Cognitive Radio Sensing Information-Theoretic Criteria Based

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***Abstract*— In this paper[1], we explore the Information-Theoretic Criteria, namely, Akaikes Information Criterion (AIC) and Minimum Description Length (MDL) as a tool to sense vacant sub-band over the spectrum bandwidth. The proposed technique is motivated by the fact that an idle sub-band (Normal process) presents a number of independent eigenvectors appreciably larger than for an occupied sub-band (Non-normal process). It turns out that, based on the number of the independent eigenvectors of a given covariance matrix of the observed signal, one can conclude on the nature of the sensed sub-band. Our theoretical result as well as the empirical results are first applied on experimental measurement campaign conducted at the Eurécom PLATON Platform. We then apply our method to an IEEE 802.11b Wireless Fidelity (Wi-Fi) signal in order to analyze the robustness of the proposed approach in presence of increased levels of noise. We argue that the proposed sub-space based techniques give interesting results in terms of sensing the white space in the spectrum.**

I. Introduction

Due to the increasing demand for additional bandwidth increasing due to both existing and new services, spectrum policy makers and communication technologists are seeking solutions for this apparent spectrum scarcity. Meanwhile, measurement studies have shown that licensed spectrum is relatively unused across time and frequency [1]. To provide the necessary bandwidth, a critical rethinking of the spectrum regulatory requirements is essential. The FCC has recently recommended that significantly greater spectral efficiency could be realized by de-ploying wireless devices that can coexist with the licensed (primary) users, generating minimal interference while taking advantage of the available resources. The current approach for spectrum sharing is regulated so that wireless systems are assigned fixed spectrum allocations, operating frequencies and bandwidths, with constraints on power emission that limits their range.
Clearly, the introduction of this revolutionary paradigm poses many challenges across all layers of a cognitive radio system design, from its application to its implementation. The spectrum usage is concentrated on certain portions of the spectrum while a significant amount of the spectrum remains unused. We have a basis for classifying the spectra into three broadly defined types [2]:
1. Black spaces, which are occupied by high power interferes some of the time,
2. Grey spaces, which are partially occupied by low power interferes,
3. White spaces, which are free, no one send information on this band, but it is occupied by natural and artificial forms of noise(e.g. thermal noise, transient reflections, etc.).
Black spaces is obvious forbidden to send on it because of the high power interferes, so the whites and the Grey spaces are the candidates for use by unlicensed operators.

Spectrum sensing has been identified as a key enabling cognitive radio to not interfere with primary users, by reliability detecting primary users signals. So sensing requirements are based on primary user modulation type, power, frequency and temporal parameters.
Spectrum sensing is often considered as a detection problem. Many techniques were developed in order to detect the holes in the spectrum band. Focusing on each narrow band, existing spectrum sensing techniques are widely categorized into energy detection [3] and feature detection [4]. The recent work on detection of the primary user has generally adopted this technique. However, the performance of the energy detector is susceptible to unknown or changing noise levels and interference. 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. Thus, the energy detector is prone to the false detection triggered by the unintended signals [5]. On the other hand, cyclostationary models have been shown in recent years to offer many advantages over stationary models [4]. Thus, cyclostationary feature detection performs better than the energy detector. However, it is computationally complex and requires significantly long observation time.

In this paper, we use an information-theoretic based sub-space analysis for the detection of vacant sub-bands in the spectrum. The proposed technique hinges on the assumption that the Normal process is known to have full rank covariance matrix. Accordingly, we investigate the number of independent diversity branches[2], possibly the number of significant eigenvalues, determined by the

[1]The work reported herein was also partially supported by the GRACE and Cruise.

[2]denoted as *stochastic Degrees of Freedom* (DoF) in the following.

value which minimizes the Akaikes Information Criterion (AIC) and/or the Minimum Description Length (MDL) and conclude on the nature of the sensed sub-band. In other words, a sub-band is said to be *idle* if the number of independent eigenvectors tends to be appreciably large with respect to the other sub-bands.

The rest of the paper is organized as follows: In Section II, we briefly present the model structure adopted throughout this work. The sub-space based detection is introduced in Section III. In Section IV, we present results from empirical and Section V concludes the paper.

