Fast and Reliable Sensing Using a Background Process for Noise Estimation

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***Abstract*—This paper presents an efficient way to ensure a good detection performance by implementing algorithms running in background a reliable noise estimation process. The proposed solution operates at two different time scales: a slow time scale to determine in adjacent sub-bands the supposed slowly varying noise level, and a faster time scale to determine in the band of interest the presence of signal, using a reliable energy detection solution. In order to identify the free bands where the noise variance can be estimated, the paper describes several blind and semi-blind strategies based on the statistical properties of the received signal. One of the benefits of the proposed solution is that the output of the described algorithm can populate the database of free/occupied bands, which classically needs to be regularly updated in a cognitive radio architecture.**

I. Introduction

The electromagnetic radio spectrum is a scarce natural resource, the use of which by telecommunication systems is licensed by governments. For a long time, spectrum management was based on rigid partitioning. As a consequence, most of the spectrum bands are vastly underutilized, even in urban environments. However, with the increasing demand of wireless products and services (especially bandwidth-greedy applications), a need for new technologies and policies meant to support a greater density of wireless devices has arisen [1]. Fortunately, emerging technologies including Cognitive Radio and Software-Defined-Radio (SDR) [2], are contributing to make this possible.

A Cognitive Radio system uses sophisticated signal processing at least at the physical layer in order to adapt to the environmental changes. Cognitive Radio could then provide means to efficiently use the electromagnetic spectrum by autonomously detecting and exploiting empty spectrum (*spectrum White Spaces*) or by intelligently sharing spectrum with other users (e.g., by meeting given interference constraints). Arising from the evolution of software radio, Cognitive Radio presents the possibility of numerous revolutionary applications.

On 23^{rd} September 2010 FCC published a report 10-174 [3] with the scope of finalizing rules to make the unused spectrum in the TV bands available for unlicensed broadband wireless devices. The report was favorable to geo-location with database approach, but leaves a backdoor open for any other contribution from the spectrum sensing research field.

If the geo-location database access method is not providing adequate and sufficient reliable protection, spectrum sensing should be used in order to help identifying the White Spaces in the considered frequency band. Spectrum sensing has come a long way and today it is sufficiently developed and reliable for determining access to the TV bands and other spectrum.

In the Cognitive Radio context, a mobile radio system occupies as a secondary user a given spectrum band denoted by B_0. This means that the secondary user is currently using B_0 to transmit and receive data because the owner of the band, the primary user, was previously detected as absent from its band B_0.

The secondary user (or opportunistic user) is allowed to occupy B_0 provided that it is able to stop using B_0 immediately if the primary user decides to use B_0. The secondary system may have sensing capabilities and thus be able to detect the incoming primary user very quickly and with a very high reliability.

In order to address the situation described above, different types of signal detectors have been developed. The most typical detector (and also the simplest one) is the Energy Detector (ED) [4]. The ED is very fast, but it is very reliable only if the noise variance is known or well estimated. Aside from possibly taking a longer acquisition time, the methods that reliable estimate the noise variance also need to be able to evaluate the presence/absence of the useful signal in the analyzed band.

The current state of the art, therefore, consists in making a compromise: either use a fast detector and accept that the ED performance is possibly affected by a bad noise variance estimate, or choose a detector different from ED to obtain very high performance, which in turn will be slower. In other words, having a very high probability of detection and a fast algorithm altogether still remains a challenge.

The remainder of this paper is organized as follows. The next section describes the system and signals model, the main assumptions and the addressed problem. Section III presents the detection issues of the detectors relying on wrong noise estimation. The proposed method is explained in Section IV. Finally, simulation results are presented in Section V and the conclusions are discussed in Section VI.

II. System and Signal description

A. System description

We consider the system depicted in Fig. 1 with a primary system transmitting in a frequency band which is also accessed by an opportunistic secondary system. We assume that the Cognitive Radio nodes are endowed with a sensing capability.

