Spectrum Sensing for Cognitive Radio Exploiting Spectral Masks

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***Abstract*—In this paper[1], we will provide a straightforward look at semi blind spectrum sensing technique exploiting spectral masks. The proposed spectrum sensing technique is deployed on two stages. At a first level, the spectral masks database is built during the synchronization phase of the transmission, then in a second processing, a matched filter based detection is deployed to infer the nature of the sensed signals. Simulation results obtained for noisy OFDM signals witness the efficiency of the proposed detector. The performance comparison with a simple matched filter shows that the new designed scheme achieves close performance to matched filtering while preserving a fundamental property of blind processing.**

***Index Terms*—Cognitive radio, blind sensing, spectral masks, matched filtering.**

I. Introduction

During the last decades, we have witnessed a great progress and an increasing need for wireless communications systems in order to satsfy costumers demands of more flexible, wireless, smaller, more intelligent and practical devices and thus markets invaded by smartphones, PDAs, tablets and Netbooks.

All this need for flexibility and more ”mobile” devices lead to more and more needs to afford the spectral resources that shall be able to satisfy costumers need for mobility. But, as wide as spectrum seems to be, all those needs and demands made it a scarce resource and highly misused.

Trying to face this shortage in radio resources, telecommunication regulators and standardization organisms recommended sharing this valuable resource between the different actors in the wireless environment. The Federal Communications Commission (FCC), for instance, defined a new policy of priorities in the wireless systems, giving some privileges to some users, called Primary Users (PU) and less to others, called Secondary Users (SU), who will use the spectrum in an opportunistic way with a minimum interference to PU systems.

Cognitive Radio (CR) as introduced by Mitola [1], is one of those possible devices that could be deployed as SU equipments and systems in Wireless networks. As originally defined, a CR is a self aware and ”intelligent” device that can adapt itself to the Wireless environment changes. Such a device is able to detect the changes in Wireless network to which it is connected and adapt its radio parameters to the new opportunities that are detected. This constant track of the environment change is called the spectrum sensing function of a CR device.

Thus, spectrum sensing in CR aims in finding the holes in the PU transmission which are the best opportunities to be used by the SU. Many statistical approaches already exist. The easiest to implement and the reference detector in terms of complexity is still the Energy Detector (ED). Nevertheless, the ED is highly sensitive to noise and does not perform well in low Signal to Noise Ratio (SNR). Other advanced techniques based on signals modulations and exploiting some of the transmitted signals inner properties were also developed. For instance, the detector that exploits the built-in cyclic properties on a given signal is the cyclostationary Features Detector (CFD). The CFD do have a great robustness to noise compared to ED but its high complexity is still a consequent draw back. Some other techniques, exploiting a wavelet approach to efficient spectrum sensing of wideband channels were also developed [2]. The signal spectrum over a wide frequency band is decomposed into elementary building blocks of subbands that are well characterized by local irregularities in frequency. As a powerful mathematical tool for analyzing singularities and edges, the wavelet transform is employed to detect and estimate the local spectral irregular structure, which carries important information on the frequency locations and power spectral densities of the subbands. Along this line, a couple of wideband spectrum sensing techniques are developed based on the local maxima of the wavelet transform modulus and the multi-scale wavelet products.

There are several spectrum sensing techniques that were proposed for CR [4]. A few completely blind sensing methods that do not consider any prior knowledge about the transmitted signal have been derived in the literature, but all of them suffer from the noise uncertainty and fading channel variations. One of the most popular is the energy detector (ED) [5]. Despite its easy implementation and low complexity, the ED does not perform well at a low signal-to-noise-ratio (SNR) and cannot differentiate between noise and signals. Moreover, this kind of detector is inconvenient when the level of noise is completely unknown. Two other blind techniques were proposed at EURECOM. The first technique analyzes the distribution of the primary user received signal to sense vacant frequency sub-bands over the spectrum band. Specifically, the

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distribution analysis detector (DAD) exploits model selection tools like the Akaike information criterion (AIC) to detect vacant holes in the spectrum band [6] [7]. In this paper, we present a novel approach to spectrum sensing combining a spectral mask estimation via algebraic tools and matched filtering approach. The paper is organized as follows. After the presentation of the common framework study in Section II, the spectrum sensing techniques are discussed in Section III. In Section IV, the performance evaluation and advantages are described. Finally, Section V concludes the paper.

