Experimental Study of Spectrum Sensing Based on Distribution Analysis

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Abstract: Spectrum sensing has been identified as a key enabling cognitive radio (CR) to not interfere with primary users, by reliability detecting primary users' signals. Based on the OpenAirInterface platform, we performed at EURECOM a sensing demonstration in order to illustrate the spectrum sensing concept in one hand and to assess some of the existing algorithms performances in other hand. The platform is designed for a full software-radio implementation, in the sens that all protocol layers run on the host PCs under the control of a Linux real time operating system. The demonstration is composed of two nodes: a primary user with a varying transmission gain and four possible carrier frequencies, and a secondary user (or CR) user implementing three sensing algorithms (Energy detection, cyclostationarity detection, and model selection based detection). At the second node, the sensing results as well as their corresponding measured signal to noise ratio (SNR) over the four sub-bands are displayed in real time.

Keywords: Cognitive radio, OpenAirInterface platform, Spectrum Sensing, Model Selection Detection, Energy Detection, Cyclostationarity Detection.

1. Introduction

Historically, spectrum licensing and access have been static, leading to a low spectral efficiency as shown in a number of studies. For example, in [1] the spectrum occupancy measurements show that in some locations or at some times of day, 70 percent of the allocated spectrum may be sitting idle. This means that there are many *holes* in the radio spectrum that could be exploited. While this observation stands in some contrast to the general picture of spectrum allocation that one can infer from a frequency allocation chart, the presence of spectrum holes is understandable given how inefficiently radio resources, and spectrum in particular, are in fact utilized in current systems.

Recently, the FCC [2] has recommended that significantly greater spectral efficiency could be realized by deploying wireless devices that can coexist with the primary users, generating minimal interferences while taking advantage of the available resources. This class of devices that can reliably sense the spectral environment over a wide bandwidth, detect the presence/absence of legacy users (primary users) and use the spectrum only if the communication does not interfere with primary users is defined by the term cognitive radio [3].

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Cognitive radio is an emerging wireless communications concept in which a network or a wireless node is able to sense its environment, and especially spectrum holes, and change its transmission and reception chains to communicate efficiently without interfering with licensed users. Spectrum sensing has been identified as a key enabling cognitive radio to not interfere with primary users, by reliability detecting primary users' signals and it is often considered as a detection problem. Focusing on each narrow band, existing spectrum sensing techniques are widely categorized into energy detection [4] and feature detection [5]. While it is simpler and less computing, the energy detector suffers from the fact that its performances are susceptible to unknown or changing noise levels and interferences. In addition, the energy detector does not differentiate between modulated signals, noise, and interference but can only determine the presence of the signal. It does not work if the signal is direct-sequence or frequency hopping signal, or any time varying signal. On the other hand, cyclostationary models have been shown in recent years to offer many advantages over stationary models. Thus, cyclostationary feature detection performs better than the energy detector. However, it is computationally complex and requires significantly long observation time. Recently, a new sensing method [6] based on model selection tools like Akaike information criterion (AIC) [7] and Akaike weights [8] has been proposed. Using the Akaike weights information, this method can decide whether the received signal distribution fits the signal once or not. As we don't need any prior information about either the received signal or the noise, then the detection of vacant frequency band is done blindly. Indeed, the computation burden of this method still lower as well as the energy detector.

In this paper, we present the software and hardware architecture of the sensing demonstration that we performed in our laboratory. It is based on the OpenAirInterface platform available at EURECOM [9]. As we are involved in the Eureopean SENDORA project [10], the aim of this demonstration is first to illustrate the spectrum sensing concept and second to assess the the detection performances of some of the existing algorithms.

The paper is organized as follows. The next section describes the OpenAirInterfce platform. In Section 3., the sensing demonstration is presented and the implemented detection algorithms are described. Measurements and results are provided in Section 4., and Section 5. concludes the paper.

2. OpenAirInterfce Platform

The spectrum sensing demonstration that we performed is based on the OpenAir hardware/software development platform at Eurecom. The platform consists of dual-RF CardBus/PCMCIA data acquisition cards called CardBus MIMO I (see Fig. 1). The RF section is time-division duplex and operates at 1.900-1.920 GHz with 5 MHz channels and 21 dBm transmit power per antenna for an OFDM waveform. EURECOM has a frequency allocation for experimentation around its premises in Sophia Antipolis. The cards house a medium-scale FPGA (Xilinx X2CV3000) allowing for an embedded HW/SW system implementing the physical layer. Besides implementation in the FPGA, for advanced PHY algorithms and real-time testing prior

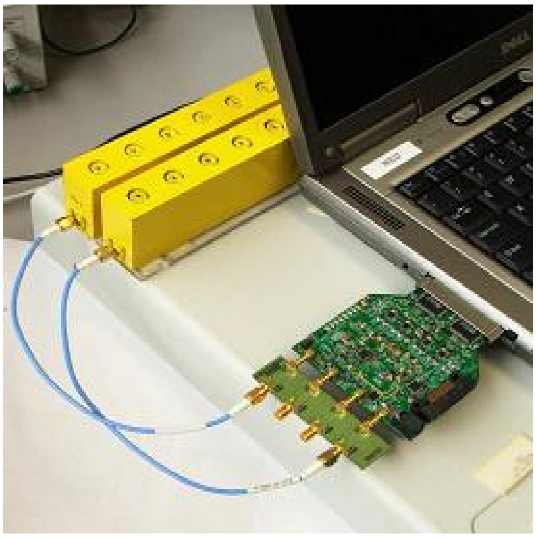

Figure 1: User equipment with PCMCIA Card.

