Spectrum Sensing in Cognitive Radio Using GLRT Approach

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Abstract: Spectrum sensing is the most crucial part in cognitive radio. The hunger for increased bandwidth requirement has led to explicit research in the field of spectrum sensing techniques. Generalized likelihood ratio test (GLRT) seems to be a technique where energy optimization is possible and hence in this paper we investigated energy detection and GLRT for spectrum sensing for cognitive radio. Our technique shows generalized likelihood ratio test (GLRT) that reduces probability of false alarm versus the probability of detection for different input energy levels. We also carry out simulation with respect to cooperative spectrum sensing to analyze the Probability of Interference.

Keywords: GLRT, Cognitive Radio, Spectrum Sensing, Probability of Detection.

I. INTRODUCTION

Ever increasing needs of bandwidth for radio communication has been the driving force in the research for communication systems. New application like mobile internet, wireless sensor networks and other has striving to increase the speed to communication due to lack of bandwidth. Due to such impact on communication technologies Cognitive Radios (CRs) have merged as a technology to provide solutions for wireless communication in limited bandwidth that integrate radio technology and networking technology to provide efficient use of radio spectrum, a natural resource, and advanced user services. The cognitive radio technology aims to provide better services by efficient utilization of the channel using spectrum sensing technology. The emerging cognitive radio scenario is of current interest to both policy makers and technologists because of the potential for order-of-magnitude gains in spectral efficiency and network performance. Protocol research to be supported with the planned experimental system includes discovery and self-organization, cross layer protocols for PHY adaptation, cooperation and competition mechanisms, spectrum etiquette procedures, and cognitive radio hardware/software performance optimization.

Cognitive Radio Features [1]

Cognitive radio technology combines hardware and software concepts together for multiple frequency use and spectrum sensing. A Cognitive Radio incorporates multiple sources of information, determines its current operating settings, and collaborates with other cognitive radios in a wireless network. The promise of cognitive radios is improved use of spectrum resources, reduced engineering and planning time, and adaptation to current operating conditions. Some features of cognitive radios include:

- Sensing the current radio frequency spectrum environment: By means of this the system is able to scan different frequencies present in the channel and also the locations of transmitters and receivers. This gives a clear picture of all the bands that may be used by the system for its own communication.

- Policy and configuration databases: As far as the changing of system frequency is concerned at the run time, different policies regarding the bandwidth utilization are formed to come with a full proof system. Configuration databases would describe the operating characteristics of the physical radio. These databases would normally be used to constrain the operation of the radio to stay within regulatory or physical limits.

- Self-configuration: As the radios may have several modules in the configuration line, all must adapt to the changing frequencies at the same time in order for the system to operate properly. Some might call this “plug-and-play.”

- Mission-oriented configuration: The reconfigurability is may be in a local environment as hence the system shall also take into consideration the geographical requirements while in operation.

- Adaptive algorithms: User demands are to be taken into considerations while designing such a system and the algorithm should adapt itself to the needs of the users.

- Distributed collaboration: Cognitive radios will exchange current information on their local environment, user demand, and radio performance between themselves on regular bases. Radios will use their local information and peer information to determine their operating settings.

- Security: Radios will join and leave wireless networks.
II. SPECTRUM SENSING

A “Cognitive Radio” is a radio that meets the user requirement shall scan the channel completely in order to provide best channel utilization and exploit the system completely to provide high efficiency [2]. While many other characteristics have also been discussed as possible additional capabilities, we will use this more restricted definition and consider

![Cross layer functionalities related to spectrum sensing](image)

Figure 1 shows various functions related to spectrum sensing with respect to the Medium Access Control and Physical Layer of the communication reference model. Cognitive radio technique is considered as secondary as the channel is already occupied in instances by the primary user. The bandwidth freed by primary users at time shall be scanned by cognitive radio and adopted suitably without affecting the primary communication system. [3, 4, 5]. There is no requirement by the primary users to change their system requirement or infrastructure. Therefore, cognitive radios should be able to independently detect primary user presence through continuous spectrum sensing. The sensitivity rates for different types of users are different. For example, TV broadcast signals are much easier to detect than GPS signals, since the TV receivers’ sensitivity is tens of dBs worse than GPS receiver. In general, cognitive radio sensitivity should outperform primary user receiver by a large margin in order to prevent what is essentially a hidden terminal problem. This is the key issue that makes spectrum sensing very challenging research problem. Meeting the sensitivity requirement of each primary receiver with a wideband radio would be difficult enough, but the problem becomes even more challenging if the sensitivity requirement is raised by additional 30-40 dB. This margin is required because cognitive radio does not have a direct measurement of a channel between primary user receiver and transmitter and must base its decision on its local channel measurement to a primary user transmitter[6]. This type of detection is referred to as local spectrum sensing and the worst case hidden terminal problem would occur when the cognitive radio is shadowed, in severe multipath fading, or inside buildings with high penetration loss while in a close neighborhood there is a primary user whose is at the marginal reception, due to its more favorable channel conditions. Even though the probability of this scenario is low, cognitive radio should not cause interference to such primary user. The implementation of the spectrum sensing function also requires a high degree of flexibility since the radio environment is highly variable, both because of different types of primary user systems, propagation losses, and interference. The main design challenge is to define RF and analog architecture with right trade-offs between linearity, sampling rate, accuracy and power, so that digital signal processing techniques can be utilized for spectrum sensing, cognition, and adaptation. This also motivates research of signal processing techniques that can relax challenging requirements for analog, specifically wideband amplification, mixing and A/D conversion of over a GHz or more of bandwidth, and enhance overall radio sensitivity [7, 10, and 11].

