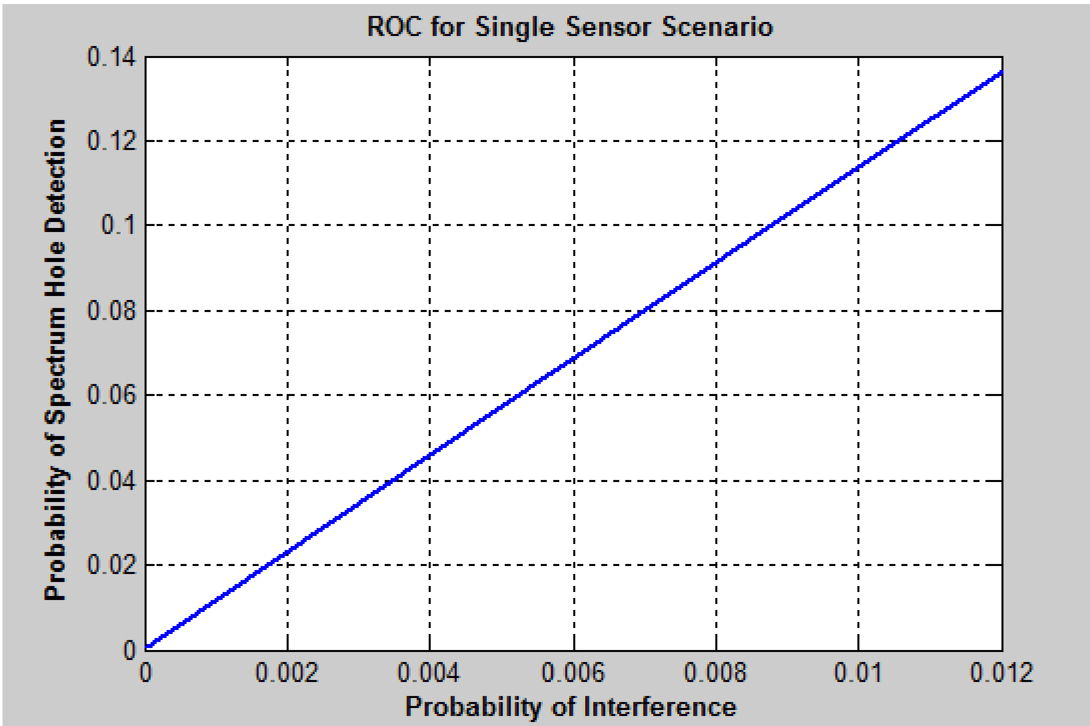

Figure 5: Performance of the Individual Sensors, Restricted P_I Range (0.001 – 0.01)

Figure 4 presents the ROC for the individual node's energy detector. These detectors are designed so that each of the nodes individually achieves the interference probability constraint. As the individual nodes employ optimal likelihood ratio test, achieving the classic concave ROC is expected. In Figure 5, the analysis is restricted within the probability of interference range that is of interest. It presents the performance of the individual detectors that satisfies the interference probability constraint which ranges from 0.001 to 0.01 (same values used in [15]). In this range the performance of the detectors behaves linearly with the interference probability constraint.

4.2 Results for Decision Fusion Rules at the Fusion Center

Here, counting rule and linear decision metric criterion are considered for fusing the decisions. The threshold at the fusion center is fixed using simulation such that it satisfies the interference probability constraint. The simulation results for both the fusion rules are given in the following sections:

i. Results for the Counting Rule fusion strategy

Table 1: Performance at the fusion center using Counting Rule

Probability of Interference	**Probability of Spectrum Hole Detection**		
	Single Sensor	*Counting Rule without concavification*	*Counting Rule with Concavification*
0.001	0.011439109664045	0.012139078341014	0.012139078341014
0.004	0.045713325455676	0.064920258249641	0.064920258249641
0.007	0.079771970995179	0.116425368289638	0.116425368289638
0.01	0.113568554314532	0.157917720964208	0.157917720964208

In this subsection, the performance of the fusion center obeying counting rule fusion strategy is presented. The simulation result clearly shows the improvement in performance as a result of cooperation among all the participating nodes. Under the counting rule fusion strategy, the fusion center counts the number of sensor decisions which is in favor of the hypothesis H_1. In other words, counting rule determines how many cooperating nodes decided the presence of a primary user and compares this collective decision with a threshold that satisfies the interference probability constraint.

