Efficient Spectrum Sensing and Testbed Development for Cognitive Radio Based Wireless Sensor Networks

Thesis submitted in partial fulfilment
of the requirements for the degree of

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by

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CERTIFICATE

It is certified that the work contained in this thesis, titled "Efficient Spectrum Sensing and Testbed Development for Cognitive Radio Based Wireless Sensor Networks" by Sumit Kumar (201032005), has been carried out under my supervision and is not submitted elsewhere for a degree.

Date	Advisor: Prof. G Rama Murthy

To My Family and Friends

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Abstract

Problem of spectrum scarcity has not only affected cellular communication bands but is continuously pushing freely available ISM bands to its limits. Devices which work in ISM band were developed without the consideration of co-existence and interoperability. Proliferation of cheap wireless devices and systems utilizing the ISM band is creating spectrum scarcity in the band which is nonetheless severe compared to cellular communication spectrum scarcity. WSN is one of the systems whose performance is being severely affected by other ISM band systems such as Wi-Fi, Bluetooth etc. Concept of cognitive radio has been applied to WSN in order to opportunistically utilize the freely available licensed bands. This gave origin to cognitive radio based wireless sensor networks (CRWSN). But, existing cognitive radio algorithms such as spectrum sensing, spectrum prediction and spectrum monitoring etc. cannot be applied to CRWSN in their existing forms because of the inherent limitations of CRWSN such as limited battery life, less computational power and implementation issues. In this thesis, we address three problems (i) Efficient Spectrum Sensing Technique for CRWSN (ii) Real Time Spectrum Monitoring technique for CRWSN & (iii) Testbed Development for CRWSN

In first part of the thesis, we present an energy and time efficient method of spectrum sensing technique for CRWSN using doubly cognitive architecture (DCA). DCA is based prediction followed by sensing. It predicts not only with respect to time but space also. Hence for CRWSN, which can be highly mobile in nature, DCA is well suited for the task of spectrum sensing. Apart from predicting the primary user spectrum usage pattern, DCA assigns the order of spectrum sensing in case multiple channels are required to be sensed for their vacancy and channel characteristics. We, further enhanced the DCA by adaptive FFT resizing to make it faster and more energy efficient. Adaptive FFT resizing assigns proportionate FFT points to the channels in accordance with their probability of vacancy, while performing the spectrum sensing operation. Our experiments on the CRWSN testbed show that DCA is more efficient with 42% and 19% of average normal spectrum discovery time.

In the second part of the thesis, we present a novel method to detect the reappearance of primary user in real time. This method senses a part of the bandwidth of interest in order to capture the primary user reappearance immediately without any significant lag compared to contemporary state of the art methods. Contemporary spectrum monitoring methods suffer from real time detection requirement, unreliable prediction and inefficient bandwidth utilization. Our proposed method of partial sensing based spectrum monitoring successfully addresses all these issues. Additionally, our method is computationally simpler and does not require any additional hardware or software add-on in the existing system in order to deploy it in real time. Our experiments on the CRWSN testbed show that partial sensing-based spectrum monitoring outperforms periodic spectrum monitoring with average PU detection time (3sec.) and variance (1.85), which are significantly reduced to 0.27 and 0.12 times the average of 11 seconds and variance of 15.42 of periodic spectrum monitoring. Time-bandwidth-product of partial spectrum monitoring is found to be 50% more than periodic spectrum monitoring leading to higher bandwidth efficiency.

In the third and final part of the thesis, we have presented a testbed for CRWSN which is first of its kind. It can emulate all the basic as well as advanced functionalities of a wireless sensor network such as localization, clustering, mobility as well as the significant functionalities of a cognitive radio network such as dynamic spectrum access (DSA), dynamic reconfiguration, spectrum sensing and spectrum monitoring etc. Additional functionalities include multi-hop off frequency relaying, cooperative spectrum sensing and location information through GPS integration. The testbed is developed with commercial off the shelf(COTS) state of the art FPGA based SDR hardware, USRP and open source signal processing SDK GNU Radio. The testbed is fully modular with respect to both hardware and software.

Keywords: Cognitive Radio, Spectrum Sensing, Cognitive Wireless Sensor Networks, Spectrum Monitoring, Testbed

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Patent

- **A SYSTEM FOR IMPLEMENTATION OF DOUBLY COGNITIVE WIRELESS SENSOR NETWORKS,** India Patent Application 3779/CHE/2011, Filed November 3, 2011, Inventors: Sumit Kumar, Garimella Rammurthy

Journal

- **Doubly Cognitive Architecture Based Cognitive Wireless Sensor Network,** International Journal of Wireless Networks and Broadband Technologies Vol. 1, Issue 2, June 2011
  Authors: Sumit Kumar, Deepti Singhal, Garimella Rammurthy

Conferences

- ***Cognitive Base Station Design for Efficient Spectrum Utilization in Cellular Network***, Eleventh International Conference on Wireless and Optical Communications Networks WOCN2014, June 2014
  Authors: Sumit Kumar, Kunal Sankhe, Garimella Ramamurthy, Chandan Pradhan
- ***Efficient Spectrum Sensing/Monitoring Methods and Testbed Development for Cognitive Radio based WSN***, 2014 Wireless Innovation Forum Conference on Communications Technologies and Software Defined Radio (SDR-WInnComm 2014),
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Book Chapters

- "**Cognitive Wireless Sensor Networks**" in Intelligent Sensor Networks: The Integration of Sensor Networks, Signal Processing and Machine Learning Taylor and Francis, CRC Press, December 13, 2012,
  Authors: Sumit Kumar, Deepti Singhal, Garimella Rammurthy
- "**Mobile Wireless Sensor Networks: A cognitive Approach**" in Wireless Sensor Networks : From Theory to Applications ,Taylor and Francis, CRC Press
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- "**Co-operative Mesh Networks**" in Wireless Technologies: 3G and Beyond Springer, May 28, 2013
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- "**Medical Cyber Physical Systems**" in CyberPhysical Systems- A Computational Perspective, CRC Press, Taylor & Francis Group, LLC, Florida, USA
  Authors: Sumit Kumar, Garimella Rammurthy

Chapter-1

Introduction

Wireless communication is one of the fastest growing segments of the communication industry since the last decade. There has been wide proliferation of cheap wireless devices and systems enabled with bandwidth hungry applications. This is leading to collision and spectrum scarcity making reliable wireless operation very difficult. Systems such as Wireless Sensor Networks (WSN) are also getting affected due to crowding in the ISM band. Concept from cognitive radio technology is being applied in order to enable dynamic spectrum access (DSA) in WSN. But still there are bigger challenges because of the inherent architectural difficulties of WSN such as less computational capability, limited battery life etc. Due to these, the obvious algorithms used in Cognitive radio applications can't be used in their original form. Critical research & development is required in order to tailor them for WSN application in an environment with DSA. This chapter discusses issues related to spectrum scarcity for WSN system followed by need to apply cognitive radio applications such as DSA etc. The chapter is organized as follows. In Section 1.1, underlying motivation for the thesis work is discussed. This is followed by mentioning the problem statement in Section 1.2. In Section 1.3, our contributions are listed and finally the chapter is concluded by mentioning the thesis organization in Section 1.4.

1.1 Motivation

Wireless communication is one of the fastest growing segments of the communication industry since the last decade. As a result, wireless systems have become ubiquitous with several applications such as cellular telephony, wireless internet as well as various portable devices such as smart phones, tablets etc. Additionally, new applications such as wireless sensor networks, smart home appliances and remote telemedicine and many more etc. are emerging from research ideas to concrete systems. Any wireless system, in order to establish a communication link, requires a dedicated frequency channel. Though completely invisible, frequency spectrum is an important and limited resource of wireless communication. With the incredible growth in the number of wireless systems and services, availability of high quality wireless spectrum has become severely limited [1]. This term is called spectrum scarcity. One of the very basic reasons for this spectrum scarcity is licensing of the channels by the telecom regulatory authorities. Once a band is licensed, it can be used by subscribed users only. Due to licensing, some cellular communication frequency bands are heavily overloaded with traffic. But at the same time, other freely available cellular communication frequency bands cannot be used by subscribers of other cellular networks due to licensing issues, even though they are completely unused at that particular moment of time. Even though licensing is required from the commercial point of view, it leads to inefficient utilization of the spectrum.

A similar spectrum scarcity exists in freely available ISM band. From past few years, a tremendous growth in number of devices operating in ISM band has been observed. Some of the protocols which are designed for ISM band are IEEE 802.11(a,b,g,n), ZigBee and Bluetooth. But during the development of these protocols, the issue of co-existence was not taken into account. Hence, when there are devices working in the same area, working with these protocols, collisions become inevitable [4]. Unfortunately there is no regulation on the frequency spectrum in ISM bands devices [3]. Hence, the issue of spectrum scarcity is more severe than cellular communication bands. It is continuously pushing the spectrum utility and efficiency in the ISM bands to their limits [2].

One of the significant example is WSN. WSN is one of the notable application which has emerged due to tremendous growth in wireless communication technology in ISM band. It works on ZigBee protocol which uses freely available ISM band 2.4GHz - 2.48GHz [5]. In the same band, other devices working on different protocols are also active such as, smart phones on Wi-Fi (IEEE 802.11) and Bluetooth etc. It leads to packet drop in both the networks i.e. ZigBee and IEEE 802.11[4]. Figure 1.1 shows the frequency occupancy chart of ZigBee and Wi-Fi.

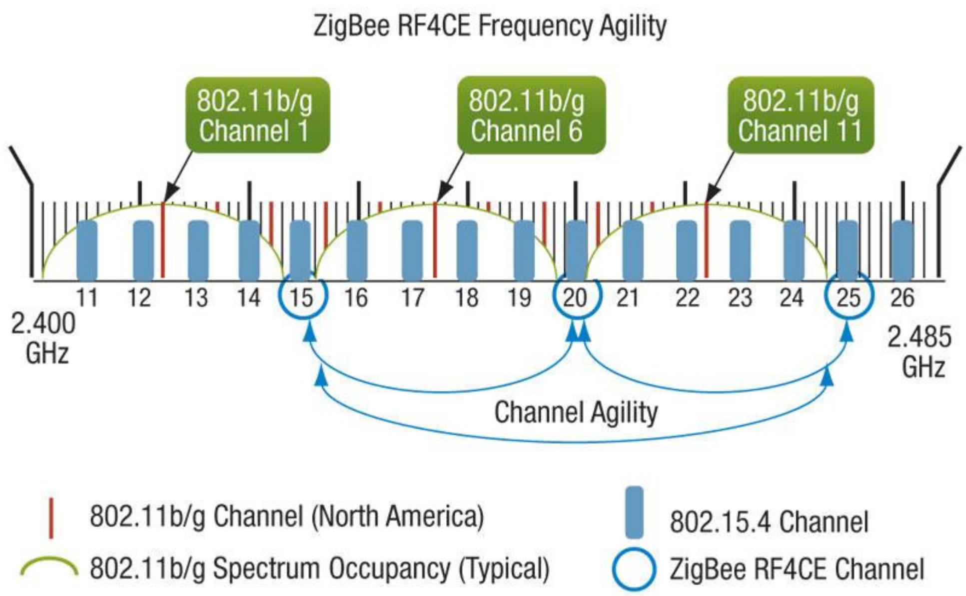

Figure 1.1 Frequency agility of ZigBee and Wi-Fi[6]

We observe that only 4(15,20,25,26) out of 16 channels of ZigBee are non-overlapping with the channel of Wi-Fi. Hence, in the scenario where both Wi-Fi and ZigBee are operational, collision is inevitable [4]. Data from wireless sensor networks is very critical in nature and disaster may happen in case of loss of data or delay in data.

A survey by FCC in [1] reveals that almost 85% of the time, licensed spectrum bands are vacant both spatially and temporally. Using a technology called Cognitive Radio, the vacant bands of the spectrum can be utilized efficiently in dynamic and efficient manner [1]. This is also termed as dynamic spectrum access (DSA) [1]. Using DSA, the vacant bands of the cellular mobile spectrum or any other licensed/unlicensed spectrum can be utilized opportunistically and efficiently. In order to facilitate DSA, efficient spectrum sensing is required, through which a vacant band is sensed along with the estimated time duration of its vacancy [7]. Once a free channel is discovered, it can be utilized by the needy user or network for an estimated vacancy time. Needy user can be either a cellular user subscribed to other vendor or a wireless sensor network or a smartphone user seeking data transmission/Wi-Fi connectivity. In this thesis work we call the licensed users us Primary user (PU) and the needy/opportunistic user as Secondary user (SU).

Once a connection is established, it is required to monitor the re-arrival of the PU. Once the PU comes back, the SU has to vacate the current channel and hop to another free channel. Time is very critical in this process .i.e. the PU has to be detected in the shortest time possible and channel has to be vacated in the shortest time possible. All these procedures have to be performed while maintaining acceptable Quality of Service (QoS) and minimum data loss.

In order to test and benchmark the solutions and algorithms developed to address the aforementioned issues, a suitable testbed is required. The testbed should be capable of emulating all the functionality of a cognitive radio network (CRN) as well as WSN. The algorithms can be tested and evaluated on this testbed before any field deployment. A testbed helps to evaluate the merits and demerits of any system and hence helps in improving its performance through iterative procedure. This helps in improving the system before field deployment.