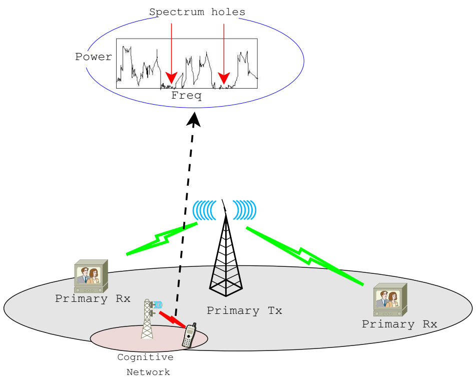

Fig. 1. Cognitive Radio access to a licensed spectrum: Cognitive Radio senses the spectrum in order to find spectrum holes where it could transmit.

In Fig. 1, the spectrum sensing allows to detect possible primary signals in order to stop any secondary transmission. Then, the cognitive system monitors the primary frequency band for *spectrum White Spaces* and uses these frequencies to transmit. One example of such primary systems is the TV broadcast. It has already been proven that the TV spectrum is underused and thus secondary systems can transmit using digital techniques needing much smaller amount of spectrum [5]. It can be envisaged to apply the same cognitive strategy to LTE Network system. The LTE system should use White Space spectrum (e.g., $470-790MHz$) in addition to their own licensed spectrum. This additional spectrum allows mobile operators to gain additional bandwidths, which is in the benefit of the user. In other words, it could be used to enhance the coverage or capacity for a mobile operator.

It is worth noting that, thanks to its relatively low infrastructure cost and compatibility with legacy primary systems, spectrum sensing is being considered for inclusion in the IEEE 802.22 standard for cognitive wireless regional area networks operating in unused television channels [6].

B. Signal Description

This section is related to the general description of the Primary User's (PU) transmitter. The primary user can be a DVB-T system transmitting in the $470-790MHz$ band, or a Programme Making and Special Event (PMSE) system transmitting in the $470-790MHz$ band.

While the DVB-T and LTE systems are using Orthogonal Frequency Division Multiplexing (OFDM) techniques, the PMSE devices are usually employing Frequency Modulations (FM) or Quadrature Phase Shift Keying (QPSK) modulations [7]. In the next paragraphs we describe the primary user signal characteristics (i.e., OFDM, FM and QPSK).

1) OFDM Signal Description: DVB-T is the standard for the broadcast transmission of digital terrestrial television. As previously mentioned, this standard uses the OFDM modulation scheme for signal transmission. An OFDM baseband signal can be generated using the expression

$$s_{\text{OFDM}}(t) = \frac{1}{\sqrt{N}} \sum_{k=0}^{K-1} \sum_{n=0}^{N-1} a_{k,n} e^{-\frac{2jn(t-T_G-kT_S)}{T_U}} g(t-kT_S), \quad (1)$$

where T_U is the useful OFDM symbol time, T_G is the cyclic prefix length, and $T_S = T_U + T_G$ is the total OFDM symbol duration time, which is obtained by adding a cyclic prefix to the useful symbol period. K is the number of OFDM symbols, N is the number of subcarriers, $g(t)$ is the shaping function equal to 1 if $0 \leq t < T_S$ and 0 otherwise. The sequence $a_{k,n}$ represents the transmitted data symbol at subcarrier n and OFDM symbol k. For instance, the sequence $a_{k,n}$ could be provided from a QPSK modulation.

2) PMSE Signal Description: Programme Making and Special Events can use digital modulations such as QPSK or analog modulation such as FM. In the next subsections we are describing the QPSK and FM signal expressions.

a) QPSK modulation: In QPSK modulation, the information is encoded in the phase of the transmitted signal. The complex constellation after sampling at the QPSK symbol period T_S can be written as [8]

$$a \in \left\{ \frac{A}{\sqrt{2}} \cos\left(2\pi \frac{n-1}{4}\right) + j\frac{A}{\sqrt{2}} \sin\left(2\pi \frac{n-1}{4}\right) \right\}, \quad (2)$$

where $n \in \{1, 2, 3, 4\}$ and A^2 is the symbol energy.

b) Frequency Modulation: Let the baseband data signal be $s(t)$ and the sinusoidal carrier be $c(t) = A_c \cos(2\,\pi\, f_c\, t)$, where f_c is the frequency of the carrier and A_c is its amplitude. The frequency modulation combines the carrier with the baseband data signal to get the transmitted signal as

$$s_{\text{FM}}(t) = A_c \cos\left(2\,\pi\, f_c\, t + 2\,\pi\, f_\Delta \int_0^t s(\tau)\, d\tau\right). \quad (3)$$

The instantaneous frequency is then expressed as $f(t) = f_c + f_\Delta\, s(t)$, where f_Δ is the frequency deviation.