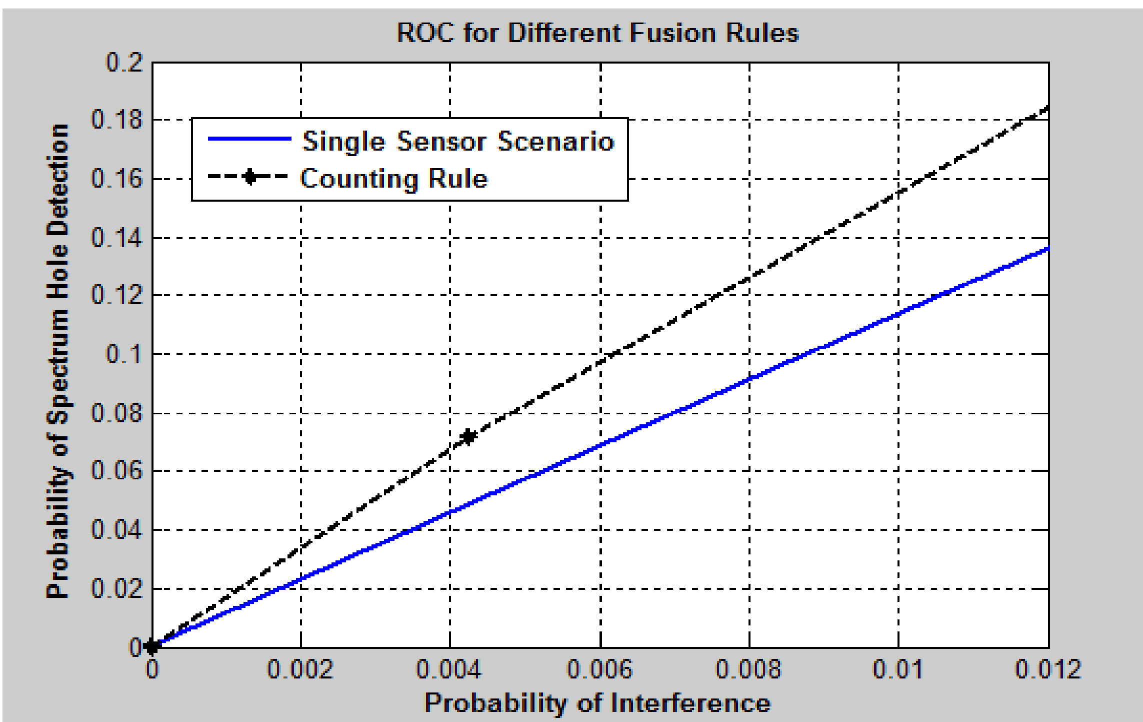

Figure 6: Performance of the Counting Rule

Table 1 presents the simulation results on interference probability and performance of the fusion center in detecting spectrum holes under counting rule. It also corroborates the fact that cooperation among the cooperating nodes improves the performance of the fusion center. This can be seen from the comparison between the results for single sensor scenario and counting rule scenario as shown in Figure 6.

Table 1 also shows that making use of hidden concavity of the ROC, in other words using the convex hull of the ROC does not have any influence on the performance of the fusion center. The impact of concavification of ROC on the performance of the fusion center deserves more analysis and will be considered in the later sections.

ii. Results for the Linear Decision Metric fusion strategy

Table 2: Performance at the fusion center using Linear Decision Metric

Probability of Interference	**Probability of Spectrum Hole Detection**		
	Single Sensor	*Linear Decision Metric without concavification*	*Linear Decision Metric with Concavification*
0.001	0.011439109664045	0.013573790127412	0.013643721022501
0.004	0.045713325455676	0.067402759482035	0.06940260012952
0.007	0.079771970995179	0.118590355821092	0.119473883492101
0.01	0.113568554314532	0.159546156773901	0.163083630101612

The results in this subsection is based on the assumption that the fusion center generates a linear decision metric using the individual node's decisions and compare this decision metric with a threshold determined by simulation to satisfy interference probability constraint. The theoretical aspect of the linear decision metric was discussed on section 3.3 (ii).