1.2 Problem Statement

In this thesis work, following issues have been addressed

- Efficient Spectrum Sensing in CRWSN
- Real Time Spectrum Monitoring in CRWSN
- Testbed Development for CRWSN

Efficient spectrum sensing is a challenging task in CRWSN for two reasons. First, CRWSN nodes does not have much computational complexity compared to a CRN terminal. Second, CRWSN nodes have limited battery power. Hence, it is not feasible to deploy any computationally complex and energy consuming algorithm in the CRWSN nodes. The existing methods for spectrum sensing, which has been developed for CRN, are not suitable to be deployed in CRWSN because of their higher computational complexity and energy consumption. Additionally, the spectrum sensing algorithms for CRWSN have to be fast enough to meet the PU and SU occupancy and vacancy requirements.

The next issue which we have addressed is spectrum monitoring. Spectrum monitoring is a very challenging task and unfortunately very less attention has been given to it by the research community. Without an adequate spectrum monitoring technique, any CRWSN opportunistic user will not be able to find the arrival of the PU in time. This will lead to an inevitable collision. The existing methods for spectrum monitoring, which have been developed for CRN, are not suitable to be deployed in CRWSN. The reason is their higher computational complexity and energy consumption.

Finally we have worked towards development of a testbed which can emulate functionalities of both a CRN as well as WSN. There has been testbeds for CRN as well as WSN, but to the best of our knowledge, there no existing testbed bed which is capable of emulating the functionalities of both. We have worked in the direction of developing a test bed which demonstrates cognitive radio features such dynamic spectrum access, spectrum sensing, spectrum monitoring, dynamic reconfiguration as well as WSN features such as clustering, multi-hop communication, relaying and cooperation. We have also put efforts in order to emulate mobility features in the testbed which is very significant while emulating a WSN.

1.3 Contributions

- We have developed Doubly Cognitive Architecture (DCA) based spectrum sensing for CRWSN. It uses temporal as well as spatial information in order to predict the spectrum vacancy. We have implemented the same on the CRWSN testbed.

- We have enhanced DCA further with adaptive FFT resizing in order to reduce spectrum sensing complexity and sensing time in the CRWSN nodes. We have implemented the same on the CRWSN testbed.

- We have developed partial sensing based spectrum monitoring. This methods works in real time and instantaneously detects the presence of the PU. We have implemented the same on the CRWSN testbed.

- We have developed a testbed for CRWSN which is first of its kind in the world to the best of our knowledge. The testbed is equipped with significant features such as user access to realize re-configurability, dynamic spectrum access, user mobility and cooperation between CRWSN nodes. The testbed can serve as a development platform providing insights into CRWSN.

1.4 Thesis Organization

This thesis is organized into five chapters. Brief overview of the content of each chapter is given below:

The first and current chapter-1 introduces the readers to the motivation behind our work. It also provides a brief overview of our work and explains our contribution in an attempt to solve the problem of efficient spectrum sensing, spectrum monitoring, multi-hop relaying. The chapter also discusses the need for a CRWSN testbed.

In Chapter-2 an overview of our work is presented with brief introduction to several of our proposed ideas and contributions. Additionally we have discussed related work and potential applications where our ideas and contributions can be significantly useful.

In Chapter-3 we have proposed doubly cognitive architecture (DCA) for spectrum sensing in CRWSN. We also have discussed the enhancement of DCA through adaptive FFT resizing. Implementation of DCA on the CRWSN testbed is discussed along with the obtained results.

In Chapter-4 we have discussed Partial sensing based spectrum monitoring for the arrival of primary user. Implementation of this method on CRWSN testbed is discussed along with the analysis of obtained result.

In Chapter-5 we have discussed the CRWSN testbed. Both hardware and software aspects of the testbed are discussed in detail. This is followed by discussion on multi-hop off frequency relaying and the operation of the testbed.

Finally in Chapter-6 we have summarized our work and discussed future directions.

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Chapter-2

Background and Literature Survey

In this chapter, we develop the necessary background for Cognitive Radio terminologies and CRWSN. We discuss in detail about the existing work in the area with their merits and demerits. The chapter is organized as follows. In Section 2.1, we discuss importance of spectrum sensing in cognitive radio networks. This is followed by a brief description of some of the mainstream spectrum sensing techniques for CRN. In Section 2.2, we discuss importance of spectrum prediction in CRN followed by extensive literature survey on the same. Equipped with the knowledge of spectrum sensing and spectrum prediction, in Section 2.3, we discuss the requirements of spectrum sensing in a CRWSN. In Section 2.4, we discuss spectrum monitoring and its importance in CRN followed by some of the mainstream techniques used for the same. Finally, in Section 2.5, we discuss some of the existing testbeds for CRN and WSN followed by testbed requirements for a CRWSN.

2.1 Spectrum Sensing in Cognitive Radio Networks

Spectrum sensing is the key technology to enable a cognitive radio for opportunistic and dynamic usage of the bands which are not temporarily occupied by licensed users [1]. Spectrum sensing captures the information of spectrum usage and existence of PU. Although it has been more than 15 years since the spectrum sensing concept was introduced by Joe Mitola [2], it is still one of the most challenging tasks in a cognitive radio network. A number of spectrum sensing methods have evolved to find vacant bands which are based on a variety of techniques. We can broadly classify them into following categories.

- **Energy based detection**
- **Cyclostationary detection**
- **Matched filter detection**

In the following Sections, we discuss in detail about these categories with some notable examples.

2.1.1 Energy based Detection

It is the most common way of spectrum sensing because of its low computational cost and least implementation complexity [3]. Compared to other methods (which are mentioned in the following Sections), it is more generic. It doesn't require the knowledge of PU's signal characteristics [3]. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor in that particular environment [3]. Energy detection is usually performed in frequency domain using FFT and obtaining the power spectral density (PSD) of the frequency bins of interest. Figure 2.1 shows a typical block diagram for energy based detector.

Figure-2.1 Block diagram of energy based spectrum detector [4]

A typical PSD for user present and user absent is shown in Figure 2.2

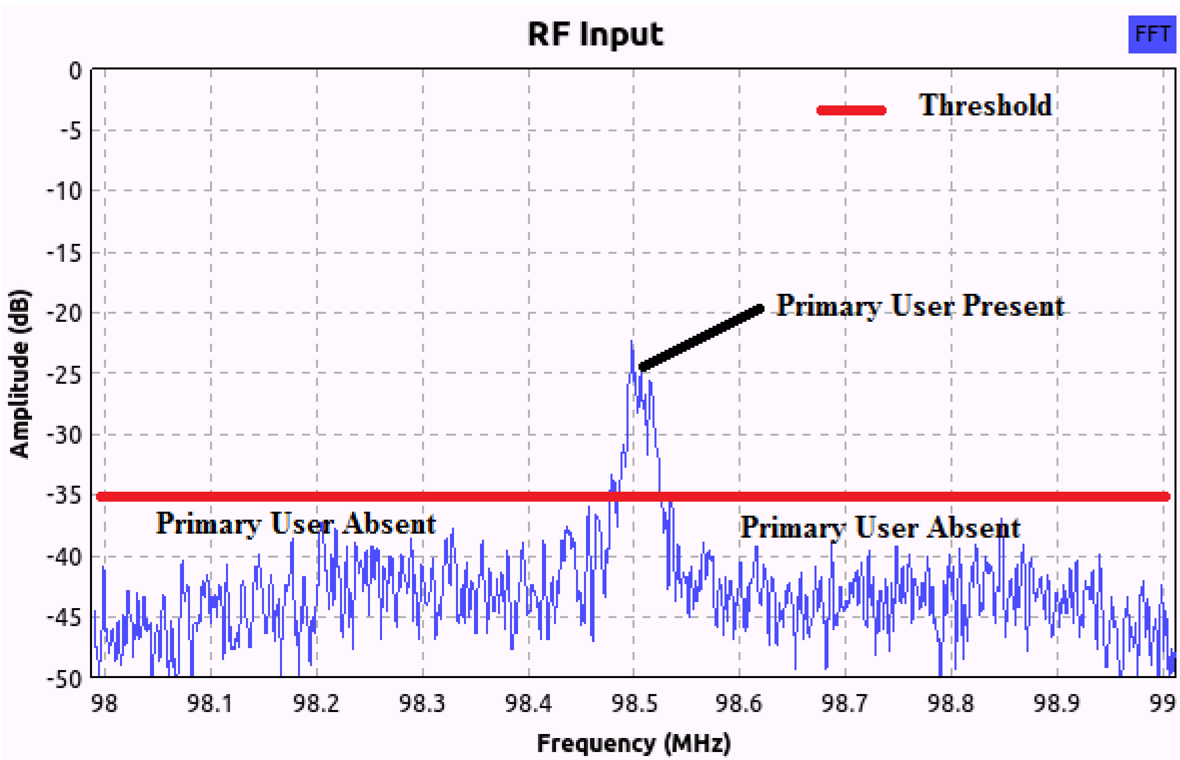

Figure 2.2 PSD when PU is present/absent

In the Figure 2.2, the thick red line denotes the threshold which is at -35 dbm. At a center frequency of 98.5MHz, we can see that a user is present with a transmit power level of -22 dbm.

Some of the challenges with energy detector 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 signal-to-noise ratio (SNR) values [5]. Some of the notable variants of energy based detection can be found in [6][7][8][9].

2.1.2 Matched Filter Detection

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known [10]. Matched filter operation is equivalent to correlation in which the unknown signal is convolved with the filter whose impulse response is mirrored and time shifted version of the reference signal. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of miss detection [11] as compared to energy detection based methods that are discussed in Section 2.1. In fact, the required number of samples to process, grows as O(1/SNR) for a given target probability of false alarm at low SNRs for matched-filtering [11].

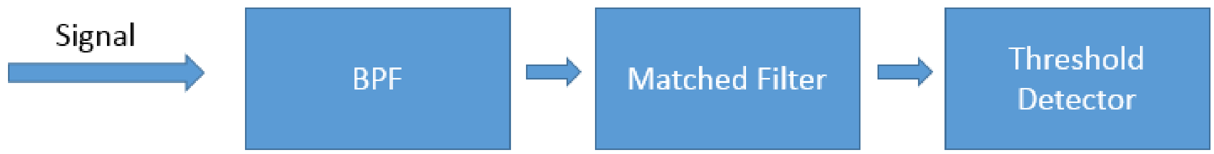

Figure- 2.3 Block diagram for a matched filter detector [4]

However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format. Since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large [5]. Another disadvantage of matched filtering is large power consumption as various receiver algorithms need to be executed for detection [12].

2.1.3 Cyclostationary Detection

Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the Cyclostationary features of the received signals [5][13][14]. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation [15] or they can be intentionally induced to assist spectrum sensing [16]. Instead of PSD, which is used in Energy detection, cyclic correlation function is used for detecting signals present in a given spectrum. Block diagram of a typical Cyclostationary feature detector is shown in Figure 2.4.

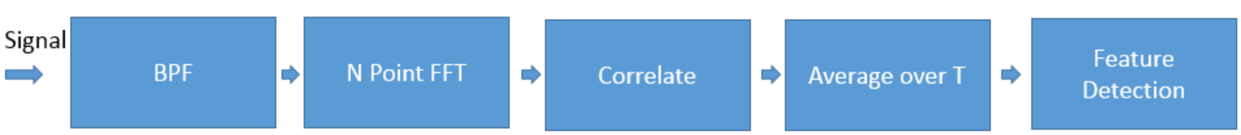

Figure-2.4 Block diagram of Cyclostationary feature detector [4]

One of most prominent features of Cyclostationary feature based detection algorithms is differentiation of noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are Cyclostationary with spectral correlation due to the redundancy of signal periodicities [17]. Furthermore, Cyclostationarity can be used for distinguishing among different types of transmissions and primary users [18]. Disadvantages of Cyclostationary feature based detectors is very high implementation complexity and high energy consumption [5].

2.1.4 Cooperative Spectrum Sensing

Additionally, there are other methods which utilize the methods/categories mentioned above in order to enhance the reliability/speed of the results of spectrum sensing. One of the noticeable method is cooperative spectrum sensing [20]. In cooperative spectrum sensing, multiple spectrum sensing entities work in unison and merge their spectrum sensing results in order to come up with a better and reliable result. Figure 2.5 shows a typical scheme for cooperative spectrum sensing.

