Evaluation of Required Sensing Time for Multimedia Transmission Over Cognitive Ultra Wideband System

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Abstract—Limited available spectrum and the inefficiency in the spectrum usage necessitate the use of Cognitive Radio (CR) approach to exploit the existing wireless spectrum opportunistically. To achieve the goal of CR, it is a fundamental requirement that the cognitive user (CU) performs spectrum sensing to detect the presence of the primary user (PU) signal before a spectrum is accessed to avoid interference from other wireless users. In Ultra Wideband (UWB) system which utilizes low power transmission, detection of PU is a key problem in a low signal-to-noise ratio (SNR) condition. This paper presents preliminary works in determining the quality of service (QOS) requirements for multimedia delivery in cognitive UWB. The proposed cross-layer design for multimedia transmission is presented. The paper also highlights the use of probability of detection to assess the channel conditions. Finally, we conclude with some future works on issues of medium access control (MAC) layer and time slot allocations for video applications.

Keywords—Sensing time, cognitive UWB, multimedia

I. INTRODUCTION

Considering the next generation (xG) communication networks, which is an amalgamation of a large number of networks and heterogeneous wireless architecture, combined with the increased user mobility makes it difficult to promise the same grade of service quality at all parts of the network. The demanding networking environment of wireless communications imposes several challenges in terms of network design, channel estimation, propagation and radio resource management offering a variety of high quality multimedia applications. Overcoming these issues becomes even more demanding due to non-uniform spectrum allocation, various radio resource management policies, the scarcity of radio resources, the inherent transmission impairments of wireless links, and user mobility.

The key enabling technology of xG networks is the cognitive radio (CR)[1]. S. Haykin [2] defined CR as an intelligent wireless communication system that is aware and learns from its environment and adapts its internal states by making corresponding changes in certain operating parameters. CR technology takes advantage of the spectrum holes by intelligently identifying and using them, and possibly releasing it when required by the primary users (PUs). In CR networks, PUs shall be protected while secondary user (SU) access the spectrum either in underlay or overlay mode. The xG communication components are as illustrated in Fig. 1. Close interactions among protocol functions held at various layers indicate that a cross layer design approach is demanded for CR system. Currently, issue of CR deployment in xG evolves around the following technical challenges:

a) How to sense spectrum and model/anticipate the behavior of the primary users (PUs).

b) How to manage and decide the available spectrum to meet user QoS requirements. These management functions involve spectrum analysis and spectrum decision.

c) How to share the available spectrum resources fairly.

d) How to maintain seamless communication during transition (handoff) of selected frequency channels.
higher priority than best effort traffic in the admission control. Centralized and distributed MAC protocol was proposed to determine the optimal power allocation and data rate. The work was further enhanced in [9] by future traffic prediction. N. El-Fishawy in [10] used interference margin as key parameter in the admission control. The link request is only admitted if the interference is less than the threshold limit allowed for the UWB system. Then, appropriate power and data rate were assigned to each link request. Further related literature can also be found in [11]-[15]. Despite the literatures show that video quality is improved through adaptation of certain parameter to varying channel condition, none of them discuss how the sensing was carried out and scheduled in the MAC protocol.

In CR, sensing activity is considered as the most crucial function to determine spectrum holes before any adaptation or management action can be taken. Periodicity in channel sensing and channel estimation need to be carefully considered especially in multimedia application [24]. In most cases, CR device has to postpone all its transmission during spectrum sensing. This may result in negative impact to video application that is more sensitive to delay. For example, if longer time is allocated for sensing, the overall throughput will decrease. On the other hand, the probability of accurately detecting spectrum holes will be reduced if the sensing time is not efficiently allocated. In [16], two sensing scheduling was proposed, namely channel state information (CSI) based and queue state information (QCI) based. In CSI based sensing scheduling, SNR was used in determining the appropriate time slot for spectrum sensing activity. While QCI based sensing scheduling takes total queue of the packet in the buffer into consideration. The work assumed sensing time takes about 20%-50% of the superframe. In [25], sensing is set at the start of every Group of Picture (GOP). However, the optimal sensing period was not discussed in specific.