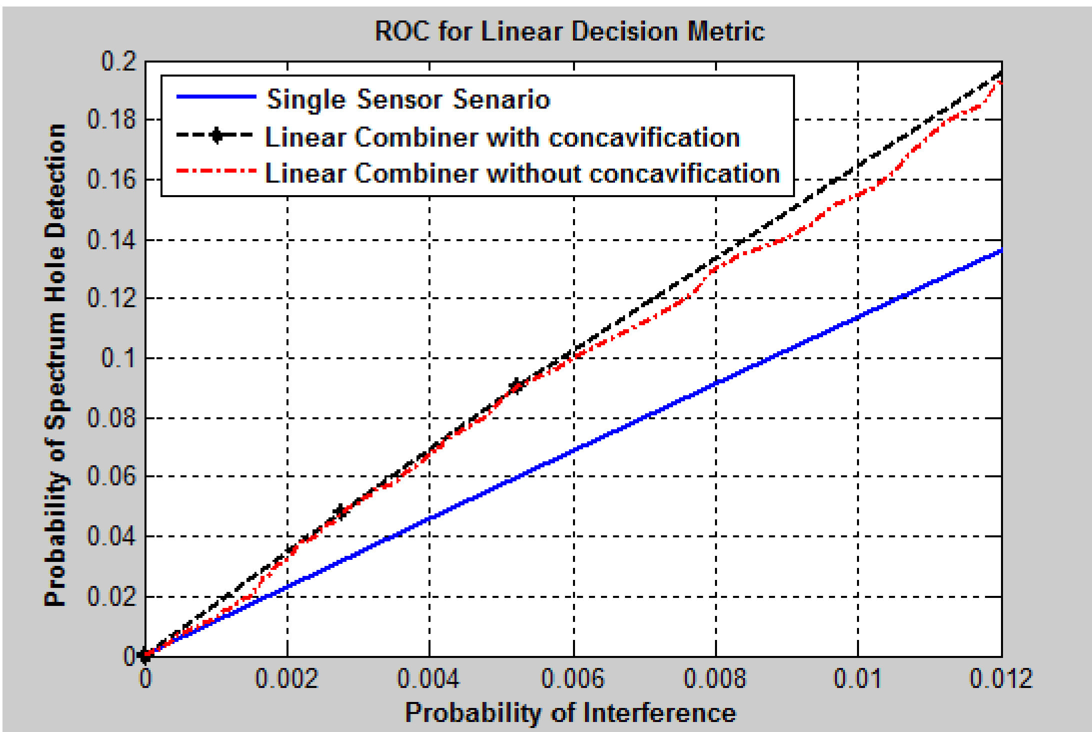

Figure 7: Performance of the Linear Decision Metric

Table 2 presents the simulation results for linear decision metric scenario. As in all previous cases, the individual sensor nodes are designed such that each of them individually satisfies the interference probability constraint. The impact of cooperation among the cooperating nodes is evident from the results. The performance of the fusion center is reasonably higher than that of single sensor scenario. Also as expected the performance of the fusion center increases as we increase the tolerance of interference with the primary user transmission. The simulation result in this case also demonstrates the improvement in performance as a result of concavification of the ROC at the fusion center.

Figure 7 illustrates the performance of the fusion center when the individual sensors satisfy the interference probability constraint of 0.01. As we can see in Figure 6, the use of concavification enhances the performance of the fusion center under linear decision metric rule. This justifies employing concavification of ROC at the fusion center to achieve improved performance in detecting spectrum holes.