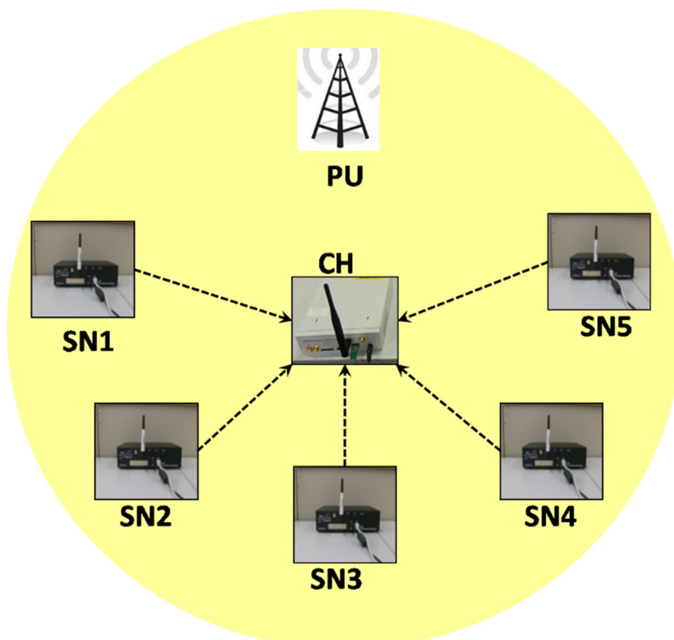

Figure 2.5 Cooperative spectrum sensing [21]

PU : Primary user
SNi : ith spectrum sensor
CH : Spectrum sensing information dissemination center

Theoretically, it has been shown that if k radios combine their independent measurements, then the probability of detection of the system Q_d [22] monotonically increases as a function of k as given by,

$$Q_d = 1-(1-Pd)^k \quad (1)$$

In addition, the probability of false alarm for the system Q_f [23] also monotonically increases as follows,

$$Q_f = 1-(1- P_f)^k \tag{2}$$

Where, P_d and P_f are the individual probabilities of detection and false alarms without cooperative sensing. However, the net effect is improvement in PU detection performance. Cooperative sensing also helps in eradicating the issue of hidden node [24].

In general, detection accuracy increases with the complexity of the spectrum sensing method [3]. The spectrum sensing methods which are simpler and faster often suffer from higher probability of false alarm and relatively smaller probability of detection. While implementing any such method on hardware for real time operation, several tradeoffs are required. Table-2.1 compares the three categories of spectrum sensing under several parameters.

Table-2.1 Comparison of Major Spectrum Sensing Categories [3]

	Detection accuracy	**Delay**	**Implementation complexity**	**Knowledge of PU Signal**	**Energy Consumption**
Energy Detector	Moderate	Best	Least	No	Least
Matched Filter Detector	Moderate	Moderate	High	Yes	Moderate
Cyclostationary Detector	Best	Slow	Very High	Yes	High

Unfortunately, none of the existing methods of spectrum sensing for cognitive radio can be used in their current form in a CRWSN environment. CRWSN nodes inherently suffer from energy scarcity and computational limitations. Even if we consider a non CRWSN environment i.e. we discard the limitations of energy and computational complexity, so far only energy based detection has been implemented in hardware with reasonable level of complexity [5]. Matched filter detector and Cyclostationary detector have also been implemented, but the hardware complexity and delay too high to commercialize them [5] for real time deployment.

Fortunately, there exists a pattern in PU usage of the channels and existing methods for prediction such as artificial neural networks [25], auto-regressive modelling [26] and time serial forecasting [27] can be used to find the underlying pattern. Once the underlying pattern on PU channel occupancy is predicted, the results can be used to simplify the spectrum sensing operation. This simplification leads to significant amount of reduction in spectrum sensing time and energy. In the next Section, we have discussed in detail about some of the state of the art spectrum prediction methodologies.

2.2 Spectrum Prediction in Cognitive Radio Networks

It is a well-established fact that, there exists a pattern in primary user spectrum/channel usage [3]. The pattern exists in spatial, temporal, angular as well as code domain [3]. Channel access patterns of primary users can be identified and used for predicting spectrum usage in [28]. Spectrum prediction refers to the methods which exploit the pattern in primary user spectrum occupancy and predicts whether the channels will be vacant or occupied at a given instant of time or not. Using spectrum prediction methods, the process of spectrum sensing is speeded up and both computational complexity and energy consumption are also reduced [28]. Using a reliable prediction scheme, the unlicensed users will sense only those channels which are predicted to be idle but not all the channels. This saves significant amount of time and energy. Though, predicting the spectrum occupancy status can relax the computational requirements of the spectrum sensing unit. But in order to fully rely on spectrum prediction methods, the prediction method has to be very reliable otherwise it may lead to collision and data loss between PU and SU transmission[29][30].

Spectrum prediction is performed by processing the past occupancy/vacancy status of that channel. Several prediction methods have been used/developed in order to predict the channel occupancy status. Significant examples can be found where authors have modelled the PU occupancy model with artificial neural network (ANN)[31] and autoregressive models(AR)[32]. In the following Section, we discuss, some prominent work in the direction of spectrum prediction where the authors a have modelled PU channel occupancy with either ANN or AR models*. In all the mentioned methods the underlying spectrum sensing technique is based on energy detection. For spectrum prediction, several methods have been used.*

In [33] the authors have developed ANN based spectrum prediction module where multi-layer perceptron has been used. Authors have used 2 hidden layers with 20 neurons in each layer, while the final output has only 1 neuron. The order of predictor was set to 4. The significant feature of this ANN based model is that, it does not require the prior knowledge of the traffic characteristics of the PU since obtaining prior knowledge about PU in a real time environment can be very difficult in most of the situations. One of the limitations of this model is that it does not use the result of prediction judiciously. The spectrum occupancy information is predicted and then spectrum sensing is performed based on prediction. It doesn't not exploit the underlying fact that some of the channels are more probable to be vacant compared to other channels. Another demerit of this prediction methodology is that, it applies equal point FFT for energy detection in all the channels which are predicted as vacant. FFT is one of the most power consuming operation during energy based spectrum sensing [34]. Since, at a given time, all the channels are not equiprobably vacant. Hence, it is wasteful to use same size FFT to all the predicted channels, in order to find if the predicted values are correct or not.

In [35], authors have modelled the primary user channel occupancy data as a time series model and applied regression techniques in order to predict future values. But a serious flaw of this method is that, they are not doing actual spectrum sensing in real time. This operation can be very risky and is entirely dependent upon the accuracy of the spectrum prediction mechanism.

In [36], the authors have used ANN modeling to predict the PU channel occupancy status, similar to [35], but they are not performing any spectrum sensing in the real time. Hence, the entire reliability of the system becomes dependent on the prediction methodology .i.e. the configuration of the ANN. It may severely lead to detection accuracy during real time deployment.

Chunyan et al. [37] discuss Lempel-ziv compression based spectrum prediction mechanism which reduces the spectrum sensing time. In their approach, the order in which the available channels should be sensed is determined. But this technique neither exploits the spatial spectrum occupancy pattern, nor performs PU activity prediction. It also applies equal size FFT to all the channels irrespective of their probability of being vacant which leads to higher energy consumption and higher spectrum discovery time.

Zhang et al. [38] and Bhatt et al. [39] present multi-resolution FFT approach. However, they do not consider spectrum prediction.

Jinzhao and Wu [40] discuss extensively about the ARMA modeling and coefficient selection for several scenarios. They have come up with a sequence of channels to be sensed. But, in their work, the order of sensing is determined on the basis of their signal strength. There is no implicit learning or predicting mechanism to decide where to start the sensing operation. Moreover, it applies equal size FFT on all the channels to be sensed which adds to the spectrum discovery time and energy consumption.

In our work, we have addressed the above-mentioned limitations. We exploit spatial dimension of radio environment which enables the cognitive network to capture the pattern of spectrum occupancy both temporally and spatially .i.e. we are predicting the PU channel occupancy temporally as well as spatially. This is very significant for environments where the nodes are mobile. Additionally, we combine multi-resolution FFT with spectrum prediction which is further assisted by spatial location information. This approach further saves energy and reduces spectrum discovery time.

2.3 Spectrum Sensing Requirements in a CRWSN

From Section 2.2 and 2.3, it is clear that, in the CRWSN environment, spectrum sensing algorithms cannot be used in their existing form. They have to be combined with spectrum prediction methods in order to speed up the process as well as save the precious battery power. Additionally, in order to increase the reliability of spectrum prediction methods, cooperative spectrum sensing methods can be combined as discussed in Section 2.1.4. In an essence, the requirements as well as choice of the combination of methods for spectrum sensing, spectrum prediction and cooperative sensing for a CRWSN, mainly depends on the following factors

- **Energy consumption**
- **Implementation complexity**
- **Detection accuracy**

The first two criteria are very critical as a CRWSN suffers from battery life issue like other WSN. Similarly, on tiny sized CRWSN nodes, it is very difficult to implement a spectrum sensing algorithm which is complex with respect to both hardware and signal processing algorithms such as matched filter detection and Cyclostationary detection methods. The last criterion of detection accuracy can be relaxed by deploying cooperative spectrum sensing. In a typical CRWSN deployment, there is abundance of nodes which are placed nearby and have spectrum sensing capability. Hence, a cooperative network of spectrum sensors can be readily established dynamically to perform cooperative spectrum sensing.

Analyzing the implementation simplicity, sensing time and energy consumption, in our work, we have chosen energy detection based method for the task of spectrum sensing. It is the base for our Doubly cognitive architecture (Chapter-3) and partial sensing based spectrum monitoring (chapter-4). For spectrum prediction, we have chosen both ANN approach and AR models. Lower detection accuracy has been taken care of, by deploying cooperative spectrum sensing scheme. In our work, we have deployed all these techniques on state of the art FPGA based SDR devices and USRP [41].

2.4 Spectrum Monitoring

Spectrum monitoring is still an open research problem in the Cognitive radio community. When a free licensed band is being used by the CRWSN nodes, the channel needs to be monitored throughout the ongoing communication duration, for arrival of the PU. Once the PU reappears on the same channel, the SU/CRWSN node has to immediately vacate the band and hop to another free band. Unfortunately, very less attention has been given to spectrum monitoring. Spectrum monitoring methods can be categorized in mainly three categories.

- **Primary user prediction**
- **Periodic spectrum sensing**
- **Control channel based monitoring**

In the rest part of this Section we discuss in detail about these spectrum monitoring methods.

2.4.1 Primary User Prediction

In this category, the SU predicts the reappearance of the PU and accordingly pauses its transmission in order to sense and verify the reappearance of the PU. Authors in[35][36] . Authors have used traditional methodologies for primary user reappearance prediction including ANN and AR modelling. But, this system suffers very badly in case of false alarm. In this particular scenario, there are two cases in false alarm. First, when the system predicted the reappearance of PU, but the user did not appear and second, when the system did not predict the reappearance of the PU, but the P reappeared. In first case, the system loses time and energy to sense if the primary user appeared or not, while in the second case, the system simply creates interference to the PU as well as gets interfered by the PU. Hence, in both the cases, it suffers from loss and majorly the performance is totally dependent on the prediction mechanism. This system is also not able to detect the reappearance of PU in real time.

2.4.2 Periodic Spectrum Sensing

In this category, the SU periodically pauses its transmission in order to check if the PU has reappeared or not. There is no prediction involved in this category. Authors in [42], monitor the reappearance of PU using this method. All the SUs pause their transmission periodically and go into spectrum sensing mode. Once the PU reappearance is detected, they do not transmit for predetermined period of time. At the end of the time period, again the sensing operation is performed and once a clear channel is found, retransmission is initiated along with the periodic spectrum sensing procedure. This method, also suffers from real time detection of PU reappearance since the PU reappearance can only be detected when it reappears in the periodic pause event. In other cases, the PU as well as SU deterministically faces interference from each other. Additionally, during sensing time, there is no transmission by the SU, hence time as well as bandwidth is wasted in that duration.

2.4.3 Control Channel Based Sensing

In this category, the concept of control channel is taken where the PU exchanges control information with the SU before reappearing on the channel in use. A separate chunk of bandwidth is dedicated for the control channel over which the channel status is exchanged. Authors in [43], have used this method on order to detect the reappearance of the PU. This method is able to detect the reappearance of the PU in real time. The main demerit of this method is that it requires a dedicated chunk of spectrum in order to exchange control information with the SU. In an already bandwidth scarce scenario, availability of a dedicated control channel may not be possible all the time. Moreover in case of failure of the control channel, disaster is inevitable.

In our work, we have successfully addressed and proposed a novel solution to the issue of real time detection of reappearance of PU using partial sensing based spectrum monitoring. It works with energy detection as the underlying spectrum sensing mechanism. Our method is discussed in detail in Chapter-4.

2.5 Testbeds Requirements for CRWSN

In this Section, we discuss several cognitive radio and wireless sensor network testbeds. We also discuss why there is a need to go for a separate CRWSN testbed, when many testbeds are already available. Cognitive radio testbeds developed so far primarily address only the issues of dynamic spectrum access, spectrum mobility and spectrum sharing. To the best of our knowledge, there is no testbed which is suitable for emulating a CRWSN. In order to emulate the functionalities of a CRWSN, the testbed must demonstrate node clustering, multi-hop transmission and above all, location information apart from the cognitive radio functionalities. In the following parts of this Section, we discuss some state of the art testbeds emulating a cognitive radio network and WSN.

Authors in [44] proposed a testbed which focuses on demonstrating the dynamic spectrum access and modulation adaptation parameters. However, they do not address the location information utilization. Also, the cognitive engine of the testbed lacks any spectrum prediction technique. Additionally, none of the WSN features could be emulated in this testbed configuration.

Authors in [45] have developed a very elegant testbed which is capable of demonstrating almost all the cognitive radio functionalities. However, it does not use location information, multi-hop communication and clustering which are significant features of a WSN. Moreover, it is difficult to emulate the sensor mobility in the bulky platform.

Authors in [46] have discussed another elegant architecture of cognitive radio testbed and its functionalities, but it is not suitable for demonstrating the basic functionalities of a WSN with cognitive capabilities.

