SpiderRadio: An incumbent sensing implementation for cognitive radio networking using IEEE 802.11 devices*

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***Abstract*—The new paradigm of cognitive radio (CR) is envisioned as the key enabling technology that can take advantage of the recently proposed dynamic spectrum access (DSA) policy by opportunistically operating at any unused frequency. Spectrum sensing is one of the most critical features in this CR technology, the purpose of which is to abide by the spectrum etiquette proposed by FCC and protect the primary incumbents from CR interference. In this paper, we introduce a novel dynamic spectrum sensing methodology and propose an adaptive model for primary incumbents detection. The proposed methodology is driven by observed PHY errors, received signal strengths and n-moving window sensing. Using the adaptive sensing methodology, we have implemented a software driven programmable cognitive radio testbed system (SpiderRadio) with off-the-shelf IEEE 802.11 devices and conducted extensive experiments both in indoor and outdoor setups. The experimental results demonstrate how sensing failure can be drastically reduced even with very low sensing duration using the proposed framework.**

I. Introduction

With spectrum usage being both space and time dependent, it is shown through various experimental studies that a fixed, static allocation often leads to over utilization in some bands and under utilization in others [1]. In order to eliminate the risk of such *artificial spectrum scarcity*, spectrum owners in most countries passed new amendments to define provisions for dynamic spectrum access (DSA). In DSA, provisions are being made to allow unlicensed (secondary) users to operate in the unused or under-utilized licensed bands (primary bands) opportunistically.

The success of this policy depends on the ability of secondary users to dynamically identify and access unused spectrum bands, detect the return of primary users and switch to a different band promptly upon sensing the primary user. The recently coined cognitive radio paradigm [2] is anticipated to make dynamic spectrum access (DSA) a reality. Cognitive radios (CR) can be viewed as an electromagnetic spectrum detector, which can find an unoccupied band and adapt the carrier to that band. The layer functionalities of CRs can be separated into physical and medium access control layers. The physical layer includes sensing (scanning the frequency spectrum and process signal), cognition (detecting the signal through energy detector or any other means), and adaptation (optimizing the frequency spectrum usage such as power, band and modulation). The medium access layer cooperate with the sensing measurement and coordinate in accessing spectrum.

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In the CR/DSA networks, primary incumbent sensing and detection is one of the major critical goals, the purpose of which is to abide by the spectrum etiquette proposed by FCC and protect the licensed incumbents from secondary interference. In the recent time, a lot of CR research focus on spectrum sensing (refer to [3]-[6] and references therein) most of which falls into three categories: Matched filter detection, Cyclostationary feature detection and Energy detection. While matched filter detection and feature detection provide better accuracy than energy detection, the fact remains that both the mechanisms incur tremendous computation complexity with additional energy consumption and perform much slower than the anticipated requirement [7], [8]. Energy detection although can perform faster, however, can not distinguish between secondary transmission from primary transmission. As a result, for energy detection to be successful, it is necessary to forcefully quiet down all the secondary transmissions periodically which degrades the secondary network performance.

In contrast to the aforementioned works, in this paper, we present a novel dynamic sensing methodology and implementation guidelines based on **observed PHY errors** for primary incumbents detection. The proposed incumbent sensing is adaptive in nature and driven by three parameters: *observed PHY errors*, *received energy strengths and n-moving window sensing*. More detailed discussion about each of these above terms will be presented later. Based on the guidelines, we implement a software driven programmable cognitive radio prototype system (SpiderRadio) that can configure itself automatically to sense and operate at any allowable unused frequency band. The prototype is built using atheros chipsets enabled off-the-shelf IEEE 802.11a/b/g wireless card. We emulate the Wi-Fi spectrum bands (900MHz, 2.4GHz and 5.1GHz) as primary bands in the testbed experimental setup. For setting up the primary licensee, four cordless phones as well as Agilent signal generators are configured, which can work in the Wi-Fi spectrum bands and act as primary devices. The proposed

CR prototype (based on IEEE 802.11a/b/g wireless card) is configured to be the secondary device for the implementation and testing purpose (i.e., upon sensing and detecting the emulated primary incumbents in a particular frequency channel, the CR prototype must vacate that channel and move to another unused channel). *This helps us in developing and testing our prototype without having to buy and manage several licensed spectrum bands.* The experimental results clearly demonstrate significant performance improvement based on the proposed sensing mechanism.