to HW implementation, the PHY layer is usually run in real-time on the host PC under the real-time operating system (RTOS) RTAI. The physical (PHY) layer of the platform targets WiMax and UMTS LTE like networks and thus uses multiple-input multiple-output orthogonal frequency division multiples access (MIMO-OFDMA) as modulation and multiple access technique. The MIMO-OFDMA system provides the means for transmitting several multiple-bitrate streams (multiplexed over subcarriers and antennas) in parallel.

Sampling rate	7.68 Msamp/s
Frame length	64 symbols (2.67 ms)
Symbol (DFT/IDFT) size	256 samples
Prefix length	64 samples
Useful carriers	160

Table 1: The transmitted OFDM signal parameters

The physical resources are organized in frames of OFDM symbols. A nominal OFDMA configuration is shown in Table 1. One frame consists of 64 symbols and is divided in an UPLINK transmission time interval (TTI) and a DOWNLINK TTI. More information can be found on the openairinterface.org website.

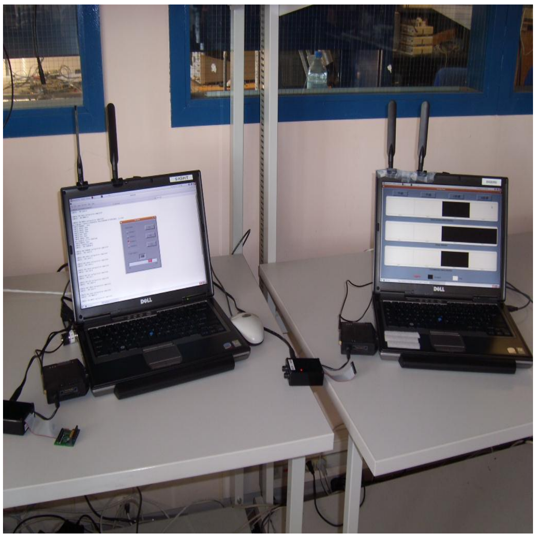

Figure 2: The sensing demonstration.

3. Sensing Demonstration

As we can see from Fig. 2, the demonstration consists of two laptops one for transmission and one for reception; each of them is equipped with the CardBus MIMO1 data acquisition card and two antennas. To simulate the SNR variation, the transmission gain (TX_G) is adjusted within the interval [0-256]. However the reception gain (RX_G) can be set manually or (by default) automatically. Three sensing algorithms were selected for this demonstration: model selection based detection, energy detection and cyclostationarity detection. They are running continuously and their results are graphically displayed in real time. At reception side, we developed a Graphical User Interface (GUI) allowing the user to select one of the four sub-bands (with 1.25 MHz of width) of the EURECOM frequency allocation around 1917 MHz, the transmission gain and running/stopping the transmission (see Fig.3). At reception side, another GUI is developed and displays, in real time, the measured SNR and the detection results of the sensing algorithms in each sub-band (see Fig. 4).

In the rest of this section, we present the main ideas of the implemented algorithms.

3.1 — Energy detection

The block-diagram of an energy detector is given in Fig. 5. The input band-pass filter selects the center frequency and bandwidth W of interest. Following that, a squaring device measures the received signal energy and an integrator determines the observation time T. Finally, the output of the integrator, V, is compared with threshold K to decide whether the signal is present or no.

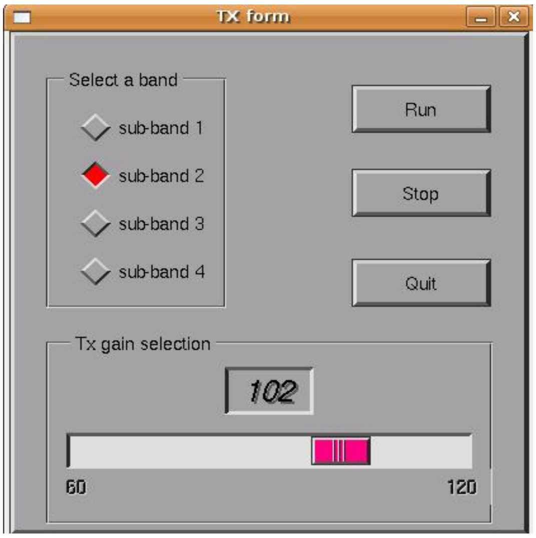

Figure 3: Graphical user interface for transmission side.

Figure 4: Graphical user interface for sensing side.

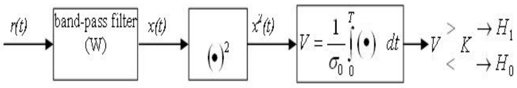

Figure 5: Typical block diagram of an energy detector.