Authors in [47] discuss a cognitive radio testbed which is the closest in emulating sensor network functionalities. However, it lacks location information to demonstrate the localization and clustering phenomena of WSN.

In our testbed, we have primarily focused on emulating the node clustering, multi-hop relaying, and location information besides the generic functionalities of a cognitive radio testbed. The primary advantage of our testbed is that it can be used as a generic cognitive radio testbed too, with additional functionalities of multi-hop relaying and mobility through location information. Some of the other significant features include cooperative spectrum sensing, multi-hop off frequency relaying, spectrum monitoring and location information through GPS. Moreover the CRWSN testbed developed by us is made by commercial off the shelf(COTS) parts and is modular in nature compared to other testbeds where exclusive hardware were developed to meet the requirements of the testbed. Hence, our CRWSN testbed is easy to deploy as well as replicate along with the easiness to update the software and hardware. Details and operation of the testbed are discussed in detail in chapter-5.In the Table-2.2, a comparison of the existing testbeds is provided for reference.

Table-2.2 Comparison of existing testbed with our CRWSN testbed at IIIT Hyderabad

Testbed	**CR features**	**WSN Features**	**Modular**	**COTS**	**Prediction Methods**	**Spectrum monitoring**	**Spatial information**
[44]	Yes	No	No	No	No	No	No
[45]	Yes	No	No	No	Yes	Yes	No
[46]	Yes	No	No	No	Yes	Yes	No
[47]	Yes	Yes	No	No	No	Yes	No
CRWSN, SPCRC, IIIT Hyd	Yes	Yes	Yes	Yes	Yes	Yes	Yes

2.6 Summary

In this chapter, we discussed the background of spectrum sensing, spectrum prediction and spectrum monitoring for a cognitive radio network. We came to know about the basic requirements of spectrum sensing and spectrum monitoring in the context of CRWSN where the system suffers from a variety of limitations. Some of them include low battery life, low computational complexity and implementation complexity etc. None of the existing spectrum sensing methods is suitable to be used in their current form in a CRWSN. We developed an idea with a suitable combination of spectrum sensing and spectrum prediction along with cooperation can be used to tailor the existing methods for a CRWSN environment. In the later part of the chapter, we discussed the importance of a testbed, customized for CRWSN scenario. We learnt that a CRWSN testbed shall possess the features of cognitive radio network as well as WSN. We took a glance at some of the state of the art testbeds and discussed the features in our proposed testbed which addresses the demerits of the existing testbeds.

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Chapter-3

Doubly Cognitive Architecture for Spectrum Sensing

In Sections 2.1, 2.2 & 2.3 we discussed spectrum sensing techniques and spectrum prediction methods for cognitive radio networks. We also discussed the requirements and selection criterion for the same in CRWSN. By doing spectrum prediction, the speed of spectrum sensing is significantly increased. This also saves the valuable battery life of CRWSN nodes. We also observed that the spectrum sensing requirements in CRWSN and found that there is very less flexibility compared to a normal cognitive radio network while selecting an appropriate spectrum sensing scheme. In this chapter, we discuss, doubly cognitive architecture based spectrum sensing for CRWSN. This is followed by improving the method through adaptive FFT resizing while performing energy detection based spectrum sensing within DCA. Remaining sections are organized as follows. In Section 3.1, we discuss DCA in detail. This is followed by a discussion on adaptive FFT resizing technique in order to speed up the spectrum sensing process in Section 3.2. Finally in Section 3.3, we discuss experiments performed in order to verify DCA and adaptive FFT methods on our CRWSN testbed (Chapter-5).

3.1 Doubly Cognitive Architecture

In this section, we discuss in detail about our DCA based spectrum sensing. Spectrum sensing is the most energy consuming task for a CRWSN [1] which already faces issues of low battery life. DCA based spectrum sensing not only addresses this issue but also efficiently reduces the spectrum discovery time.

In our work, DCA is realized with a cognitive engine which is capable of predicting spectrum occupancy not only temporally but spatially too and hence the name doubly cognitive architecture. It makes the system cognitive with respect to time as well as space. There are several cognitive engines which have the ability to predict the spectrum occupancy with respect to time [2-7]. In our cognitive engine, we have improvised the prediction process by enabling it to access location information through GPS receivers, thus exploiting the spatial domain also. The motivation behind the idea is a well-known fact that spectrum occupancy pattern exists temporally as well as spatially and hence there are patterns in spectrum occupancy in both temporal and spatial dimensions. Also, it is important to notice that spectrum occupancy prediction for one location is significantly different from the prediction results for another location. Similarly, spectrum occupancy prediction at one time stamp can be significantly different at another time stamp.

Figure 3.1 shows spectrum occupancy of the WLAN channels in 2.4GHz inside 4 labs in our campus which are widely separated. In Figure 3.1, horizontal axes are WLAN channels 1 to 11 and vertical axes are time windows. Colored squares are occupied channels and white squares are vacant channels with respect to time.

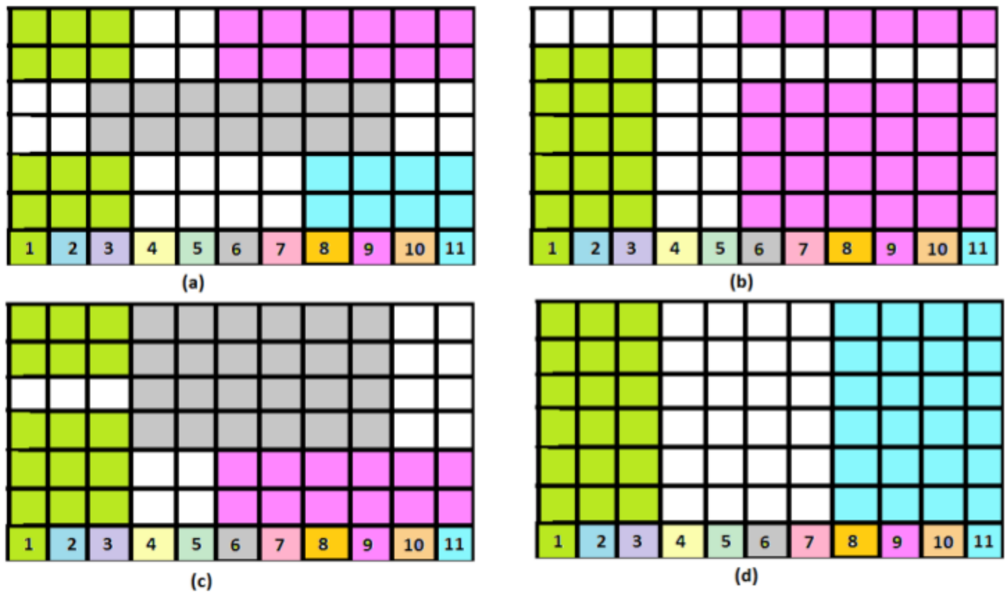

Figure 3.1 Spatial Spectrum Occupancy in 4 Labs (WLAN Channels 1 to 11)

In order to exploit the spatial spectrum occupancy patterns, we attached inexpensive GPS receiver to every CRWSN node. Details of the configuration are discussed in Chapter-5. Since we have used USRP[8] based CRWSN nodes which are attached to a PC, enabling the CRWSN nodes with GPS receivers is both inexpensive and effective in obtaining spatial spectrum occupancy information in handy manner.

In order to perform DCA .i.e. spectrum prediction with respect to time and space, we used two different approaches to model and predict the primary user traffic. One is based on artificial neural network and another is based on autoregressive modelling. Both the approaches are suitable for spectrum prediction application [1]. Both the methods do not require a priori information of the primary user's signal characteristics [1]. Once a model is developed, it is propagated to the cognitive engine to be used in real time, while DCA is in operation.

DCA is carried out in two stages. First, the location information is accessed with the help of GPS receivers and corresponding time stamps are recorded. In the second stage, based on the location information and corresponding time stamp, the cognitive engine, equipped with the corresponding model of PU traffic, mines its corresponding database to perform prediction. In Figure 3.2, we show the generic block diagram of our DCA assisted cognitive engine.

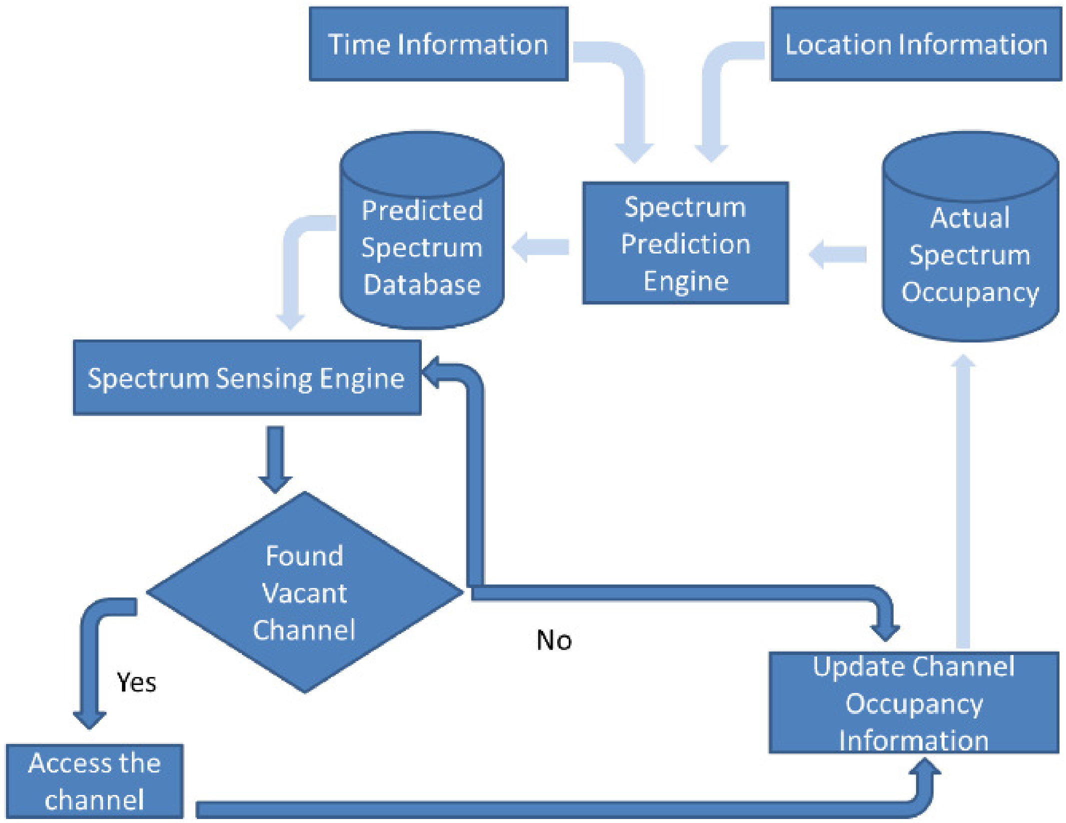

Figure 3.2 Generic Cognitive Engine with Time and Location Information

The output of cognitive engine is a sequence of all the channels ordered according to their likelihood of vacancy. A typical sequence of WLAN channels ordered with respect to their likelihood of vacancy is shown in Table 3.1.

Table 3.1 Predicted to be vacant channels in order of their likelihood of vacancy

ch-1	2.417 GHz
ch-2	2.442 GHz
ch-3	2.462 GHz
ch-4	2.427 GHz
ch-5	2.412 GHz
ch-6	2.422 GHz
ch-7	2.432 GHz

The CRWSN nodes responsible for spectrum sensing are updated with this sequence and they use it for their current time window. They start sensing with the channel at the top most position and continue with the order downwards. In Table 3.1, ch-1 is most likely to be vacant at the given time while ch-7 is least likely to be vacant at the given time. Hence in our scheme, we start sensing the channel from ch-1, and continue till ch-7 until a free channel is not found. This is significantly different from the methods where sensing takes without taking care of the likelihood phenomena into account [1]. We conducted experiments on CRWSN testbed in order to verify DCA scheme. Details of the experiments and results obtained are discussed in Section 3.3.

3.2 Enhancing DCA with Adaptive FFT Resizing

DCA scheme reduces spectrum discovery time and energy consumption by exploiting the spatial spectrum occupancy pattern in addition to the temporal spectrum occupancy pattern. In the course of enhancing DCA, we observed that FFT is the most time consuming as well as energy consuming task in the process of spectrum sensing [9]. The more is the size of FFT, the more is the time taken and energy consumed because it takes more number of clock cycles to perform the FFT operation when the number of FFT points is high [10]. This makes more sense when the channels are arranged in order of their likelihood of vacancy. Hence, there is possibility to reduce the spectrum discovery time and energy consumption by adaptively adjusting the size of FFT according to the likelihood of a spectrum chunk to be vacant at a particular time and at a particular location.

Prior to adaptive FFT resizing, all the channels were sensed with equal sized FFT in the course of energy based spectrum sensing regardless of the likelihood of vacancy of that channel temporally or spatially. But the question arises is why to allot higher size FFT to a channel which is less probable to be vacant. To address this issue, we propose a scheme where higher size FFT will be used with channels which are highly likely to be vacant while lower size FFT for channels having less probability of vacancy.

To theoretically evaluate our scheme of adaptive FFT resizing, we took a simple case. Suppose we have 5 different channels over which spectrum sensing has to be done. These channels are already been sorted in the order predicted by the cognitive engine.