The rest of the paper is organized as follows. We discuss the existing literature that relates to this research in Section II. In Section III, we present our proposed sensing/detection model and methodology. The testbed setup and the experimental results are demonstrated in section IV. Conclusions are drawn in the last section.

II. Related Work

There are several ongoing research that deal with the idea of cognitive radio (refer to [9]- [11] and the references therein). However, the above-mentioned works mostly investigate the multi-channel MAC protocols for dynamic spectrum access without providing much attention to the spectrum sensing and incumbent detection. The IEEE 802.22 working group is also currently investigating a new standard, Wireless Regional Area Networking ("WRAN") [7] based on cognitive radios.

The present literature on spectrum sensing is still in its emergence. Among several of the recently proposed incumbent detection techniques, cyclostationary feature detection is one method for detecting primary incumbents by exploiting the cyclostationary feature of the signal [12]. However, the biggest disadvantages in this method are the increased computational overhead, consistent bandwidth loss and high time-consumption [8]. Moreover, some knowledge of primary users' signal is necessary in this approach which may not be available in the first place. Also, with cognitive radio envisioned to be integral part of future first responders' networks in public safety bands and other under-utilized bands, such additional complexity and larger energy consumption proves to be severely inefficient. Alternative to the cyclostationary detection, *energy detector* based approach is another common way of spectrum sensing because of its low computational overhead and implementation complexities [13]. Energy detection is more generic (compared to cyclostationary method) as receivers do not need any knowledge on the primary users signal. The primary incumbents can be detected by comparing the output of the energy detector with a threshold which depends on the noise floor. However, the biggest challenge with energy detection is that it can not distinguish between secondary transmission from primary transmission. As a result, for energy detection to be successful, it is necessary to forcefully quiet down all the secondary transmissions periodically which degrades the secondary network performance. Other alternative spectrum sensing methods include multi-taper spectral estimation [14] and wavelet transform based estimation. Multi-taper spectral estimation is a heuristic approximation to maximum likelihood PSD estimator. While the method is fairly applicable for wide-band sensing, it is still computationally demanding.

Though most of these above-mentioned works focus on cognitive radio and spectrum sensing, the investigation is mostly through analytical studies and there are very fewer attempts to implement a *cognitive radio prototype* with incumbent detection capability compliant with the FCC's incumbent-avoidance policy. In [15], a FPGA driven cognitive radio prototype is developed which is able to sense spectrum in the UHF band based on waveform analysis. However, as high as 6.1 and 6.9 seconds are needed for the actual sensing time for W-CDMA and WLAN, respectively in this research. A feature detector design for TV bands, with emphasis on the physical (PHY) layer is presented in [16]. While most of the above approaches follow a variant of waveform analysis or energy detection, a novel approach is introduced in [17], where incumbent detection method is based on PHY/CRC error counts. Though the research in [17] shows how the PHY/CRC error counts can be an indicator of existence of incumbents by conducting various experiments, it relies on static threshold and lacks the definitive and adaptive incumbent detection model.