III. Energy Detection

Energy detection is a well known detection method [4] mainly used because of its simplicity. The basic functional method involves an energy computation block (i.e., a squaring device and an integrator) and a comparison block. The threshold used in the comparison block is chosen according to a desired false alarm probability $P_{FA,target}$ [9] and given by

$$\gamma = \frac{\sqrt{2}}{\sqrt{N}} \sigma_n^2 Q^{-1}\left\{P_{FA,target}\right\} + \sigma_n^2, \quad (4)$$

where N is the number of samples of the digital signal and σ_n^2 is the noise variance. We denote by Q^{-1} the inverse of the Q function defined by

$$Q\,(t) \equiv \frac{1}{\sqrt{2\pi}} \int_t^\infty exp\left(-\frac{u^2}{2}\right) du = \frac{1}{2}\left(1 - erf\left(\frac{t}{\sqrt{2}}\right)\right). \quad (5)$$

It can be shown that a precise knowledge of the noise variance is necessary in order to compute the threshold value γ.

Subsequently, a wrong computed threshold value is affecting both the detection probability P_D and the real false alarm probability $P_{FA,real}$, which differs from the $P_{FA,target}$. In the next subsections we are going to study reliable noise estimation methods which are using the statistical properties of the received signal.

IV. Background Noise Estimation Method

The proposed approach for energy detection consists in using two components (a) and (b), which operate in different bands and on different timescales:

- (a): A long term component, in charge of monitoring the bands B_i in the neighborhood of B_0, in order to identify a band where there is only noise, and estimate the noise variance in the identified band. This component is triggered every T_2.
- (b): A short term component, in charge of detecting a primary signal in B_0 as soon as it appears. This detector is an ED detector whose input is the noise variance estimated in the component (a). This component is triggered every T_1. As represented in Fig. 2, typically $T_1 << T_2$ and it is assumed that the noise variance is stationary during T_2.

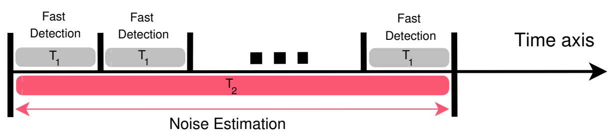

Fig. 2. Trigger periods for short and long term (background) components.

The short term component (b) is using the ED because it is fast, but the detection is reliable only when the noise variance estimates provided by (a) are very good. In order to achieve this goal, two main aspects are considered:

1) The noise variance can be well estimated on portions of bands (different from the band of interest B_0) in which it was previously checked that no signal is present.
2) The noise variance is assumed to vary slower than the periodicity T_1 at which the ED must be triggered.

Because of the 2^{nd} condition, we can address the 1^{st} one by implementing algorithms which are able to reliably detect the presence of signal, without knowing the noise variance, and which possibly take much more time than T_1. Therefore, we divide the component (a), into two main modules:

- (a_1): the module which performs the identification of the suitable band for noise variance estimation (see Fig. 3). This module may consist of any algorithm able to decide with a good reliability about the presence of signal, without any prior knowledge of the noise variance.
- (a_2): The module which performs the noise variance estimation, once an empty band B_i has been identified by module (a_1). This is performed through very classical averaging of the observed noise spectral density over the whole identified band B_i.