This paper is intended to propose an optimal sensing period to be allocated in sensing scheduling suitable for multimedia application over cognitive UWB. To elaborate further, UWB as a potential platform for CR is described in Section II. Then, existing sensing mechanisms are highlighted in Section III. Section IV presents the system design used in the simulation, followed with the result and analysis in Section V. Conclusion and future work is drawn in Section VI.

II. UWB PHYSICAL CHANNEL

Federal Communication Commission (FCC) has authorized the unlicensed use of UWB in 3.1-10.6GHz with minimum occupied bandwidth to 500MHz and a spectral mask of -41.3dBm/MHz. UWB systems can be divided into two groups, namely single band and multiband. One unique features of UWB communications, whether it is DS-UWB or MB-OFDM, with proper transceiver design, their data rate can be adapted proportionally to the signal to noise interference ratio (SINR) [3]. Assuming bandwidth of the channel, B the capacity (C) of a link from node i to node j according to Shannon theory is;

\[ C_{ij} = \lim_{B \to \infty} B \log_2(1 + \text{SINR}) \]  

Hence SINR is defined as;

\[ \text{SINR} = \frac{P_u L_{ij}}{\eta B + \sum_{k=1}^{M} a_k P_u L_{ij}} \]  

Where \( P_u \) is average transmit power of node i, \( L_{ij} \) is path loss, \( \alpha \) is path loss exponent, \( L_{ij} \) is path loss of the other nodes \( k \), \( \eta \) is background noise energy, \( M \) is number of nodes and \( a_k \) is an orthogonality factor. In equation (2), the first term of the denominator represents the AWGN noise and the second term represents multiuser interference (MUI). S. Ghassemzadeh and V. Tarokh in [6] proposed a propagation model based on 300,000 frequency response measurements that were carried out in a UWB network. Based on the field measurement, he presented the UWB path loss model as below;

\[ L_y = [L_0 + 10 \alpha \log_{10}(\frac{d_y}{d_0})] + S \quad d_y > d_0 \]

\( L_0 \) is path loss at reference distance, \( \alpha \) is path loss exponent and \( S \) is shadowing. Assuming MB-OFDM UWB with channel bandwidth equal to 528MHz and QPSK modulation technique is used, the bit error rate (BER) and energy per bit can be calculated directly. The probability of error in a packet of size \( L \) can be represented as [4];

\[ \text{PER}_1(L) = 1 - (1 - \text{BER})^L \]  

(4)

Link layer retransmission is a often used technique to combat channel error. If retry limit is set to \( n \), the probability of packet error after \( n \)-retry is [5];

\[ \text{PER}_2(L) = [1 - (1 - \text{BER})^L]^n \]  

(5)

From the PER, job failure rate (JFR) which represents the performance quality at the APP layer can be derived as;

\[ \text{JFR} = 1 - [1 - \text{PER}_2(L)]^m \]  

(6)

With \( m \) is number of video fragments. Equation (4) to (6) clearly shows that video quality at the APP layer is affected by the channel condition at the PHY layer. Thus, frequent updates on the SNR level are required. In CR, sensing is performed by SUs prior to accessing the shared spectrum to avoid harmful interference to the PUs. SNR is typically used to detect the presence of primary user. In this work, probability of detection is determined to the optimal sensing period for the MAC scheduling as well as to reflect channel condition. Next section will discuss further on sensing mechanism, how to determine the sensing period, and relationship of SNR to probability of detection and false alarm.