Let those probabilities be p1 > p2 > p3 > p4 > p5 where p1, p2, p3, p4 and p5 correspond to the probability of vacancy of channels c1,c2,c3,c4 and c5 respectively. Now, consider the worst case scenario i.e., the last channel in the predicted order only is free and the rest are occupied. Hence, the spectrum sensor has to sense all the channels listed in the sequence. Hence, the spectrum sensor, in our case, has to do FFT 5 times in order to find a free channel. Let's also assume that the spectrum sensing nodes can perform up to 512 point FFT without any overload and loss of samples.

With all the assumptions mentioned above, now consider two cases in the worst case scenario:

Case-1 All channels are allotted equal sides FFT, i.e.
In this case the average FFT size for the whole operation will be

$$\frac{1}{5}\sum_{i=1}^{5} P_i . fft\_size = 512\sum_{i=1}^{5} P_i$$

Case-2 Adaptive FFT resizing is used. For the sake of simplicity let's assume p1 =1/2, p2 =1/4, p3 = 1/8, p4 = 1/16 and p5 = 1/16 and we assign following FFT sizes for the channels:

c1 => 512
c2 => 256
c3 => 128
c4 => 64
c5 => 64

Notice that size of FFT is proportional to the probability of vacancy of the channel. In this case, the average FFT size for the whole operation is

$$\frac{1}{5}\sum_{i=1}^{5} P_i . fft\_size_i$$

=1/2(512) + 1/4(256) + 1/8(128) + 1/16(64) + 1/16(64)
= 344

With this simple calculation, we see that average FFT size in the worst case scenario is significantly reduced using adaptive FFT resizing scheme. Reduction in average FFT size is indication of lesser time and lesser energy consumption. We conducted experiments to show the same. Details and results of the experiment are discussed in Section-3.3

3.3 Experiments and Results

To validate DCA based spectrum sensing, we first emulated primary user traffic. We chose the most popular model for emulating PU pattern where the PU arrival rates follow Poisson distribution and PU transmission duration follows exponential distribution [10]. A script is developed in GNU Radio which is capable of tuning the center frequency of spectrum sensing by exploiting the predicted order of the channel vacancy as discussed in section 3.1. We log the time durations spent in finding the first vacant spectrum i.e., spectrum discovery time. This is compared with a normal spectrum prediction based spectrum sensing algorithm (without location information) which is also developed in GNU Radio. We iterated the experiment 50 times by changing the location of PU and SU. Fig 3.3 shows the average time required by the DCA for finding the first spectrum is significantly less compared to Normal Spectrum prediction based

Spectrum Sensing method .i.e. without location information. We also observed that DCA has an average spectrum discovery time of 3 sec and a very low variance of 2.66 while average spectrum discovery time for a normal spectrum sensing (without location information) is 7 sec and a very high variance of 13.83. A low variance indicates consistency in the spectrum discovery time over different iterations.

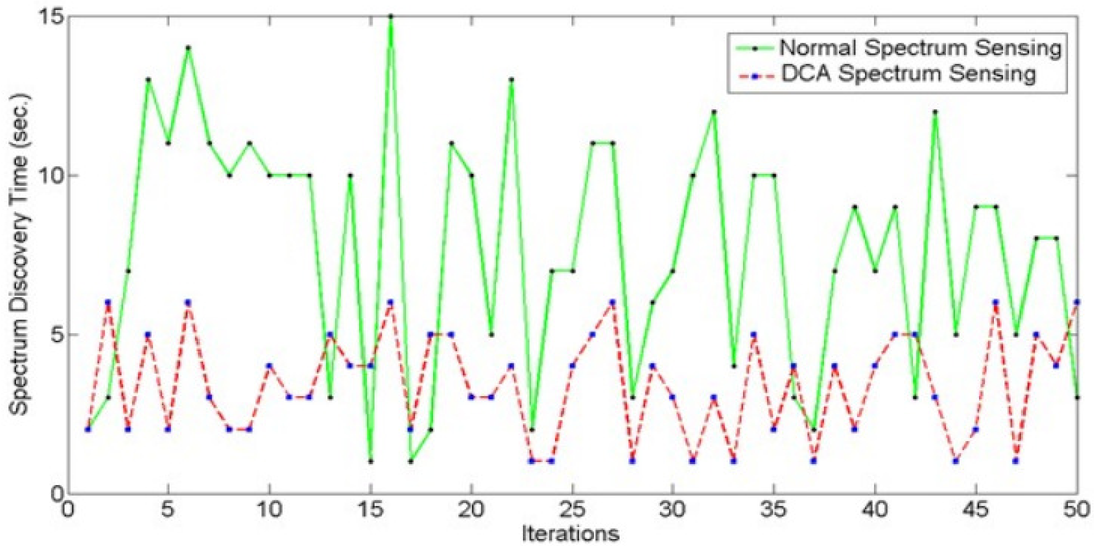

Figure 3.3 DCA vs Normal Spectrum Sensing (Without Location Information)

This experiment shows that when the system is subjected to mobility, DCA performs better than other prediction algorithms which do not take location information into account.

Following DCA based spectrum sensing, we verify our FFT size adaptation combined with DCA approach for energy detection based spectrum sensing. We prepared a set up where the USRP is programmed to scan a finite number of channels in a specific order which is determined as mentioned in section 3.1. Simultaneously, a PU traffic pattern is emulated as discussed in section 3.2. In case-1, we assigned 1024 point FFT for all spectrum sensing cycles. In case 2, we assigned FFT size to the spectrum sensing according to their probability of vacancy. We recorded the time spent in both the cases

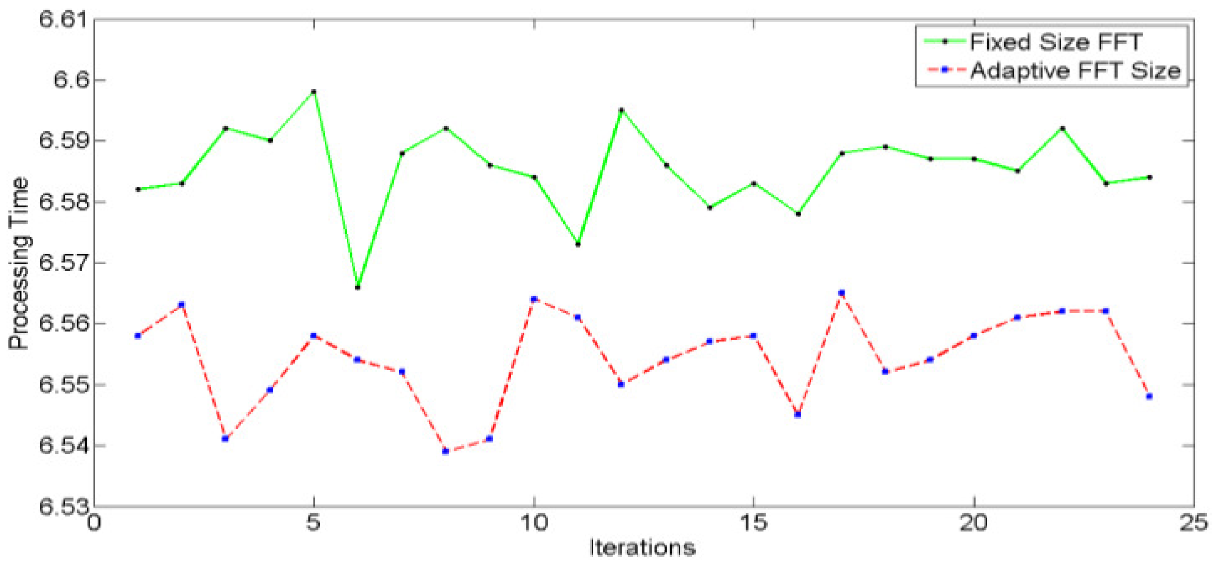

Figure 3.4 Processing time for Fixed FFT Size vs Adaptive FFT Size

The plot in Fig. 3.4 shows that time spent in uniform sized FFT based spectrum sensing is significantly higher than that of adaptive sized FFT based spectrum sensing in the entire spectrum sensing events. This experiment shows that adaptive FFT resizing while performing DCA, consumes lesser time to find the first vacant spectrum compared to other schemes where uniform FFT size is applied. Table 3.2 shows the experimental parameters of DCA

Table 3.2 Experimental Parameters of DCA

Parameters	**Value**
Modulation Schemes	BPSK, QPSK, 16QAM
Transmission Technique	NC-OFDM
DCA(Fixed FFT Point)	512
DCA(Adaptive)	512, 256, 128, 64, 16
Spectrum Sensing Technique	Energy Detection
Frequency	2.4GHz - 2.48GHz
Transmission Bandwidth	200 KHz
Sampling Rate	1 MSPS
Average Distance between PU and CH	3.5 Meters
Average Distance Between CH and RN	4 Meters

Average Distance Between RN and BS	4 Meters
Spectrum Prediction Method	ANN, AR

3.4 Summary

In this chapter, we discussed DCA based spectrum sensing which does prediction with respect to temporal as well as spatial domain. Performing prediction in the spatial domain makes this system comparatively reliable and fast when the CRWSN nodes are mobile .i.e. when the location of the nodes keep changing. We observed that the spectrum discovery time is significantly reduced. The DCA system performs even better when adaptive FFT resizing is used. Adaptive FFT resizing saves time as well as battery life of CRWSN nodes.

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Chapter-4

Partial Sensing Based Spectrum Monitoring

In section 2.4, we discussed several issues of spectrum monitoring in a cognitive radio network. Requirements of spectrum monitoring is almost same in a CRWSN compared to a cognitive radio network except that the method has to be energy efficient and computationally very less complex in order to realize the same in hardware and signal processing algorithms. In this chapter, we have discussed partial sensing based spectrum monitoring for CRWSN. The chapter is organized as follows. In Section 4.1, we give the background of spectrum sculpting in OFDM. This is followed by a discussion on applying spectrum sculpting technique to realize partial sensing based spectrum sensing in CRWSN, in Section 4.2. Finally, in Section 4.3, we discuss experiments performed on CRWSN testbed in order to verify the partial sensing technique.

4.1 OFDM Spectrum Sculpting

OFDM stands for orthogonal frequency division multiplexing. It uses orthogonal overlapping subcarriers in order to utilize frequency diversity and parallel transmission of data [1]. A typical block diagram of an OFDM transceiver and OFDM spectrum is shown in Figure 4.1.

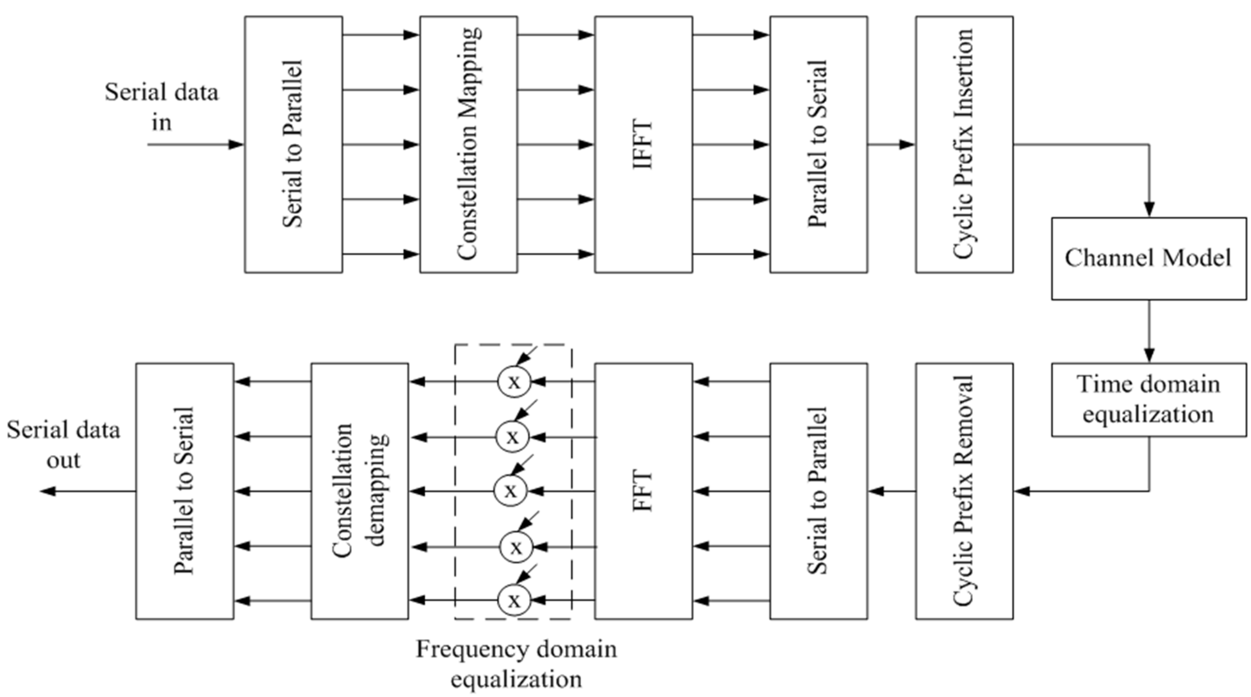

Figure 4.1 OFDM Transceiver

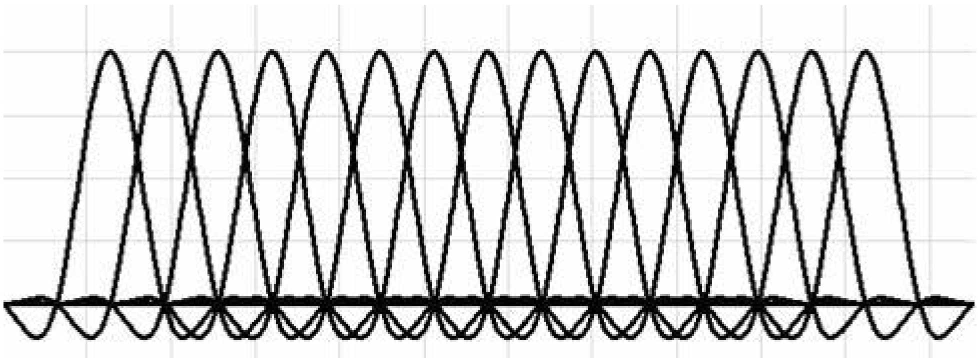

Figure 4.2 OFDM Spectrum

OFDM operation essentially comprises of IFFT at the transmitter and FFT at the receiver. Number of FFT points in any OFDM operation corresponds to number of orthogonal subcarriers. Using FFT/IFFT based subcarrier modulation technique gives the freedom to suppress any of the subcarriers as required. This is also called NC-OFDM (non contiguous OFDM) [2]. For example, see Figure 4.3. In the OFDM spectrum, we have two primary users within the bandwidth of interest.