II. System Model

In this section, we describe the system model that will be used throughout this paper. For the radio channel measurement we have chosen to thoroughly investigate the DVB-T primary user system. In this system, the transmitted signal is convolved with a multi-path channel and a Gaussian noise is added. The received signal at time n, denoted by x_n, can be modeled as:

$$x_n = A_n s_n + e_n \tag{1}$$

where A_n being the transmission channel gain, s_n is the transmit signal sent from the primary user and e_n is a stationary, Gaussian noise with zero mean. The goal of spectrum sensing is to decide between the following two hypotheses:

$$x_n = \begin{cases} e_n & \mathrm{H}_0 \\ A_n s_n + e_n & \mathrm{H}_1 \end{cases} \tag{2}$$

We decide a spectrum band to be unoccupied if it contains only noise, as defined in H_0; on the other hand, once there exist primary user signals besides noise in a specific band, as defined in H_1, we say the band is occupied. Let P_F be the probability of false alarm given by:

$$P_F = P(\mathrm{H}_1 \mid \mathrm{H}_0) = P(x_n \text{ is present} \mid \mathrm{H}_0) \tag{3}$$

that is the probability of the spectrum detector having detected a signal under hypothesis H_0, and P_D the probability of detection expressed as:

$$\begin{aligned} P_D &= 1 - P_M = 1 - P(\mathrm{H}_0 \mid \mathrm{H}_1) \\ &= 1 - P(x_n \text{ is absent} \mid \mathrm{H}_1) \end{aligned} \tag{4}$$

the probability of the detector having detected a signal under hypothesis H_1, where P_M indicates the probability of missed detection.

We develop in this paper a common framework to make a comparison of three blind sensing algorithms. In order to decide on the nature of the received signal, we calculate a threshold for each detector. The decision threshold is determined using the required probability of false alarm P_{FA} given by (3). The threshold Th for a given false alarm probability is determined by solving the equation:

$$P_{FA} = P(T(x_n) > Th | H_0) \tag{5}$$

where $T(x_n)$ denotes the test static for the given detector. Note that, for each detector we compute a particular threshold Th that tests the decision statistic based on a fixed false alarm probability value.

III. Spectrum Sensing Techniques

A. Matched Filtering

Matched filter is the optimum detector of a known signal in the presence of additive Gaussian noise. It is the linear filter that maximizes the SNR of the output. The output of the matched filter is given by

$$y = s^H \Sigma_n^{-1} x \tag{6}$$

where x is the observation vector, s is the known deterministic signal to be detected, and Σ_n is the noise covariance matrix. Assuming that the noise is Gaussian it follows that the output y is Gaussian as well since it is a linear transformation of a Gaussian random vector. The mean of y is zero under H_0 and $s^H \Sigma_n^{-1} s$ under H_1. The variance is $s^H \Sigma_n^{-1} s$ under both hypotheses. Consequently, the hypothesis test may be defined as:

$$y \mathop{\gtrless}_{H_0}^{H_1} \lambda$$

B. Algebraic Spectrum Estimation

The AD is a new approach based on the advances lead in the fields of differential algebra and operational calculus. In this paragraph we present how such technique can be used in order to estimate spectrum shape. In this approach, the mathematical representation of the amplitude spectrum of the received signal X_n in frequency domain is assumed to be a piecewise N^{th} order polynomial signal expressed as follows:

$$X_n = \sum_{k=1}^{K} \chi_k[n_{k-1}, n_k] p_k(n - n_{k-1}) + E_n \tag{7}$$

where $\chi_k[n_{k-1}, n_k]$ is the characteristic function, $p_k(n)$ is an N^{th} order polynomials and E_n is the additive corrupting noise. K is the number of subsection, and n is the normalized frequency. For simulation results, $M/K = 1000$.