III. SENSING MECHANISMS

The goal of spectrum sensing is to decide whether PU is absent or present. There are three aspects of PU detection that need to be verified and quantified in order to define metrics for CR systems [17];

a) The time until detection of the PU.

b) The time needed to clear the spectrum once a PU has been detected.

c) The reliability of PU detection; the probability of detection, \( P_d \) and the probability of false alarms, \( P_f \).
In local sensing, each SU senses the spectrum within its geographical location and makes a decision on the presence of PUs based on its own local sensing measurements. Three well-known local sensing techniques are matched filter detection, energy detection, and cyclostationary feature detection. While the matched filter can perform coherent detection, energy detection is a non-coherent detection method that uses the energy of the received signal to determine the presence of primary signals. Feature detection exploits the inherent periodicity in the received signal to detect primary signals with a particular modulation type [18]. In order to mitigate the multi-path fading and shadowing effects, cooperative detection methods among multiple CR users are proposed in [19]. In this research, energy detector is chosen due to the assumption that SU has limited information on the primary signal (i.e. only the local noise power is known). Hence energy detector is optimal. Also, IEEE 802.22 standard on cognitive radio has spectrum sensing via energy detection in its provision.

One of the remaining challenges of spectrum sensing in cognitive networks is the detection of the PUs in a very short time [20]. Multiband Orthogonal Frequency Division Multiplexing (MB-OFDM) has been introduced as a strong candidate to be the platform for underlay Cognitive UWB [21]. Since multi-carrier sensing can be exploited in OFDM-based cognitive networks, the overall sensing time can be reduced. However, this necessitates the use of a large number of carriers, which increases the design complexity. Furthermore, the noise power is often fixed, and the detector performance can only be improved by increasing the signal energy $N A^2$, where $A$ is the amplitude of a transmitted signal. Practically, power constraints frequently rule out the possibility of increasing $A$; thus, we must increase the number of samples $N$. Increasing $N$ typically means an increase in the time and resources necessary to reach a decision; so it is desirable to minimize the number of samples needed to detect the primary user within a given detection error probability.

### A. Channel Sensing Hypotheses

The sampled received signal, $X[n]$ at the SU receiver will have two hypotheses as follows:

$$H_0: X[n] = W[n]$$  \hspace{1cm} \text{if PU is absent}

$$H_1: X[n] = W[n] + S[n]$$  \hspace{1cm} \text{if PU is present} \hspace{1cm} (7)

where $n = 1, ..., N$; $N$ is the number of samples. The noise $W[n]$ is assumed to be additive white Gaussian (AWGN) with zero mean and variance $\sigma_w^2$. $S[n]$ is the primary user’s signal and is assumed to be a random Gaussian process with zero mean and variance $\sigma_s^2$. The goal of the local spectrum sensing is to reliably decide on the two hypotheses with high probability of detection, $P_d$, and low probability of false alarm, $P_f$. $P_f$ and $P_d$ can now be defined as the probabilities that the SU’s sensing algorithm detects a PU under $H_0$ and $H_1$, respectively.

If the detector mistakes $H_0$ for $H_1$, a false alarm occurs, and a spectrum opportunity is overlooked by the detector. On the other hand, when the detector mistakes $H_1$ for $H_0$, we have a miss detection, which potentially leads to a collision with PUs.

### B. Statistical Model of Energy Detector

The energy detector is known as a suboptimal detector, which can be applied to detect unknown signals as it does not require a prior knowledge on the transmitted waveform as the optimal detector (matched filter) does. Fig. 2 depicts block-diagram of an energy detector. The input bandpass filter selects the center frequency, $f_s$, and bandwidth of interest, $W$. This filter is followed by a squaring device to measure the received energy and an integrator which determines the observation interval, $T$. Finally, output of the integrator, $Y$, which serves as decision statistic, is compared with a threshold, $\gamma$, to decide whether signal is present or not.

$$Y = \sum_{n=1}^{N}(X[n])^2$$ \hspace{1cm} (8)

It is well known that under the common Neyman-Pearson detection performance criteria, the likelihood ratio yields the optimal decision [22]. Hence, the energy detector performance can be characterized by a resulting pair of $(P_f, P_d)$ that is estimated as

$$P_f = P(Y > \gamma \mid H_0)$$

$$P_d = P(Y > \gamma \mid H_1)$$ \hspace{1cm} (9)

Since we are interested in low signal-to-noise ratio of PU (SNR= $\sigma_s^2/\sigma_w^2$) regime, large number of samples should be used. Then

$$P_f = Q \left( \frac{y-N\sigma_w^2}{2N\sigma_w^2} \right)$$ \hspace{1cm} (10)

$$P_d = Q \left( \frac{y-N(\sigma_s^2+\sigma_w^2)}{\sqrt{2N(\sigma_s^2+\sigma_w^2)}} \right)$$ \hspace{1cm} (11)

Thus the number of samples needed for PU detection is

$$N = 2 \left[ Q^{-1}(P_f) - Q^{-1}(P_d) \frac{SNR}{SNR} - Q^{-1}(P_d) \right]^2$$ \hspace{1cm} (12)

$N$ can also be defined as the product of sensing time times sampling frequency.