III. Sensing/detection of primary incumbents

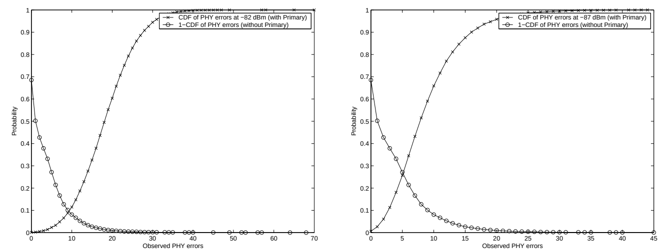
Incumbent detection is probably the most important feature of cognitive radio MAC and the entire secondary communication based on dynamic spectrum access is dependent on this as spectrum is shared with licensed devices. However, as mere energy, noise and interference detection is not sufficient to distinguish a primary incumbent communication from other cognitive radio (secondary) communications, thus it is important to develop a modified approach for accurate sensing/detection. Note that, the preamble of the packets transmitted by primary incumbents will always be different than that of the cognitive radio nodes thus building the basis for sensing/detection in our methodology. A PHY error is reported from the wireless physical layer interface to the upper layers if packets/signal without the intended 802.11 PHY preamble is observed by the physical layer interface [17]. Thus whenever the primary incumbents are present and transmitting, cognitive radios present in that channel will observe packets with different packet preamble or corrupted packet preamble (known as **observed PHY errors**). The biggest advantage of such PHY error-based methodology is that unlike energy detection, the CRs need not forcefully quiet down periodically.

However, there are several major challenges in the above-mentioned PHY error-based sensing approach. Firstly, the number of observed PHY errors are not fixed due to the unreliable nature of wireless medium. Secondly, even for a stable wireless channel quality, the number of observed PHY errors vary drastically based on the received energy strength. Thirdly, depending on the duration of sensing (sensing window), the observed PHY errors also vary. Lastly, and probably the most important, in our cognitive radio framework, we no longer assume the notion of periodic sensing by forcefully making all the radio nodes quiet because of the degraded throughput outcome. Rather, the CR nodes are allowed to carry out communications even at the time of sensing; however, the challenge with such approach is that the number of observed PHY errors may actually be suppressed.

Clearly, a simple static threshold of observed PHY error thus is not sufficient to sense/detect incumbents. If the threshold is set too low, the cognitive radio will incur high number of false alarms (assuming the existence of primary incumbent while the primary incumbent is actually not present). On the other hand, if the threshold is set too high, there will be a high probability of mis-detection (concluding there is no primary incumbent while the primary incumbent is actually present). Thus a methodology is needed to understand the distribution of PHY errors with received energy strength and other factors and a dynamic threshold study is necessary to accurately sense/detect the primary incumbents.

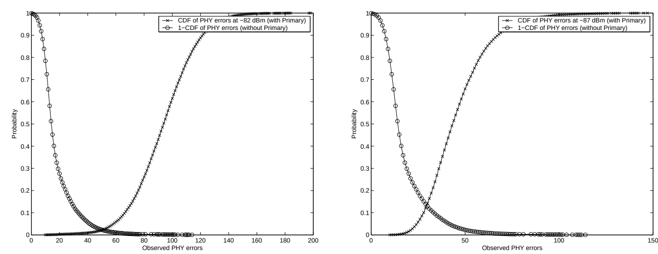
We study the distribution of observed PHY errors both in the presence and absence of primary incumbents (cordless phones and Agilent spectrum signal generator are configured and used as primary devices for the experiment purpose) and under different received energy strengths. We setup the primary devices with different transmitting powers and at various distances from the SpiderRadio nodes such that the received energy strength at the SpiderRadio varies from -82 dBm to -102 dBm. The reason behind choosing such low received energy for the experiment is the maximum uncertainty in the number of observed PHY errors at such low received energy. With the received energy strength from the primary incumbents being higher than the order of -80 dBm, the number of PHY errors is distinctly observed to be much greater than the scenario when primary incumbent is not present, making the detection decision very easy. Thus in this research, we focus solely on the low received energy strength from the primary incumbents for its complex uncertain nature. For sensing purpose, we consider our basic sensing window duration as 20 ms during which the number of observed PHY errors are reported to the upper layers. Note that, any other sensing duration could also be chosen as a basic sensing window as long as the PHY errors can be accurately reported through interrupt signaling from the wireless card physical layer to the upper layer.