4.3 Comparing Results with different decision making criterion

Table 3: Performance of Different Fusion Rules

Probability of Interference	**Probability of Spectrum Hole Detection**		
	Single Sensor	*Counting Rule*	*Linear Decision Metric*
0.001	0.011439109664045	0.012139078341014	0.013643721022501
0.004	0.045713325455676	0.064920258249641	0.06940260012952
0.007	0.079771970995179	0.116425368289638	0.119473883492101
0.01	0.113568554314532	0.157917720964208	0.163083630101612

This section compares and comments on the simulation results found under different detection and fusion rules. Table 3 provides the results from single sensor scenario, counting rule and linear decision metric scenario. The improvement of performance in the counting rule and linear decision metric over the single sensor scenario demonstrates the usefulness of cooperation in detecting spectrum holes.

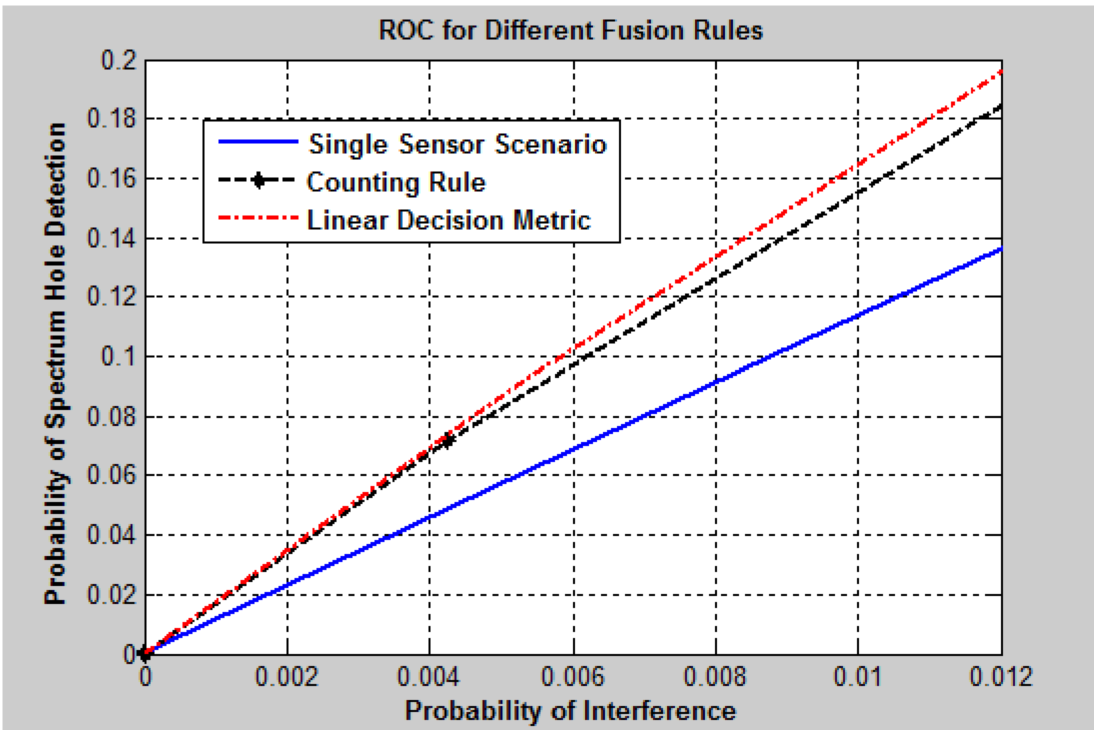

Figure 8: Comparing Performance of Different Fusion Rules

Simulation results in Figure 8 show that the fusion center performs slightly better under linear decision metric strategy compared to that under the counting rule strategy. In both cases, performance measurements are achieved after employing concavification of the ROC, which is not purely concave in shape due to the suboptimal nature of the fusion strategy. Although not evident from the counting rule scenario, the slight improvement in performance under linear decision metric strategy justifies the use of concavification on the ROC at the fusion center.

There is another interesting aspect of linear decision metric scenario. Both counting rule and linear decision metric works on linear combination of some processed version of the decisions received from the individual sensor nodes. This becomes evident from the fact that if the weight vector for linear decision metric is replaced by all “1”, then the performance of the fusion center matches that under counting rule. So, the counting rule fusion strategy can be considered as a specific form of linear decision metric fusion strategy with suboptimal, identical values for the weight vector in (11). The results provided in Table 1 also support the above statement. As both the fusion strategies are linear in nature (differs only on weight vector values), the performance under both the fusion strategy do not differ by much. Only a small gain is achieved by optimizing the weights.