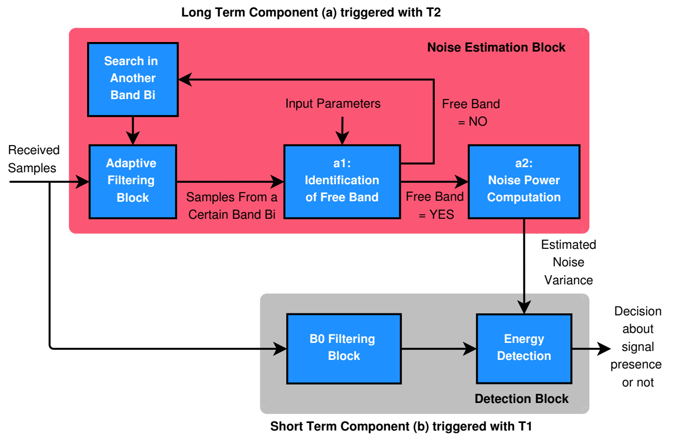

Fig. 3. Fast energy detection using a background process for noise estimation.

Algorithms used by (a_1) can be statistical based (e.g. kurtosis computation, Expectation Maximization) or could exploit for example cyclostationary properties. All these methods use different input parameters described in Table I. While the statistical methods need the use of Fast Fourier Transform (FFT), the method exploiting the cyclic properties directly uses the incoming samples from B_i.

TABLE I
Input Parameters for Identification of Free Band B_i

Method	FFT needed	Input Parameters
Kurtosis	Yes	Gaussian Noise Assumption
Expectation Maximization	Yes	A Mixture of 2 Distributions Assumption
Cyclic Cyclostationary	No	Cyclic Frequencies Knowledge

The methods described in Table I are further explained in the next paragraphs:

1) Kurtosis computation [10], which exploits the fact that the kurtosis (well known 4^{th} order statistic) is zero for a Gaussian signal. So if the kurtosis is different from 0, a priori it means that there is a signal in addition to the noise (see Fig. 5). It is known that the kurtosis $\mathcal{K}$ of a real random variable ζ with zero mean has the expression

$$\mathcal{K} \overset{Def}{=} \frac{E[\zeta^4]}{E[\zeta^2]^2} - 3. \tag{6}$$

Exploiting that the real and imaginary FFT parts of a Gaussian signal remain Gaussian, we use kurtosis on the FFT samples ζ of the incoming signal.

2) Expectation Maximization (EM) algorithm [11], [12], which checks if the incoming signal in bands $B_i \neq B_0$ is from a mixture composed of 2 Probability Density Functions (PDF) with 2 variances and 2 mixing probabilities. If so, it means that there is not only noise in the considered band. The

benefit of using the EM algorithm for module (a_1) is that it is very easy to implement in a completely blind context (no assumption about what to look for), and it can also provide the band occupancy. It can therefore be performed for narrow frequency bands identification. Note that same as kurtosis implementation, EM operates on the samples of the FFT of the incoming signal. In [12] it is showed that EM can be used for more complex mixtures such as generalized Gaussian Mixtures, but herein we suppose a mixture of two Gaussians.

For a fixed number of available FFT samples m, let Z be a variable denoting which one of the 2 distributions the sample ζ_j (with $j = 0, \ldots, m-1$) belongs to. The estimation steps can then be described as:

Initialization: For $\forall i = 1, 2$, at the incremental time $t = 0$, set variance $\sigma_i^{t=0}$, mixing probabilities $p_i^{t=0}$ and means $\mu_i^{t=0}$ as in [12]. Let the $\Theta_{1\times 6}$ be the vector of the unknown parameters $\Theta_{1\times 6} = [(\mu_1, \mu_2), (\sigma_1, \sigma_2), (p_1, p_2)]$.

E-step: The computation of the membership probabilities

$$p(z_j = i \mid \zeta_j, \Theta^t) = \frac{p(\zeta_j \mid z_j = i, \Theta^t) p_i^t}{\sum_{k=1}^{2} p(\zeta_j \mid z_j = k, \Theta^t) p_k^t} \quad (7)$$

for $j = 0, \ldots, m-1$ and $i = 1, 2$.