In figure 1(a) and 1(b), we present the cumulative distribution function (CDF) and complementary cumulative distribution function (1-CDF) of the observed PHY errors with primary incumbent present and the primary incumbent not present respectively from the experimentally observed data at different received energy strengths. The sensing duration is assumed as 20 ms, i.e., 1-sensing window. Note that, CDF of the observed PHY errors with primary incumbent present is actually the representation of the probability of mis-detection given a certain PHY error threshold. Similarly, (1-CDF) of the observed PHY errors with primary incumbent NOT present is actually the representation of the probability of false alarm given a certain PHY error threshold. From the figure 1(a) and 1(b), it is clear that low threshold will reduce the mis-detection probability, however will increase the false alarm probability. On the other hand, high threshold will increase the mis-detection probability while reduce the false alarm case. Thus, if we need to minimize both false alarm and mis-detection probabilities simultaneously with equal weightage,



(a) (b)

Fig. 1. CDF and (1-CDF) of PHY errors for 1-sensing window at received signal strength a) -82 dBm, and b) -87 dBm



(a) (b)

Fig. 2. CDF and (1-CDF) of PHY errors for 5 window case at received signal strength a) -82 dBm, and b) -87 dBm

the intersection of the two curves gives the optimal minimized probability of error. The corresponding x-axis value will be the optimized threshold.

Note that, with 1-sensing window sensing, the simultaneous minimization of both the probabilities give us the optimal threshold; however, as the figure 1(a) and 1(b) indicate, the minimized error probability is around 0.11 when received energy strength is -82dBm and around 0.25 with worse received energy strength of -87dBm. This clearly indicates that with diminishing received energy strength, the performance of 1-sensing window also degrades steadily. Therefore, in this work, we introduce an n-moving sensing window methodology, i.e., PHY errors are observed over n-sensing window durations and moved continuously. Note that, n can take any value of 2, 3, 4 and so on. For illustration purpose, we present the experimentally observed results over 5-moving window in figure 2(a) and 2(b). Note that, with 5-moving window sensing strategy, the simultaneous minimization of both the probabilities give us the optimal threshold and as the figure 2(a) and 2(b) indicate the minimized error probability is now around 0.01 for -82dBm and 0.12 for -87dBm.

Given the experimentally observed results of mis-detection and false alarm, we now investigate the analytical model of mis-detection and false alarm probability distribution. For finding the correct model of the distributions, we follow the multi-variate regression analysis with curve fitting. Denoting P_m as the mis-detection probability, it can be expressed as,

$$P_m = \frac{1}{1 + e^{\alpha(\beta - r)}} \tag{1}$$

where, r is the normalized observed PHY errors. The parameters, α and β are functions of number of moving window strategy and received energy strength and are given by,

$$\alpha = \lambda_1 + \lambda_2 S + \lambda_3 e^{-n} + \lambda_4 S^2 + \lambda_5 (e^{-n})^2 + \lambda_6 S e^{-n} \quad (2)$$

where, n denotes the number of moving window strategy, S denotes the received energy strength and λ_i's are the regression variables. For example, the values of λ_i's as derived:

$$\lambda_1 = 55.1; \lambda_2 = -40.7; \lambda_3 = 405; \lambda_4 = 9.23; \\ \lambda_5 = -342; \lambda_6 = -59.4; \quad (3)$$

Similarly, the function of β can then be given by

$$\beta = \mu_1 + \mu_2 n + \mu_3 e^S + \mu_4 (e^S)^2 + \mu_5 n e^S \quad (4)$$

where, μ_i's are the regression variables and derived as:

$$\mu_1 = -0.0717; \mu_2 = 0.0197; \mu_3 = 0.0432; \\ \mu_4 = -0.00171; \mu_5 = 0.00225; \quad (5)$$

Similar to the mis-detection probability expression, the false alarm probability can be expressed as, $P_f = \frac{1}{1+e^{-\alpha'(\beta'-r)}}$, where α' and β' are also the functions of number of moving window strategy and received signal strength and can be derived in the exact similar manner as mentioned above.