3.2 — Cyclostationarity Detection

To detect the cyclostationarity over the received signal, we make the choice of the well known statistical test proposed by Dandawat and Giannakis [11]. This test uses the asymptotic properties of the cyclic autocorrelation function estimates $\hat{R}_{xx}^N$. For a candidate cycle-frequency α, it makes the following hypotheses testing:

$$\begin{array}{lcll} H_0 & : & \hat{R}_{xx}^N = \epsilon_{xx}^N & \text{for all arguments} \\ H_1 & : & \hat{R}_{xx}^N = R_{xx} + \epsilon_{xx}^N & \text{for some arguments} \end{array} \tag{1}$$

where R_{xx} is the (nonzero) cyclic autocorrelation function at cycle-frequency α of the process x, and ϵ_{xx}^N is a zero mean random variable. The asymptotic statistics of ϵ_{xx}^N are a classic result, from which an hypothesis test is built, allowing one to take statistical decision.

3.3 — Model Selection Based Detection

It is well known that the ambient noise can be modeled using Gaussian distribution. Thus, this approach proposes to analyze Akaike weights information in order to determine the position of vacant bands in the spectrum of the received signal [6]. We consider that the ambient noise can be modeled using Gaussian distribution and its norm can be modeled using Rayleigh distribution. The Akaike weights can be interpreted as an estimate of the probability that the received signal distribution fits the Gaussian one, and given by:

$$\mathrm{W}_j = \frac{e^{\frac{1}{2}\Phi_j}}{\sum_{i=1}^{N} e^{\frac{1}{2}\Phi_i}} \tag{2}$$

where Φ_j denotes the AIC differences defined by:

$$\Phi_j = \mathrm{AIC}_j - \min_i \mathrm{AIC}_i \tag{3}$$

where $\min_i \mathrm{AIC}_i$ denotes the minimum AIC value over all analysis windows [6].

In particular, we scan the spectrum band of the received signal with the mean of frequency sliding window. For each sub-band of interest, we first compute AIC values and then the Akaike weights. Once we get the corresponding values, we shift the window by one sample till the end of the band. Following taht, we give the position of vacant sub-bands over the spectrum. In fact, the maximum value of Akaike weights determines the position of one vacant sub-band (called reference sub-band). Finally, we fix a threshold in order to decide on the nature of the received signal. Here, we can decide whether primary user signal exists or not. If the computed Akaike weights of Gaussian distribution is lower than the threshold, we can conclude that any primary user signal exists (vacant sub-band). Then, a secondary user can utilize the sub-band. Otherwise, if the computed Akaike weights of Gaussian distribution are larger than the threshold, the decision information of the algorithm is the presence of the primary user (occupied sub-band).

4. Measurements and Results

In addition to the illustration aspect of the demonstration, we are also interested on the empirical performances study of the above detection algorithms. Fig. 6 shows the experimental probability of detection versus SNR ranging between -18 dB and 0 dB at a constant false alarm rate ($P_F = 0.05$) for the three sensing detectors. From this figure, we can observe that the energy detector is the worst due to the fact that it doesn't have any prior information about the noise level (or variance) that should be estimated every time the detector is run. However the best performances are obtained with the cyclostationary detector since it is independent from the noise and the received signal parameters (cycle-frequency) are known at sensing side. When prior knowledge about either the noise or the received signal are unavailable to the sensing node, the model selection based detection will take the advantage over the two other methods as it can detect in a blind way.

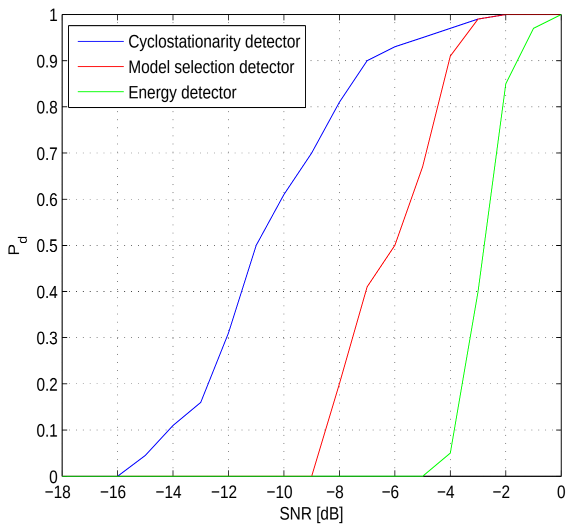

Figure 6: Probability of detection vs. SNR for the model selection detector, energy detector and cyclostationary detector with $P_F = 0.05$.

5. Conclusion

We have presented the sensing demonstrator that we performed at EURECOM. It is based on the OpenAirInterface platform and illustrates the concept of spectrum sensing, the actual major difficulty faced by the cognitive radio. Experimental results show the powerful of the cyclostationarity detector and the model selection based detector over the energy detector. However a great benefit in term of detection performances can be reached when cooperation among second user is considered. In a next step, the demonstration will be evolved to consider more than one second user in order to measure the benefit from cooperation.

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