It can be seen that in the low SNR regime, the number of samples required that meets specified $P_d$ and $P_f$ scales approximately as $1/SNR^2$. Therefore, as SNR decreases, the number of samples needed for PU detection increases, i.e. the sensing time becomes longer. It is desirable to have a high $P_d$ since the higher the probability a CR network correctly detects the presence of PU, the better protection for primary operation. Meanwhile, a low $P_f$ is favorable for a better opportunistic access for SU.

### IV. System Design

This work is basically motivated from our proposed cross layer design framework as in [17],[24] and illustrated here again in Fig. 3. In this study, SNR is used as the main performance metric. Tarokh propagation model was
considered with $L_0$ is 50.5dB, path loss exponent ($\alpha$) is equal to 1.7 and shadowing ($S$) is 2.8dB.

When a PU is active, smaller RSSI is detected at the receiver of CR device due to high interference from PU user. Thus, SNR at CR device become smaller (bad channel condition). In practice, SNR of the primary user is not known by the CR device. Thus, simulation was carried out to determine the optimal SNR range to meet the QoS requirement set for video application.

![Fig. 3. Proposed cross layer design framework [17],[24]](image)

Energy detection sensing mechanism is considered in the simulation. To guarantee a minimum level of interference to PUs, who by right, should not be affected by the SUs transmission, this scenario can be realized by fixing $P_d$ at a satisfactory level, e.g. 90%. On the other hand, $P_f$ is set low (10%) to give higher opportunity to SU or CR user to access the channel. In term of sensing scheduling, it is assumed that for each channel, at least one slot within the superframe must be scheduled for sensing. The scheduling is also based on round robin TDMA access. SNR is varied from -10dB to 0dB to investigate the impact to sensing time under worst case scenario.

![Fig. 4. BER performance vs. SNR](image)

The impact of channel condition to the performance at the application layer is as shown in Fig. 6. To simulate the actual video input, Foreman video is used and three retry limits is allowed. The impact to video performance is still in acceptable range (<8% of JFR) when the SNR is between -3dB to -1dB. However, when SNR is below -3dB, the received video quality deteriorates significantly.

![Fig. 5. SNR performance vs. distance](image)

![Fig. 6. JFR performance vs. SNR](image)

The performance in terms of probability of detection against SNR of the channel is studied. It can be observed from Fig. 7 that as SNR decreases, the number of samples increases to achieve the target $P_d$. In other words, it takes longer sensing time to detect a PU at lower SNR. The result should serve as a reference of what is the appropriate time slot allocation for sensing scheduling. Taking -6dB [26] as the worst case SNR for MB OFDM UWB, the graph shows that approximately 256 samples are required to achieve the target $P_d$ of 90%. Using the relationship between the number of samples and sampling
frequency as mentioned above, thus the required sensing time is 0.5μsec. This sensing time can be used in designing the optimal MAC scheduling. The graph also indicates that the sensing period can be adaptively adjusted according to the channel condition.

![Plot of PC against number of sample for various SNR](image)

**Fig. 7.** Probability of detection against number of sample for various SNR.

**VI. CONCLUSIONS**

In this paper, SNR as the main QoS metric at the PHY layer is further extended to determine the appropriate sensing time for cognitive UWB. The result obtained should serve as appropriate sensing period for the cognitive UWB that support multimedia delivery. By doing so, optimal time slot allocation can be assigned for sensing activity and data transmission. Findings in this work will be implemented in our future work of designing optimal resource allocation for UWB MAC.

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