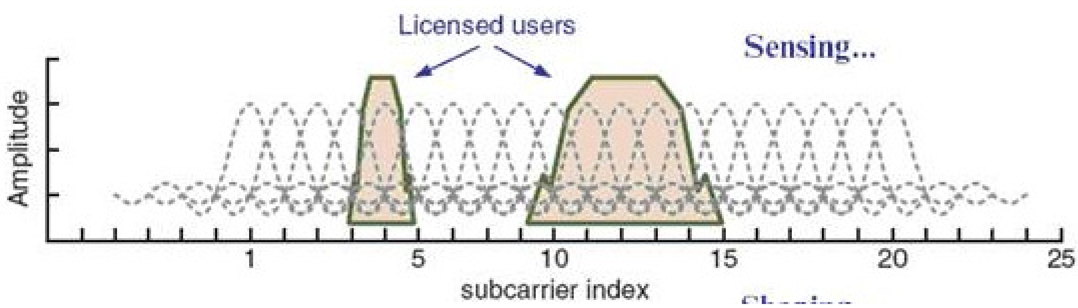

Figure 4.3 PU present in the bandwidth of interest

It is impossible for a SU to transmit using normal OFDM with this scenario as it will interfere with the PU transmission. Using spectrum sculpting, it is possible to suppress the subcarriers where PU is present. In order to do that; consider the case shown in Figure 4.3. Here, we have 20 orthogonal and overlapping subcarriers. Out of them, 5th,11th,12th and 13th are occupied by the primary user. Remaining subcarriers are not in use by the PU and can be used by the SU opportunistically. In order to do so, a vector of 0s and 1s is created in such a way that it has 0s at all the subcarrier index where PU is present while 1 at all the places where PU is absent. So for the case above, such vector will look as follows:

1	1	1	1	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1

Following to this, the output of IFFT at the transmitter is multiplied with this vector. The multiplication, effectively suppresses all the subcarriers which are occupied by the PU. Further filtering smooths the spectrum even more and limits the spurious transmission in the PU occupied spectrum. Effectively, the sculpted transmission looks as shown in Figure 4.4.

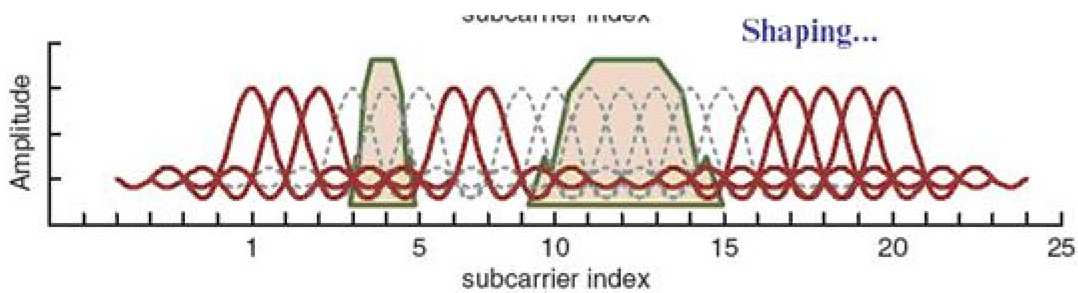

Figure 4.4 Sculpted Spectrum for opportunistic transmission

4.2 Partial Sensing Based Spectrum Monitoring

Using the concept of spectrum sculpting, we came up with the idea of partial sensing based spectrum monitoring for CRWSN. It is named as partial sensing because instead of sensing whole bandwidth of interest, it senses only a small chunk of the same. In this Section, we explain the methodology which is followed by partial sensing based primary user monitoring technique.

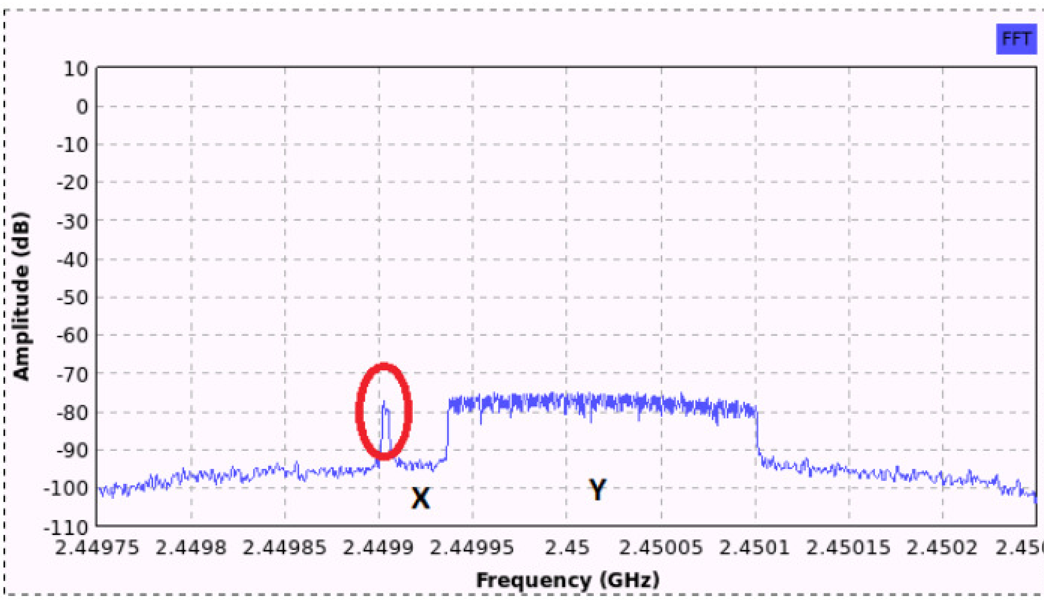

Figure 4.5 NC-OFDM for partial spectrum sensing

Consider total free bandwidth is X+Y. We leave a chunk of the spectrum unused i.e., **X** with the help of NC-OFDM (non-contiguous OFDM) [2] while use the rest part of bandwidth i.e., **Y** for transmission and reception. Figure. 4.5 shows the scheme. With NC-OFDM spectrum sculpting technique, it is possible to use even that little chunk of spectrum which is remained in the leftmost part of the spectrum, for transmission and reception purpose. While the CRWSN is using **Y**, the receiver is configured to monitor the power level in the unused chunk **X** simultaneously.

The scheme is also simple in terms of implementation. In a typical OFDM receiver, after the FFT operation, as shown in Figure. 4.1, the receiver gets power in each of frequency bins. In the

Figure. 4.1, every line coming out of FFT block corresponds to a frequency bin. By monitoring the power level in the FFT bins falling in the region **X,** the receiver can immediately detect the appearance of the PU.

The motivation came from the fact that licensed users of a particular vendor in mobile communication channels have fixed bandwidth per user (200 KHz for GSM). Hence in case the PU reappears, the chunk of band left unused **X** will get filled by the RF power. This phenomenon can be efficiently utilized at the OFDM receiver to monitor the PU arrival.

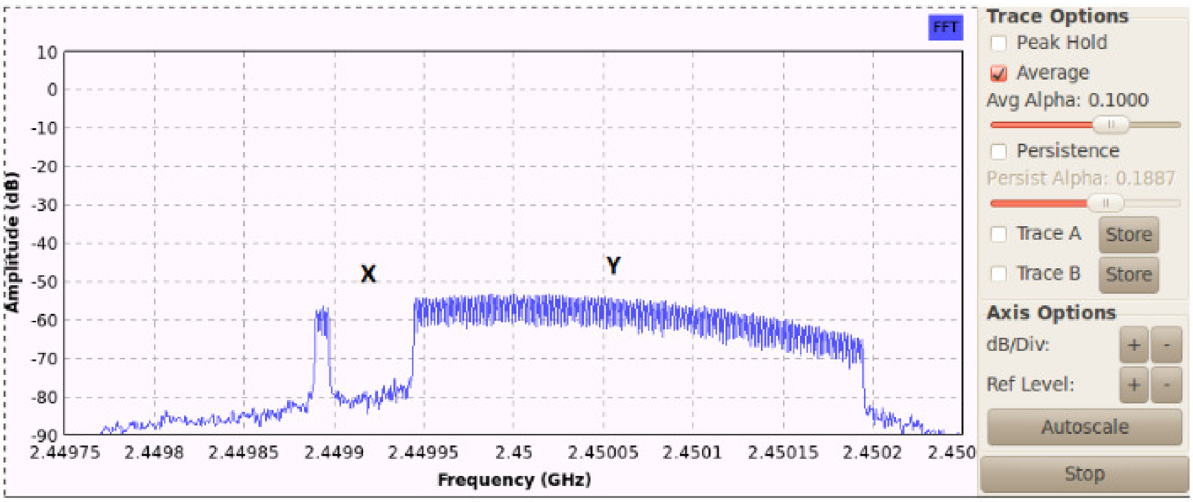

Figure 4.6 Primary user absent

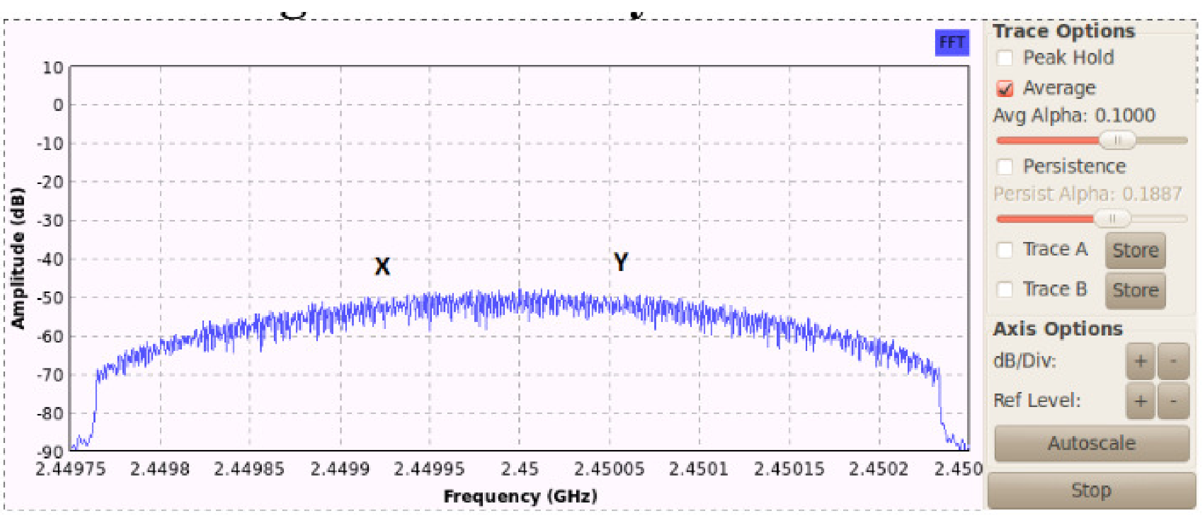

Figure 4.7 Primary user present

In Figure. 4.6, we see that the power level in **X**, in the absence of PU is -80 dB, while the same is -50 dB when the PU reappears in the band, Figure. 4.7. This sharp rise in power level i.e. 30 dB can be compared to some threshold and the PU appearance can be immediately detected.

Detection is practically performed by taking the average power in the bins and comparing them to a threshold. Threshold can be found in numerous ways depending on a particular situation [3].

In the unified framework which our CRWSN architecture follows, where all the CRWSN nodes transmit and receive using OFDM only, partial sensing based monitoring is readily realizable with minor change in the signal processing algorithm and no change in the hardware architecture. The following Section discusses the experiments performed to verify the efficiency of this spectrum monitoring technique.

4.3 Experiments and Results

We have deployed this method in our CRWSN testbed operation. Our method gives better results compared to periodic spectrum sensing [4] and PU activity prediction based spectrum sensing [5]. Following is the description of the experiment.