M-step: The upgrades on the means

$$\mu_i = \frac{\sum_{j=0}^{m-1} p(z_j = i \mid \zeta_j, \Theta^t) \zeta_j}{\sum_{j=0}^{m-1} p(z_j = i \mid \zeta_j, \Theta^t)}, \quad (8)$$

the upgrades on the variances

$$\sigma_i^2 = \frac{\sum_{j=0}^{m-1} p(z_j = i \mid \zeta_j, \Theta^t) \left|\zeta_j - \hat{\mu}_i\right|^2}{\sum_{j=0}^{m-1} p(z_j = i \mid \zeta_j, \Theta^t)} \quad (9)$$

and the upgrades on the mixing probabilities

$$p_i = \frac{\sum_{j=0}^{m-1} p(z_j = i \mid \zeta_j, \Theta^t)}{\sum_{k=1}^{2} \sum_{j=0}^{m-1} p(z_j = k \mid \zeta_j, \Theta^t)}, \quad (10)$$

for $i = 1, 2$.

3) Cyclostationary Detection (CD) [13], [14], which checks if the incoming signals in bands $B_i \neq B_0$ exhibit some cyclic frequencies. Herein we are using the Generalized Likelihood Ratio Test [13] for one cyclic frequency $\neq 0$, from Table II. If the signal exhibits cyclic properties, this means that there is not only noise in the considered band, because the noise is stationary.

TABLE II
CYCLIC FREQUENCIES FOR DIFFERENT SIGNAL TYPES

Type of Signal	Cyclic Frequencies
OFDM	$k/T_S, k = \pm 0, 1, 2, \ldots$
FM	$\pm 2 f_c$
QPSK	$\pm k/T_S, k = \pm 0, 1, 2, \ldots$
Noise	0

V. Numerical Results

Please note that the kurtosis is computed from the real and imaginary parts of FFT, separately. In Fig. 4 we have found by simulation that the kurtosis value is highly dependent of the frequency band occupancy. If the band occupancy is low, kurtosis becomes high. For example, for a 10% band occupacy we were not able to detect an interferer (i.e., transmitter in the noise estimation band B_i) with INR below $-14dB$. Therefore, this method should be prefered for detecting narrowband signals (e.g., FM by definition, or OFDM signals only if the analyzed band is wide enough).

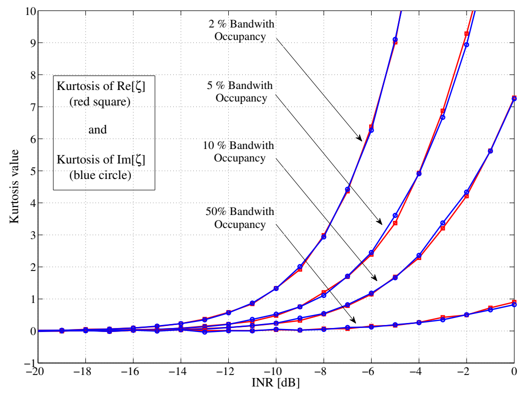

Fig. 4. Adjacent sub-band B_i detection using kurtosis, as a function of INR and of analyzed frequency band occupancy.

In Fig.5 we have represented the kurtosis detection method, by estimating the kurtosis in a sliding window 10 times larger than the interferer frequency band. This graph clearly shows that kurtosis increases where there are interferers.

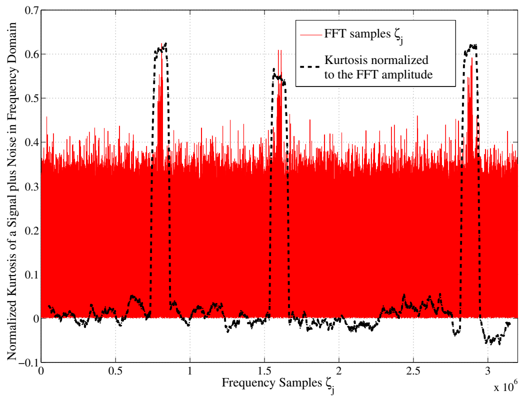

Fig. 5. Adjacent sub-band B_i detection using kurtosis. Use case involving 3 narrowband interferers (FM) each with $INR = -15dB$.