Note that, at any stage of the sensing, when a cognitive radio makes a wrong decision about a primary incumbent (sensing failure), it faces one of two possible costs in terms of time units. If the wrong decision results in mis-detection, the cost (penalty) on the cognitive radio will be primary network policy specific and the cognitive radio will be blocked from spectrum access for a certain time. Note that, throughout this paper, we assume the cost as time units consumed. We assume this cost as C_1. On the other hand, if the wrong decision results in false alarm, the cognitive radio chooses to switch to some other clear band and it faces a cost of finding a clear spectrum band in the game. We assume this cost to be C_2. Once the probabilities of mis-detection and false alarm probabilities are calculated depending on observed PHY errors, n-moving window strategy and received signal strength, the aim is to find out the **dynamic optimized threshold** such that the penalty due to mis-detection and false alarm is minimized. The optimization problem now becomes minimization of the total expected cost as given by $E(C) = C_1 \times P_m + C_2 \times P_f$. Expanding $E(C)$, it can be written as

$$E(C) = \frac{C_1}{1 + e^{\alpha(\beta - r)}} + \frac{C_2}{1 + e^{-\alpha'(\beta' - r)}} \quad (6)$$

To find out the **dynamic optimized threshold**, r, the first derivative of (6) with respect to r is equated to 0, as given in

$$\frac{C_1 \alpha e^{\alpha(\beta-r)}}{[1 + e^{\alpha(\beta-r)}]^2} - \frac{C_2 \alpha' e^{-\alpha'(\beta'-r)}}{[1 + e^{-\alpha'(\beta'-r)}]^2} = 0. \quad (7)$$

Solving mathematical derivations, we find the optimal threshold, $r = r^*$, such that it is satisfied by,

$$\frac{cosh(\frac{\alpha(\beta - r^*)}{2})}{cosh(\frac{\alpha'(\beta' - r^*)}{2})} = \sqrt{(}\frac{\alpha C_1}{\alpha' C_2}). \quad (8)$$

The second order differentiation, $\frac{d^2 E(C)}{dr^2}$, can be shown to be positive (with simple derivations), proving the function $E(C)$ to be convex with respect to r. This also proves that the optimal value of $r = r^*$ is the desired minimizer for the total expected cost $E(C)$ and thus the ***dynamic optimized threshold*** in this scenario.

IV. Testbed Setup and Experimental Results

We setup our CR networks (consisting of laptops and soekris boards at a distance of 5–20 meters from each other) communicating with TCP data stream and are enabled with proposed incumbent sensing methodology and dynamic channel switching policy. To conduct extensive testing under different channel congestion environments, we carry out experiments under different network traffic scenarios in both indoor and outdoor environment. Each laptop running Linux 2.6 operating system is equipped with Orinoco 802.11 a/b/g PCMCIA wireless card. These Orinoco devices are equipped with Atheros 5212 (802.11 a/b/g) chipsets. The TX powers of these wireless devices were set to 100mW. In this test bed, cordless phones and Agilent signal generators are configured such that they can operate in the Wi-Fi spectrum bands and act as primary device of the bands. If any primary transmission is detected, the CR node(s) trigger the dynamic synchronization and channel switching to vacate the current frequency channel.

A. Experimental Results

To evaluate the effectiveness of the proposed primary sensing/detection methodology, figure 3 shows the probability of sensing failure with 1-sensing window and compares the dynamic threshold scheme with other static threshold schemes. As evident from the figure, the proposed dynamic threshold clearly produces better results in terms of reduced number of wrong decisions; probability of sensing failure is as low as 0.018. Figure 4 shows similar results with 5-sensing window with probability of sensing failure even more reduced (0.01376) thus clearly demonstrating the effectiveness of proposed n-moving window sensing in accurately sensing the primary incumbents.