The NC-OFDM receiver is configured to monitor the power of the unused part of the chunk. For our experiment, **X** ranges from 2.44991GHz to 2.44993GHz, while **Y** ranges from 2.4499GHz-2.44991GHz and 2.44993GHz to 2.4501GHz. The NC-OFDM works with 256 point FFT at a sampling rate of 1MSPS. Hence, the frequency resolution is nearly equal to 3.9 KHz which is the ratio of sampling frequency (10^6Hz), and FFT length (256). Hence, the receiver is configured to monitor the power of frequency bins ranging from 4 to 7. To continue with the experiment, primary user traffic is emulated as discussed in Section 6. We perform several iterations to detect the time duration between PU transmission at the PU emulator and PU detection at CRWSN spectrum sensor using partial sensing. Same set of experiments were performed by periodically pausing the transmission and enabling spectrum sensing [4].

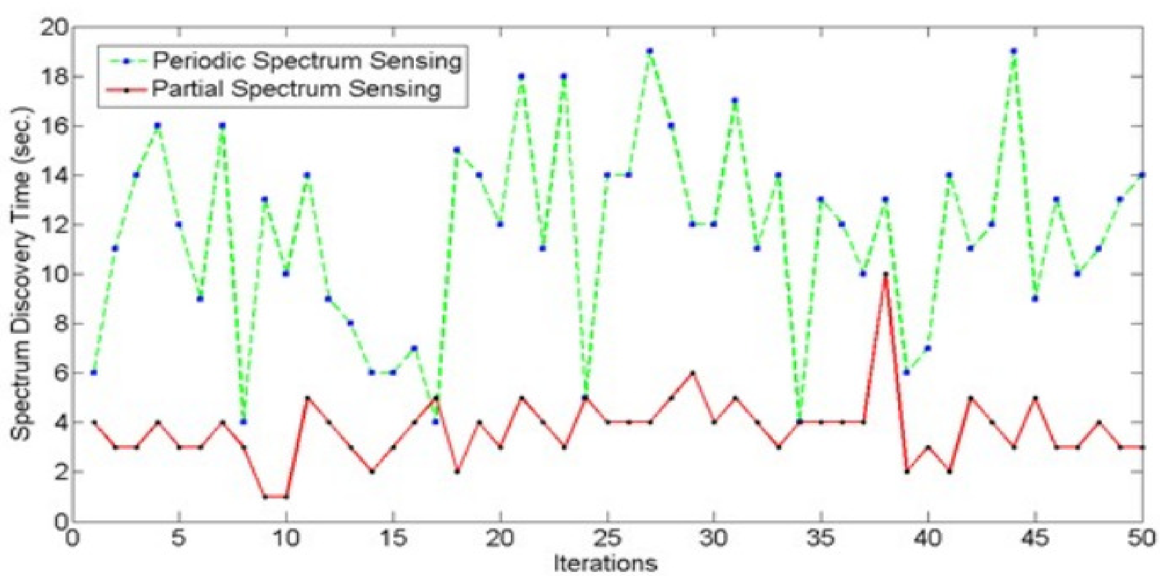

Figure 4.8 Partial Spectrum Sensing vs Periodic Spectrum Sensing

Figure. 4.8 shows comparison of spectrum discovery time between partial spectrum sensing method and periodic spectrum sensing method. Spectrum discovery time is the delay between the PU arrival time and PU detection time at the spectrum sensor. It clearly shows that PU detection time of partial spectrum sensing method is significantly less in comparison to that of periodic spectrum sensing method. We also observe that partial sensing based spectrum monitoring has average spectrum discovery time of 3sec and a significantly low variance of 1.85 while for periodic spectrum monitoring the average time is 11sec and variance is 15.42, which are very high compared to our method. A low variance in spectrum discovery time indicates consistency in detecting the PU arrival. Table 4.1 shows the experimental parameters of partial sensing based spectrum monitoring.

Table 4.1 Experimental Parameters of Partial Sensing Based Spectrum Monitoring

Parameters	**Values**
FFT Points	256
Bandwidth of Interest	200 KHz
Partially Sensed Bandwidth	20 KHz
Average Distance between PU and SU	4 Meters
Average Power in X (PU Absent)	-80 dbm
Average Power in X (PU Present)	-50 dbm
Sampling Rate	1 MSPS

Our partial sensing method is also more efficient with respect to bandwidth efficiency as the system never goes into completely zero transmission state. We considered the product of time and bandwidth as a benchmark for comparing the two approaches of spectrum monitoring. In our 40sec time frame, 10sec is dedicated for information transmission. Considering a single time frame, the time bandwidth product for partial spectrum sensing method is (200-20) KHz x 10sec = 1800K. For the periodic spectrum sensing where the user has to pause transmission every 3sec for 2sec, the time bandwidth product is 200KHz x 3sec + 200KHz x 3sec = 1200K. This shows that bandwidth efficiency of our method is 50% more than periodic spectrum sensing.

4.4 Summary

In this chapter, we discussed in detail about the partial sensing based spectrum monitoring of PU. Using the spectrum sculpting properties of NC-OFDM, the idea of partially sensing the received spectrum performs significantly well compared to other methods of spectrum monitoring. This method can be readily implemented on the existing hardware without any significant modification in signal processing algorithms. This method is faster and spectrally more efficient compared to periodic spectrum sensing.

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Chapter-5

Development of CRWSN Testbed

In Section 2.5, we discussed the need for developing a testbed for CRWSN. In this chapter, we discuss in detail about the CRWSN testbed developed at SPCRC, IIIT Hyderabad. The chapter is organized as follows. Section 5.1 discusses the properties required in a CRWSN testbed in general. In Sections 5.2 and 5.3, the hardware and software architecture of the testbed are discussed in detail respectively. In Section 5.4, we discuss a unique feature of testbed .i.e. multi-hop off frequency relaying. This is followed by operation of the testbed in order to demonstrate the basic CRWSN functionalities in Section 5.5. Finally, the chapter is concluded by mentioning possible future modifications in Section 5.6

5.1 Architecture of CRWSN Testbed

A testbed has two facets when it comes to architecture, hardware and software. Both are equally important and their appropriate choice is very critical in the operating efficiency of the testbed. On the software side, the user and developer interface of the testbed shall be as simple as possible. Mostly open source software architectures shall be preferred. Tools for signal processing and API for SDR hardware shall be flexible and modular enough to add and update them with newer functionalities with lesser efforts. On the hardware side, a testbed for CRWSN must have the ability to support multiple as well as different software defined radio (SDR) modules so that a variety of PU and SU traffic can be emulated. It should be capable of handling a range of RF frontends for covering wide frequency bands and thus it should be able to support multi frequency operations. Above all, a CRWSN testbed should be capable of accessing location information, clustering and multi-hop communication.

5.2 Hardware Specifications of Testbed

We have chosen Universal Software Radio Peripheral (USRP), an FPGA based SDR transceiver and RF frontends from Ettus Research LLC [3] for the development of our CRWSN testbed. The testbed has been developed with a modular architecture which is scalable and expandable both in hardware and software. Hardware part of the testbed consists of USRP-1 and USRP-2.
USRP-1 is used for the task of sensor nodes, i.e., information sensing from the environment. Additionally, they are used for spectrum sensing but with low bandwidth coverage. ADC of USRP-1 can sample at a maximum of 64 MSPS. But, due to USB transfer rate limitations, they can practically sense a maximum of 8 MHz in a single scan. In order to avoid spectrum sensing delay, we load each USRP-1 to sense only a bandwidth of 4 MHz. Additionally, USRP-1 is also used to emulate the PUs traffic in this testbed which emulates the PU pattern. We chose the most popular model for emulating PU pattern, where the PU arrival rates follow Poisson distribution and PU transmission duration follows exponential distribution [1]. Compared to USRP-1, USRP-2 has a larger FPGA and hence more processing capacity with lesser delay. Hence they are given the task of cluster heads (CH). In CRWSN, a CH has the responsibility to collect the sensing data

from nearby sensor node and send them to base station (BS). In CRWSN, a BS has the responsibility of collecting sensing data from all the CH and does further processing [1]. To realize the BS, we used USRP-2. We also use a spectrum analyzer, Spectran HF6060 [2], to verify the results of experiments and other algorithms with the ground truth. Apart from emulating PU, sensor nodes, CH and BS, we also place relay nodes (RN). Relay nodes are used in the cases when a single hop transmission from CH to BS is not possible. This may happen due to larger distance, shadowing etc. In such cases, CH sends the data to RN and in turn RN relays the data to BS. Hence, multi-hop transmission takes place. Frequency between CH-RN and RN-BS can be same or different depending on availability. In case of different frequency, Multi-hop Off frequency relaying takes place. Details are discussed in Section 5.4.

RF front end of the testbed consists of RFX2400 and XCVR2450 having coverage in the range 2.3-2.9 GHz and 2.4-2.5 GHz, 4.9-5.9 GHz respectively [3]. We also used Omni directional Antenna VERT2450 for all the CH, BS, RN and Sensor nodes. All the USRPs are connected with PCs which are then connected with Ethernet. Ethernet connection between all the sensor nodes act as a common control channel. This common control channel enables the Sensor nodes, CH, RN and BS to transfer and share control information with each other such as spectrum sensing information, start & pause signals etc. Additionally, the Ethernet connection helps in time synchronization of all the nodes which is compulsory for the operation of CRWSN testbed.

Table 5.1.List of Hardware Used In CRWSN Testbed

Device	**Description/Function**
USRP-1	Sensor Node, Relay Node, Primary User
USRP-2, USRP-E100	Cluster Head, Base Station
RFX-2400	RF Frontend for Sensor Nodes
XCVR-2450(Dual Band)	RF Frontend for intermediate nodes and base station
VERT-2450(Dual Band)	Omnidirectional Antenna
Spectran HF6060	Spectrum Analyzer
Blue Next USB	Real Time GPS Data Logger

In addition to the above configuration, USB based GPS receivers are also installed in all the workstations. This enables logging of location information which is packed along with the spectrum sensing and PU activity information. This information is sent over the Ethernet to a remote cognitive engine through a python client-server program. Advantage of using GPS receiver is that the radio environment maps remembers its location while training the cognitive engine which is a unique feature of DCA. Table 5.1 summarizes the list of hardware used and their functionality in our testbed.

5.3 Software Specifications of Testbed

GNU Radio has been taken as backend of software part for this testbed. It is an open source SDK for development of software defined radio waveforms and protocols. All the signal processing algorithms are implemented in C++ and are called through Python. GNU Radio provides several inbuilt scripts for spectrum sensing, transmission and reception which are customized to work with our testbed. We have developed customized modules for non-contiguous OFDM (NC OFDM), cooperative sensing and beacon assisted Tx/Rx using the existing scripts. NC-OFDM gives the flexibility of suppressing the subcarriers wherever the primary user is present. We have customized the OFDM script which comes with GNU Radio so that its carriers can be suppressed individually when required. It is 200 KHz wide and has 103 subcarriers. Details are discussed in Chapter-4. Table 5.2 summarizes the software configuration of the CRWSN Testbed

Table 5.2 Details of Software used in CRWSN Testbed

Software	**Version**
Operating System	Ubuntu 10.04 LTS
GNU Radio	3.4.0
UHD(Universal Hardware Driver)	003.004.000

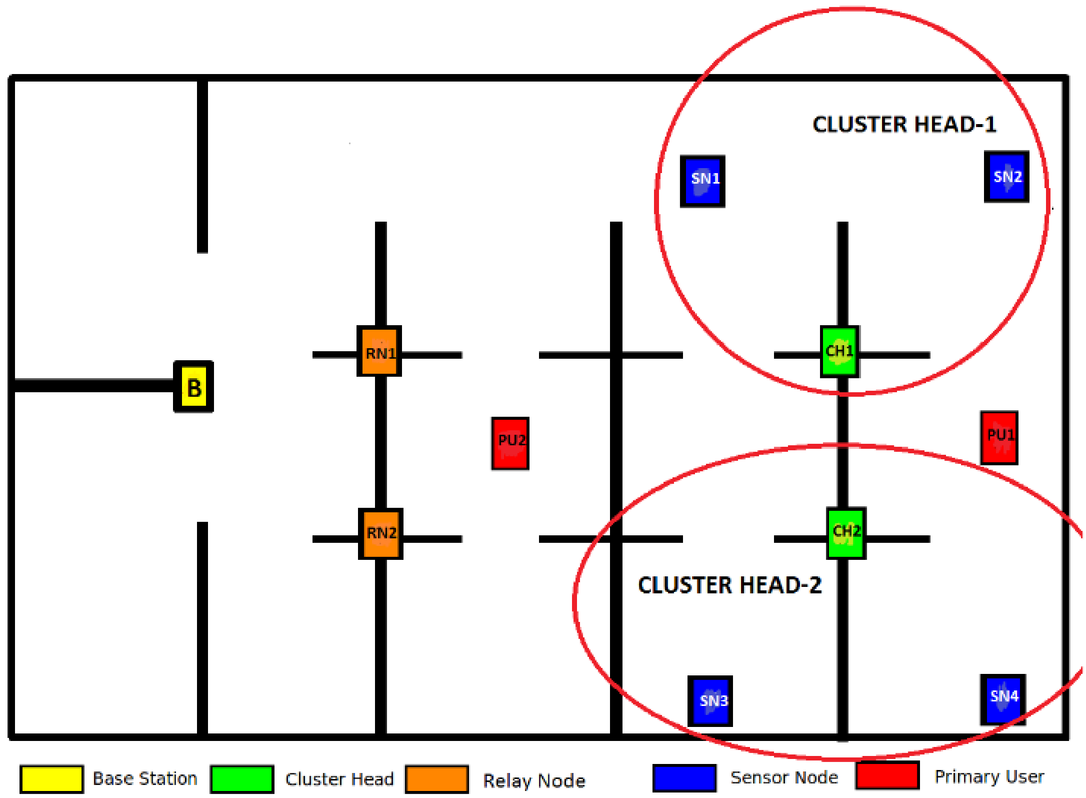

Figure 5.1 Grid view of the CRWSN testbed

A grid view of the testbed is shown in Figure. 5.1 for clarity. This testbed was installed at Signal Processing and Communication Research Center building in IIIT Hyderabad.