4.4 Observation: Interference Probability constraint satisfied by Fusion Center only

This subsection presents an interesting observation about the performance of different fusion rules at the fusion center in [15]. In [15] it was assumed that the cooperating nodes are designed such that each of them can satisfy the interference probability constraint on their own. But the analysis in this

Table 4: Performance of Different Fusion Rules under Individual sensors meeting p_I constraint

Probability of Interference		Probability of Spectrum Hole Detection				
			Counting Rule		*Linear Decision Metric*	
Nodes	Fusion Center	*Single Sensor*	Without Concavification	With Concavification	Without Concavification	With Concavification
0.001	0.001	0.01143	0.01213	0.01213	0.01357	0.01364
0.004	0.004	0.04571	0.06492	0.06492	0.06740	0.06940
0.007	0.007	0.07977	0.11642	0.11642	0.11859	0.11947
0.01	0.01	0.11356	0.15791	0.15791	0.15954	0.016308

thesis showed that, under the above mentioned assumption, the performance of different fusion rules are lower than what is presented in [15]. The simulation results under the said assumption are presented in Table 4 and the one where this assumption is not satisfied is given in Table 5.

Table 4 provides a measurement of different fusion rule performances under the individual sensors meeting the p_I constraint assumption. First two columns of Table 4 corroborate the fact that interference probability constraint is satisfied both at the individual sensors and at the fusion center. The desired level of interference is achieved at the fusion center in both cases. Table 5 presents the results when the individual nodes are not required to satisfy the interference probability constraint.

Table 5: Performance of Different Fusion Rules when Fusion Center alone meets p_I constraint

Probability of Interference		Probability of Spectrum Hole Detection				
			Counting Rule		*Linear Decision Metric*	
Sensor	Fusion Center	*Single Sensor*	Without Concavification	With Concavification	Without Concavification	With Concavification
0.04762	0.001	0.47701	0.01087	0.01816	0.01896	0.01824
0.04774	0.004	0.47797	0.07047	0.08833	0.07215	0.08892
0.04801	0.007	0.47998	0.13709	0.14889	0.13920	0.15641
0.04840	0.01	0.48307	0.20319	0.20888	0.20925	0.21218

So from the result, it is evident that the proposed performances in [15] are not achievable under the individual sensors meeting the p_I constraint assumption. At the same time Table 4 and 5 indicate that if the individual nodes are not required to satisfy the interference constraint, then the performances of different fusion rules improve reasonably.

Another interesting point to be noticed here is that that without using the concavification technique, different fusion strategies didn't have significant impact on the performance of the system. Also the impact of concavification is much more obvious from the results of Table 5. So, it can be concluded that if the individual sensors are not forced to satisfy the constraint on interference probability, randomization and concavification techniques might yield better results and different suboptimal fusion rules might show a much improved spectrum hole detection performance. Figure 9 presents the graphical representation of the above statement. We can see a reasonable improvement in the performance of the fusion center when the individual sensors are free to set their own probability of interference.