In Fig. 6, we have used OFDM symbols with 512 subcarriers and $T_G = T_U/4$. The frequency band occupancy of the interferer is only 10% of the entire analyzed frequency band B_i. The same result is also found when representing the mixing probabilities convergence as seen in Fig. 7. This result has been obtained for $INR = 0dB$, but our simulations also showed that EM cannot provide a good identification of the interferers, if $INR < -10dB$.

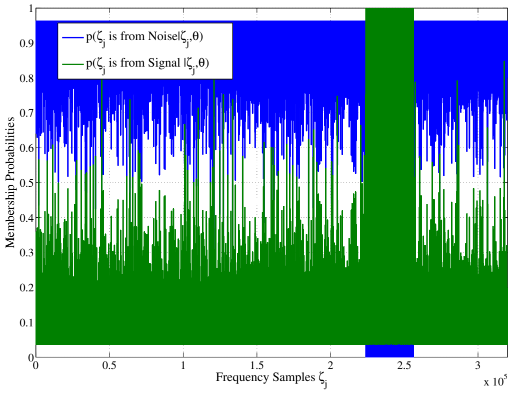

Fig. 6. Membership probabilities used for adjacent sub-band B_i detection, after 40 iterations of the EM algorithm; $INR = 0dB$.

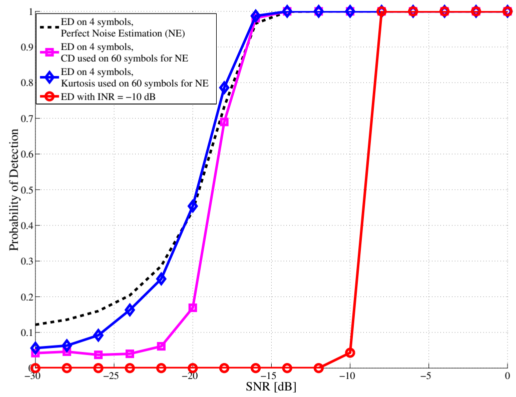

Fig. 8. Detection probability P_D in terms of SNR (in B_0), for $INR = -10dB$ (in B_i); the target false alarm probability $P_{FA,target} = 0.1$.

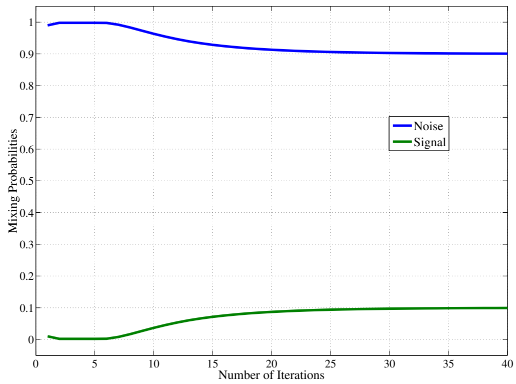

Fig. 7. Mixing probabilities are indicating 10% of the analyzed B_i band as occupied by signal and 90% only by noise.

In Fig. 8 we have compared our proposed algorithms with the ED having perfect noise estimation. For this simulation we have considered an interferer with $INR = -10dB$ and a background process time $T_2 = 15T_1$. Since the INR is high (about $-10dB$ in B_i) and the B_i occupancy is small (about 10%), the kurtosis method is the most reliable, but we expect an improvement of the cyclostationary method when we are dealing with $T_2 >> T_1$ and higher band occupancy. In this scenario, for a low INR, the kurtosis method will no longer be able to detect the interferers from secondary bands B_i.

VI. Conclusions

This paper presented a reliable sensing method using an energy detector with a background process for noise estimation. The novelty of the proposed approach resides in accurately estimating the noise in the frequency bands where other transmitters are not active. We have proved that the performance of the ideal energy detector can be asymptotically reached by using statistical signal properties such as probability density function and cyclostationarity. Furthermore, our simulations showed that while expectation maximization method is not accurate in identifying the free bands for low power levels, kurtosis method is more accurate for low band occupancy, and that the cyclostationary method is reliable for higher processing time.

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