5.4 Multi-hop Off Frequency Relaying

The CRWSN testbed developed by us has a unique feature of Multi-hop Off frequency relaying. There can possibly be situations where a common free channel could not be found between the RN-CH and RN-BS pair. To address the issue, we came up with the idea of multi-hop off frequency relaying. The idea is based on the fact that although there might be no common free channel between RN-CH and RN-B pair, free channels may be present between RN and CH as well as RN and B. This can be found by the RN during spectrum sensing information fusion. Details of spectrum sensing information fusion are given in Para-2 of Section 5.5. The first non-zero entry in the spectrum sensing result vector between RN-CH pair is used to establish radio link between RN and CH while the first non-zero entry in the spectrum sensing result vector between RN-B pair is used to establish radio link between RN and B. Using this multi-hop off frequency relaying, CH can send their data to B by relaying over different frequencies. The schematic is shown in Figure. 5.2

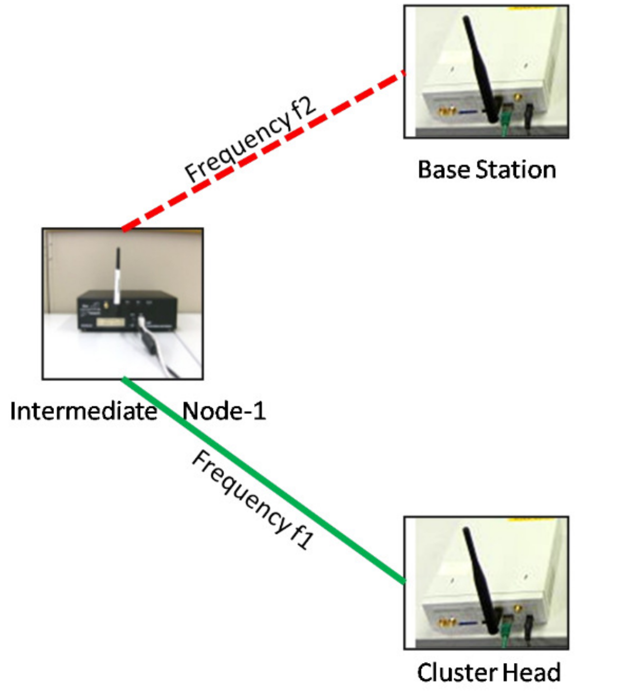

Figure 5.2 Multi-Hop Off-frequency Relaying

5.5 Testbed Operation

A cluster head (CH) and the two corresponding sensor nodes (SN1, SN2) are collectively termed as cluster. Two clusters are used namely cluster-1 and cluster-2 as shown in Figure. 5.1. In time slot 1, all the sensor nodes of each cluster start sensing the environment data. In time slot 2, spectrum sensing is initiated between SN1, SN2 and CH of each cluster. This spectrum sensing is performed with DCA and multi band spectrum sensing. In multi band spectrum sensing, the task of spectrum sensing is divided between the two sensor nodes of each cluster. In our case, SN1 senses from 2.4499 GHz to 2.45 GHz while SN2 senses from 2.45 GHz to 2.4501 GHz. Since sensor nodes of cluster1 and cluster2 are located far away from each other, they can use the same channels from 2.4499 GHz to 2.4501 GHz after performing multi band spectrum sensing.

In time slot 3, spectrum sensing vector of SN1 and SN2 is merged for each cluster. This step is called *sensing information fusion*. In this step, SN2 sends its spectrum sensing vector to SN1 for which SN1 sends an ACK. This spectrum sensing vector is fused with the spectrum sensing vector of SN1. Fusion operation is nothing but logical **AND** operation. It can be explained as follows:

Suppose Channel vacancy information vector CIV1 from SN1 is (considering only 5 channels are being sensed at a time)

1	**1**	**0**	**0**	**0**	**0**

And Channel vacancy information vector CIV2 from SN2 is

1	**1**	**0**	**1**	**1**	**0**

The logical **AND** operation of CIV1 and CIV2 will yield spectrum sensing vector as

1	**1**	**0**	**0**	**0**	**0**

Hence, channels at index 1 and 2 are vacant, while channels at index 3,4,5,6 are occupied.

In time slot 4, the resulting spectrum sensing vector is sent from SN1 to the respective cluster heads over the common control channel. Simultaneously, the same vector is appended with the location information obtained through GPS receivers of the corresponding sensor nodes and sent to the remote cognitive engine over the Ethernet connection. On the availability of spectrum sensing vector, SN1 and SN2 along with CH choose the channel corresponding to the first non-zero entry in the spectrum sensing vector.

In time slot 5, SN1 sends the data packet to CH over the chosen channel which is acknowledged by CH on a per packet basis. In time slot 6, SN2 sends the data packet to CH over the chosen channel which is also acknowledged by CH on a per packet basis. During the data transfer between sensor nodes and cluster head, cluster head (receiver) monitors the arrival of primary user according to the partial spectrum monitoring method as discussed in Section 4. In time slot 7, cluster heads CH of each cluster along with the relay nodes RN and the base station B start performing cooperative spectrum sensing for their respective radio transmission paths, i.e., CH-RN-B. We perform cooperative sensing because base station is quite far away from the cluster heads and there might be hidden nodes in between them.

In time slot 8, spectrum sensing result vector of CH and RN are merged. In time slot 9, spectrum sensing result vector of B and RN are merged. Then, the relay nodes perform fusion on the merged spectrum sensing result vectors. If a common channel is found between CH – RN and RN – B, the relay nodes RN of each cluster send the common channel information to (CH, B) sequentially in the next two cycles (time slot 10 and time slot 11). Otherwise, multi-hop off-frequency relaying method is followed for information transfer between CH-RN and RN-B as discussed in Section 5.

In time slot 12, data transmission happens between RN and CH for each cluster over the pre-decided channel. In time slot 13, RN1 sends data to B which is followed by transmission of data from RN2 to B in time slot 14. During data transmission, all the receivers keep monitoring the PU arrival using partial sensing based spectrum monitoring. The entire spectrum sensing results and PU arrival results are sent along with the location information to the remote cognitive engine for training purpose over Ethernet.

In the end of the testbed operation cycle, cognitive engine trains its predictive model based on the data collected over the time slots and update the new prediction results which are sent to the respective nodes over Ethernet.

Operation of testbed in this time slotted fashion gives the insights of basic cognitive wireless sensor network functionalities such as localization, cooperation, clustering, spectrum sensing, DSA, spectrum allocation, multi-hop communication spectrum mobility and cooperation. Format of the time slots can be modified to realize other advanced cognitive radio functionalities such as spectrum management.

5.6 Scope for Further Modifications

The CRWSN testbed developed by us has a modular architecture with respect to both software and hardware. Most of the signal processing algorithms are written in such a way that they are version independent of GNU Radio and Ubuntu. Hence, if the system goes in software update mode, the functionality doesn't get affected. Similarly, in order to upgrade the hardware, very less modification is required because most of the things are hardware independent and all the parameters are controlled through software only. Hence, in case a new SDR based upgraded hardware is deployed, the corresponding parameters can be registered in the software in order to control the same in directed fashion. In future, the system can be upgraded with master clock which will make all the CRWSN nodes time and frequency synchronized with each other. This will enable to do experimentation on cooperative relaying [5] and realizing virtual MIMO within the CRWSN.

5.7 Summary

In this chapter, we discuss in detail about the CRWSN testbed developed by us. The testbed is first of its kind and demonstrates functionality of both cognitive network as well as wireless sensor network. Additionally, it is equipped with multi-hop off frequency relaying which helps to find noncontiguous channels between nodes to the base station. We have tested DCA and partial sensing based spectrum monitoring on the CRWSN testbed. The testbed is modular with respect to software and hardware upgrades. The testbed can serve as a development platform providing insights into CRWSN. We are in the process of developing remote-access with web based reservations to enable remote users to perform their experiments related to CRWSN on this testbed.

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Chapter 6

Conclusions & Future Work

6.1 Summary

Energy efficient spectrum sensing is one of the most significant tasks in CRWSN. We proposed a novel solution addressing this issue by introducing doubly cognitive architecture based spectrum sensing. Our proposed method performs two levels of prediction compared to single level of prediction in contemporary state of the art spectrum sensing techniques. It exploits the fact that primary user spectrum occupancy has an underlying pattern in both temporal as well as spatial dimension. Two level prediction allows the cognitive engine to find the free spectrum at any given time as well as any given space with very high accuracy compared to single level spectrum prediction mechanisms. Further, we have enhanced our doubly cognitive architecture by introducing adaptive FFT resizing during spectrum sensing. Adaptive FFT resizing technique assigns FFT points to the bands in accordance to their probability of vacancy. This method saves significant amount of system clock cycles and hence the time and energy. In essence, DCA based spectrum sensing gives faster result and enhancing DCA with adaptive FFT resizing saves energy during spectrum sensing. DCA is not only useful for CRWSN but it can also be deployed in cellular cognitive radio in order to experience efficient and fast spectrum sensing.

Next issue which we have addressed in this thesis is spectrum monitoring. Spectrum monitoring is still a very challenging task in any cognitive radio based network. It is very important to deploy a reliable spectrum monitoring method in a cognitive radio network in order to avoid interference to the primary user. In alignment with the issue, a novel solution has been proposed. This method is easier to implement in the existing hardware and software architecture. This method also exhibits faster response time once the PU appears in the channel used temporarily by the SU. This method keeps monitoring a small part of the bandwidth of interest and immediately finds out the appearance of the PU. Inherently, this method is based on IFFT/FFT and therefore it uses the same hardware and signal processing algorithms, which are used by spectrum sensing module. This makes it easy to deploy on the existing SDR based CRWSN nodes. Similar to DCA, our method of partial sensing based spectrum monitoring can be used in cellular cognitive networks as well. Most of the upcoming cellular communication technologies have OFDM as their transmission and reception technology such as WiMAX, LTE and LTE-A [1]. Hence, our proposed method can be deployed without putting any significant stretch to the existing hardware and software signal processing algorithms.

In the final part of our work, we developed a CRWSN testbed which is first of its kind to the best of our knowledge. The testbed emulates all the major functionalities of a CRWSN. It consists of functionalities of both WSN and cognitive radio network. Functionalities corresponding to WSN include clustering, levelling, relaying, multi-hop communication, information dissemination and node mobility. Functionalities corresponding to cognitive radio network include dynamic spectrum access, spectrum sensing, and spectrum monitoring etc. The testbed has been developed with commercially off the shelf (COTS)state of the art FPGA based hardware USRP and open source signal processing software GNU Radio which makes it very cheap to develop and replicate. The CRWSN testbed developed by us is completely modular in nature, both with respect to software and hardware. The testbed is capable of demonstrating all the basic functionalities of a CRWSN as mentioned above. We verified our proposed method of efficient spectrum sensing and partial sensing based spectrum monitoring on this CRWSN testbed which yielded satisfactory results.

Our work will significantly help in the further development of CRWSN. It will also help to realize the CRWSN system from theory to actual filed deployment in an efficient manner.

6.2 Directions for Future Work

Our work can be extended in the following directions, evolving into more accurate and efficient system

- **Virtual MIMO:** Virtual MIMO are systems where multiple time & frequency synchronized transceiver nodes, which are not physically connected, form a MIMO system [2]. Our proposed CRWSN system can be readily adapted to such synchronization using a master clock. This will enable all the nearby CRWSN nodes to form a virtual MIMO system. Once a MIMO system is formed, advantages of MIMO can be exercised readily such as digital Beamforming, spatial multiplexing and parallel data transmission [3].

- **Prediction of DoA of PU:** Once a Virtual MIMO system has been realized, DCA spectrum sensing scheme can be further enhanced by performing prediction over direction of arrival (DoA) [4] of the primary user. In a MIMO system, using multiple antenna system, DoA operation can be readily realized. Such system will be able to predict the PU arrival in temporal, spatial as well as angular domain and will add higher degree of accuracy to a spectrum sensing cognitive engine.

- **Web based Access to the Testbed:** Currently, the CRWSN testbed developed by us can be used inside our lab only. We are looking forward to virtualize it and make it available for the CRWSN research community for experimentation purpose over the web interface. It can significantly help other researchers to test their algorithms and benchmark their performance. This will also help us to collect test data which can be used to further enhance the CRWSN testbed. Our team in SPCRC, IIIT Hyderabad is already working to develop a web based interface which will enable outside users to access the testbed through web based reservation.

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