Let S_n be the clean version of the received signal given by:

$$S_n = \sum_{k=1}^{K} \chi_k[n_{k-1}, n_k] p_k(n - n_{k-1}) \tag{8}$$

And let b be a frequency bandwidth such that in each interval $I_b = [n_{k-1}, n_k] = [\nu, \nu + b]$, $\nu \geq 0$ one and only one change point occurs. Denoting $S_\nu(n) = S_{n+\nu}$, $n \in [0, b]$ for the restriction of the signal in the interval I_b and redefine the change point relatively to I_b say n_ν given by:

$$\begin{cases} n_\nu = 0 & \text{if } S_\nu \text{ is continuous} \\ 0 < n_\nu \leq b & \text{otherwise} \end{cases} \tag{9}$$

The primary user presence on a sensed sub-band is equivalent to finding $0 < n_\nu \leq b$ in this band. The AD gives the opportunity to build a whole family of detectors for spectrum sensing, depending on a given model order N. Depending on this model order, we can show that the performance of the AD increases as the order N increases.

The proposed algorithm is implemented as a filter bank composed of N filters mounted in a parallel way. The impulse response of each filter is:

$$h_{k+1,n} = \begin{cases} \frac{(n^l(b-n)^{N+k})^{(k)}}{(l-1)!} & 0 < n < b \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where $k \in [0..N-1]$ and l is chosen such that $l > 2 \times N$. The proposed expression of $h_{k+1,n}$ was determined by modeling the spectrum by a piecewise regular signal in the frequency domain and casting the problem of spectrum sensing as a change point detection in the primary user transmission [8]. Finally, in each stage of the filter bank, we solve the following equation:

$$\varphi_{k+1} = \sum_{m=0}^{M/K} W_k h_{k+1,m} X_m \quad (11)$$

where W_m are the weights for numeric integration defined by:

$$\begin{array}{ll} W_k = 0.5 & \text{for } k = 0, M \\ W_k = 1 & \text{otherwise} \end{array} \quad (12)$$

The mask is thus obtained from the equation below:

$$Df = \prod_{k=0}^{N-1} |\varphi_{k+1}| \quad (13)$$

C. Spectral Masks based detection

In the proposed algorithm the process is done in two phases. The algorithm is "semi-blind" as it creates the a priori information to be used in a first phase, then makes benefit of the created database containing the spectrum masks.

The mask of a received signal x_n is estimated via the filter bank output: $Df = \prod_{k=0}^{N-1} |\varphi_{k+1}|$. Each detected mask is to be stored in a "database" as a first step and then the matched filtering is done by correlating the received signal x_n and the stored mask s_n. The following pseudo-code describes the sensing algorithm:

Algorithm 1 Spectral Masks based spectrum sensing

Step1: Building Masks Database **while** *receiving SYNC frames* **do**
  Estimate spectral mask given by: $Df = \prod_{k=0}^{N-1} |\varphi_{k+1}|$
  Store masks in database.
end
Step2: Detection of PU presence exploiting masks DB **while** *receiving DATA frames* **do**
  Calculate thresholds corresponding to Matched Filtering
  Compute test statistic $y = s^H \Sigma_n^{-1} x_n$.
  Compare test statistic to threshold and infer about PU presence
end

IV. Performance Evaluation

For simulation results, the choice of the DVB-T primary user system is justified by the fact that most of the primary user systems utilize the OFDM modulation format. This choice is done in the context of the European research project SENDORA [14]. The channel models implemented are AWGN, Rician and Rayleigh channels. The latter two correspond to the two different types of propagation that have to be handled in practice, namely line-of-sight (LOS) and Non-line-of-sight (NLOS). Slow fading is simulated by adding log-normal shadowing. The simulation scenarios are generated by using different combinations of parameters given in Table I. The evaluation framework for all simulations has been implemented in Matlab.