III. ENERGY DETECTION

A. Theoretical Analysis

In some cases, an optimal detector based on matched filter is not an option since it would require the knowledge of the pilot data and perfect synchronization for coherent processing. Instead a suboptimal and simple energy detector is adopted, which can be applied to any signal type. Conventional energy detector consists of a low pass filter to reject out of band noise and adjacent signals, Nyquist sampling A/D converter, square law device and integrator (Figure 2 a). Without loss of generality, we can consider a complex baseband equivalent of the energy detector [9]. The detection is the test of the following two hypotheses:

H0: \( Y[n] = W[n] \) signal absent
H1: \( Y[n] = X[n] + W[n] \) signal present

\( n = 1,\ldots, N; \) where \( N \) is observation interval
The noise samples \( W[n] \) are assumed to be additive, white and Gaussian (AWGN) with zero mean and variance \( \sigma_w^2 \). In the absence of coherent detection, the signal samples \( X[n] \) can also be modeled as Gaussian random process with variance \( \sigma_x^2 \). Note that over-sampling would correlate noise samples and, in principle, the model could be always reduced. A decision statistic for energy detector is:

\[
T = \sum (Y[n])^2
\]

Note that for a given signal bandwidth \( B \), a pre-filter matched to the bandwidth of the signal needs to be applied. This implementation is quite inflexible, particularly in the case of narrowband signals and sine waves. An alternative approach could be devised by using a periodogram to estimate the spectrum via squared magnitude of the FFT, as depicted in Figure 2 b). This architecture also provides the flexibility to process wider bandwidths and sense multiple signals simultaneously. As a consequence, an arbitrary bandwidth of the modulated signal could be processed by selecting corresponding frequency bins in the periodogram. In this architecture, we have two degrees of freedom to improve the signal detection. The frequency resolution of the FFT increases with the number of points \( K \) (equivalent to changing the analog pre-filter), which effectively increases the sensing time.

The complete system along with various parameters is modeled using MatLab code to detect the probability of false alarm versus the probability of detection that is depicted in figure 3. In addition, increasing the number of averages \( N \) also improves the estimate of the signal energy. In practice, it is common to choose a fixed FFT size to meet the desired resolution with a moderate complexity and low latency. Then, the number of spectral averages becomes the parameter used.

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**Fig 1. Cross layer functionalities related to spectrum sensing**

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to meet the detector performance goal. We consider this approach in our experiments. If the number of samples used in sensing is not limited, an energy detector can meet any desired $P_{d}$ and $P_{fa}$ simultaneously [12,13]. The minimum number of samples is a function of the signal to noise ratio $SNR = \frac{\sigma_x^2}{\sigma_w^2}$:

$$N = \frac{2\left[Q^{-1}(P_f) - Q^{-1}(P_d)\right]SNR^{-1} - Q^{-1}(P_f)}{Q^{-1}(P_d)}$$

In the low $SNR \ll 1$ regime, the number of samples required is

![Diagram](image1.png)

Fig. 2. a) Implementation with analog pre-filter and square-law device b) implementation using periodogram: FFT magnitude squared and averaging

Fig. 3 Probability of Detection Vs Probability of False Alarm

The algorithm for spectrum Sensing is presented below in form for flowchart:

![Flowchart](image2.png)

Fig. 4: Implementation steps for Spectrum Sensing.

IV. GLRT based Spectrum Sensing

Figure 5 shows the ROC curves for GLRT. It can be noticed, again, that the detection performance can be too optimistic if the conventional model (C-model) is adopted in the absence of IN. On the other hand, the performance can be pessimistic if the C-model is adopted with IN present. Moreover, one can notice from Figure 8 that the detection performance under the more realistic R-model suffers less influence of IN, as previously inferred visually in the shape of the received and covariance matrices. It is also worth mentioning that the ranges of decision thresholds used for plotting the ROC curves under the R-model were the same for the scenarios with and without IN. This is an important result, because new decision thresholds need not be computed under IN circumstances, i.e., IN need not be detected. New decision thresholds must be determined for the C-model under IN, since the corresponding ROC curves in Figure 5, with and without IN, were plotted using very different decision threshold ranges.

![ROC Curves](image3.png)

Figure 5. ROC curves for GLRT under parameter variations

Finally a comparative graph between GLRT and Energy detection method is depicted below:

![Comparison Graph](image4.png)

Figure 6. GLRT and Energy detection based spectrum Sensing.
V. CONCLUSION

In the paper, we project GLRT based spectrum sensing with a view of energy optimization in cognitive radios. The model on GLRT based spectrum sensing shows reduction in probability of false alarm versus the probability of detection for different input energy levels and hence the energy shall also be a parameter in deciding the effectiveness of cognitive systems besides their optimization techniques for energy efficiency. Also, spectrum sensing individually may not provide perfect results due to multipath effects and cooperative spectrum sensing shall be one such solution to reduce the probability of interference in primary users. Issues that are discussed in the section of cooperative spectrum sensing will need better clarifications that can be achieved or answered by further simulations.

REFERENCES