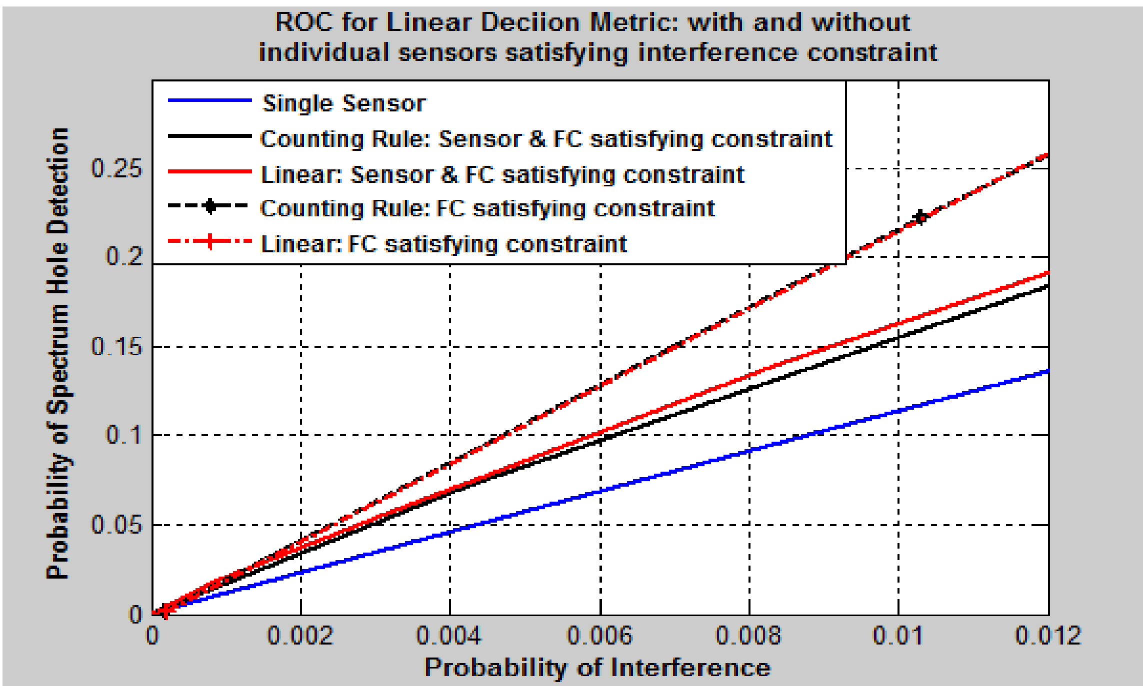

Figure 9: Comparing Performance of Different Fusion Rules: with and without individual sensors meeting interference probability constraint

CHAPTER 5

CONCLUSION AND FUTURE RESEARCH OPPORTUNITIES

The successful implementation and employment of various cognitive radio services are largely dependent on the spectrum sensing performance of the cognitive radio terminals. This spectrum sensing or user detection can be performed assuming a centralized approach or a more dynamic distributed approach. The introduction of cooperation enhances the cognitive radio network’s chance of minimizing unwanted interference with the licensed users. This report provides a brief overview of the impact of different fusion strategies on the spectrum hole detection performance of a fusion center in a distributed detection environment. Different decision or detection rule and fusion strategies, like single sensor scenario, counting rule, and linear decision metric, were used to analyze their influence on the spectrum sensing performance of the cognitive radio network. The impact of using randomization and concavification of ROC at the fusion center was taken into consideration. There was a significant increase in spectrum sensing performance when cooperation among the cognitive radios was introduced.

The simulation results strongly suggests that even when the observations at the individual sensors are moderately correlated, it is important not to ignore the correlation between the nodes for fusing the local decisions made by the secondary users. The counting rule or linear decision metric fusion strategies are useful in a system where the correlation between the observations at the users is small.

It was interesting to notice that, all the cooperating radios were assumed to be designed in such a way that they satisfy the interference probability constraint individually. The interference probability constraint was also met at the fusion center. The simulation results gave the indication that there might be a different approach: the individual nodes can be allowed to set their own interference probability constraint and the responsibility of satisfying the target interference probability can be done at the fusion center. This approach has the potential of achieving a more improved spectrum sensing performance for the system as a whole.

Spectrum sensing in cognitive radio network using distributed detection and cooperation among the individual users may lead us to a future wireless system that achieves higher data rates with limited bandwidth and power resources. However, the benefits of cognitive radio networks depend strongly on how well the channel can be utilized to increase the spectrum utilization parameter. There is a wide range of scopes for future works to analyze the progress we have made towards determining the fusion strategy the gives a improved spectrum sensing performance and minimizes interference with the licensed users of the channels.

In this thesis, it was assumed that the observations under a particular hypothesis were received at the individual sensors with correlated shadowing.

But in real life these assumptions are not always satisfied as the observations can suffer correlated shadowing under both the hypotheses, both the reporting and sensing channels can be error prone, or a number of individual sensor decisions can be biased. New schemes might extend the level of cooperation to include the sensing and access policies to be used by all the cooperating users could be jointly designed so as to maximize the net throughput of the cooperating users.

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