Bandwidth	8MHz
Mode	2K
Guard interval	1/4
Channel models	Rayleigh/Rician (K=1)
Maximum Doppler shift	100Hz
Frequency-flat	Single path
Sensing time	1.25ms
Location variability	10dB

TABLE I
The transmitted DVB-T primary user signal parameters

Fig. 1 show the output of the first stage of the proposed technique, which is the mask derived from the OFDM transmission. Those kind of masks are stored in a database and are to be matched with the received signals in the second phase.

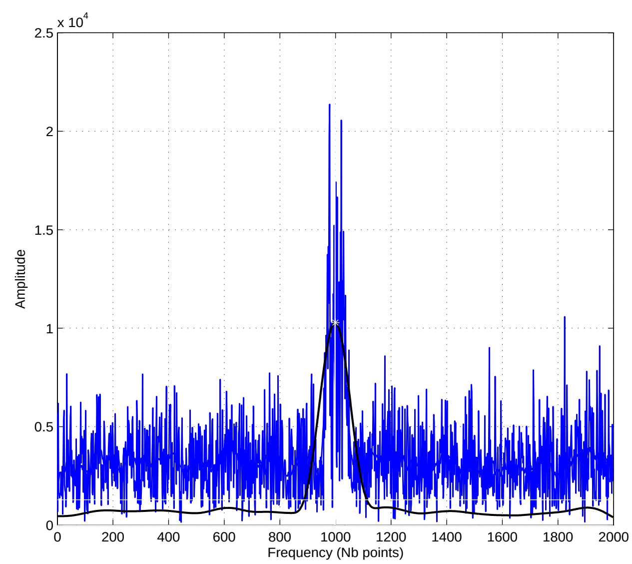

Fig. 1. Spectral Mask derivation via Algebraic framework

Fig. 2 depicts the detection comparison of a simple matched filter and the proposed technique. This figure shows the probability of detection versus SNR ranging between -20 dB and 0 dB at a constant false alarm rate ($P_{FA} = 0.05$). We used here a DVB-T primary user system with Rician channel. Threshold values are computed according to the common framework and depend only on the P_{FA} value. From the simulation results, we show that the proposed technique is performing quiet similar to the matched filtering under the same SNR condition. Our technique (star curve) is shown to operate quiet closely to the matched filtering (dots) and has the benefit to build its own signals database on a first stage and then perform a matched filtering with received signals.

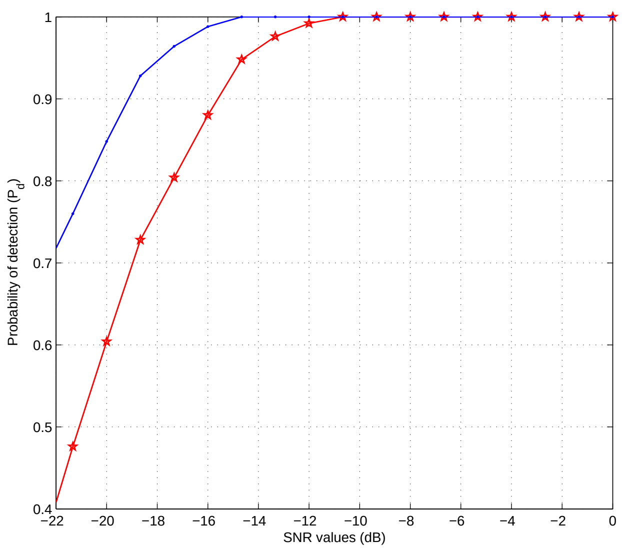

Fig. 2. Probability of detection vs. SNR with $P_{FA} = 0.05$ for a DVB-T primary user system with Rician channel.

V. Conclusion

We present in this work a new sensing technique which combines matched filtering to an algebraic method to detect spectrum masks. In a first step, we designed a filter bank, derived from an algebraic framework mostly used in control theory. Then, we applied a matched filter in order to identify and locate spectrum holes. The performance comparison with a simple matched filter shows that the new designed scheme achieves close performance to matched filtering while preserving a fundamental property of blind processing.

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