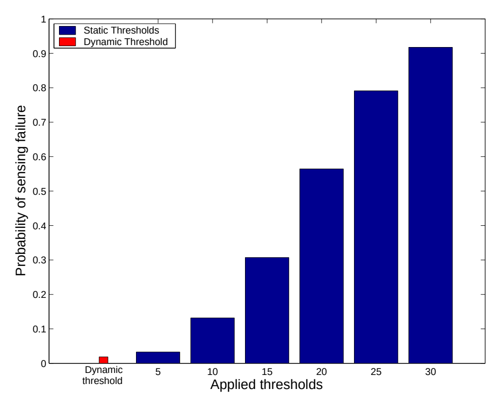


Fig. 3. Probability of sensing failure with 1-sensing window mechanism

The average penalty (cost in terms of time units) induced due to the wrong decisions (either mis-detection or false alarm) made by the CR nodes are presented in figure 5(a) and 6(a). Note that, at any stage of the sensing, when a CR node makes a wrong decision about a primary incumbent (sensing failure), it faces one of two possible costs in terms of time

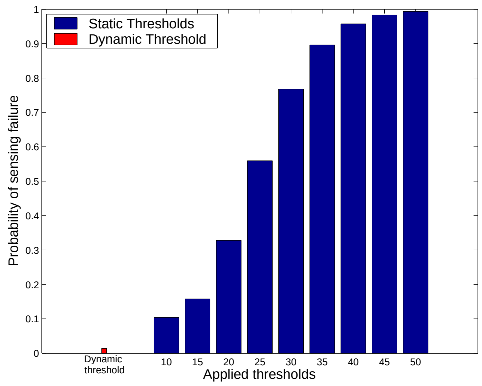
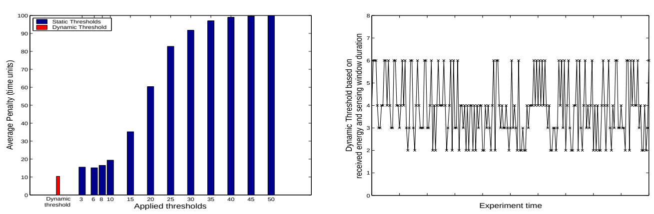


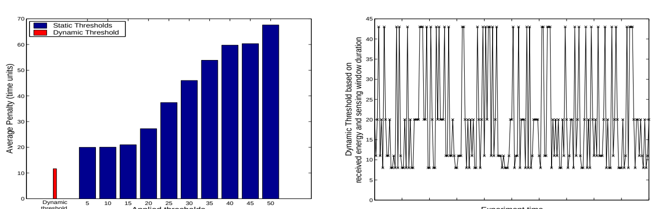
Fig. 4. Probability of sensing failure with 5-sensing window mechanism

units (spectrum access denial penalty for time C_1 in case of mis-detection or unnecessary switching cost penalty of time C_2 in case of false alarm). In our experiments, we assume, $C_1 = 100ms.$, while the value of C_2 is the actual time taken to switch and mostly varies in between 5 and 20 ms. It is seen from the figures that dynamic threshold based on received energy and n-moving window sensing clearly outperforms the static threshold mechanisms in inducing minimized penalty. For comprehensive purpose, we also demonstrate the corresponding dynamic threshold values from a snapshot of the experiment in figure 5(b) and 6(b).



(a) (b)

Fig. 5. a) Average penalty induced due to sensing failure; b) a snapshot of the corresponding dynamic thresholds as adapted by SpiderRadio based on received energy strength and 1-sensing window mechanism



(a) (b)

Fig. 6. a) Average penalty induced due to sensing failure; b) a snapshot of the corresponding dynamic thresholds as adapted by SpiderRadio based on received energy strength and 5-sensing window mechanism

V. Conclusions

A novel spectrum sensing methodology based on observed PHY errors, received signal strengths and n-moving window sensing is proposed in this paper. With the proposed sensing methodology, we have developed a generalized theoretical model that can be effectively applied to detect primary incumbents even at very low received signal strength and with very low sensing duration. To demonstrate the effectiveness of the proposed model, we have built a cognitive radio prototype (SpiderRadio) based on IEEE 802.11 MAC air-interface. Experimental results clearly demonstrate that SpiderRadio with the proposed sensing policy implementation can detect primary incumbents very fast with almost negligible sensing failure probability (as low as 0.01376).

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