II. Model Structure

The radio channel measurement system used in this paper were conducted using Eurécom PLATON Platform [6]. The PLATON Cards operate in the 1.9 GHz UMTS-TDD band using a bandwidth of 5 MHz. In this paper, we focus our analysis on one UMTS-TDD frame composed by 15 slots. Each Time Slot (TS) contains 5120 samples. The transmitted signal is convolved with a multi-path channel and a Gaussian noise is added. The received signal is first synchronized then equalized through a matched filter. The output of the matched filter is then down-sampled by a factor of 2xSF (spreading factor) to compensate for the up-sampling and spreading. In order to have an idea on the shape of the signal after passing through the channel, we plot the received signal in the time domain (see figure 1). It is clear that only the 1^{st} and the 12^{th} Time Slot contain data. The remaining TS are idle.

As the effective channel, i.e., the physical channel in conjunction with transmit and receive filters, is always band limited, it can be described in terms of samples $h[.]$ of the continuous-time impulse response. Therefore, we consider the discrete-time complex baseband equivalent channel with input-output relation given by:

$$y(n) = \sum_{l=0}^{L-1} h_l s(n-l) + w(n); \tag{1}$$

where $s(n)$ denotes the n^{th} transmitted signal assumed to be scalar complex, h denotes the discrete-time impulse response of the effective channel of L taps, $w(.)$ is the circularly additive Gaussian noise and $y(.)$ is the resulting output signal. Given the proposed channel structure, let us introduce the associated model when a set of observations is made available. We may then write:

$$\mathbf{y} = \mathbf{A}\mathbf{s} + \mathbf{w} \tag{2}$$

Where

- $\mathbf{y}^H = [y(t_1)...y(t_N)]$ is the vector of observations, with ^{H} denoting the conjugate transpose, N is the number of observations, and $y(t_i)$ denoting the observation at instant t_i,
- $\mathbf{A}$ is the NxL channel matrix,
- The signal $\mathbf{s}$ is a Lx1 vector, and $\mathbf{S}$ is the covariance matrix of the signals, i.e., $\mathbf{S} = E[\mathbf{s}\ \mathbf{s}^H]$,
- The noise $\mathbf{w}$ is a Nx1 vector assumed to be complex, stationary, and ergodic Gaussian vector process, independent of the signals, with zero mean and covariance matrix given by $\sigma^2\boldsymbol{I}$, where σ^2 is an unknown scalar constant and $\boldsymbol{I}$ is the identity matrix.

We further assume that the number $L(L < N)$ of signals are Gaussian random processes, with zero mean and positive definite covariance matrix. It follows from the assumptions above that the covariance matrix of $\mathbf{y}(.)$ is given by:

$$\mathbf{R} = \Psi + \sigma^2\mathbf{I} \tag{3}$$

where

$$\Psi = \mathbf{A}\mathbf{S}\mathbf{A}^H \tag{4}$$

The problem here is that the covariance matrix $\mathbf{R}$ is unknown in practice. When estimated from a finite sample size N, we can not estimate the exact values of the eigenvalues, thus making it difficult to determine the number of DoF merely by observing the eigenvalues.

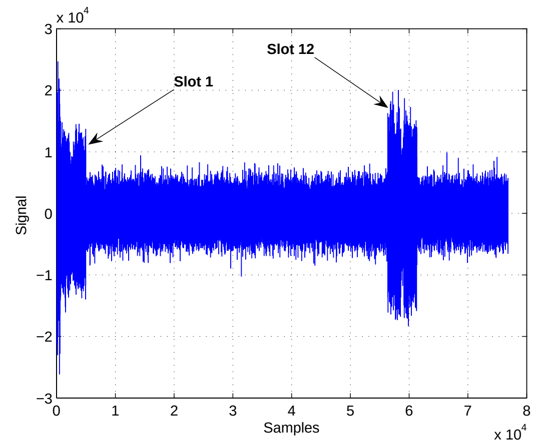

Fig. 1. The received signal with 15 TS, duration = 10 ms.

III. Sensing Information-Theoretic Criteria Based

In this section, we present a new approach to detect the idle sub-bands based on the applications of the Information Theoretic Criteria introduced by Akaike (AIC) in [7]. The proposed approach was recently used in the literature to estimate the number of significant eigenvalues of the covariance matrix of a given observation vector in [8]. As stated before, we will first present and analyze the corresponding results obtained from the channel measurements conducted at Eurécom and compare them to simulated 802.11b signals [9].

A. The Information Theoretic Criteria

The information theoretic criteria was first introduced by Akaike in [7] for model selection. Schwartz [11] addresses the following general problem:
Given a set of observations $\mathbf{y}^H(t) = [y(t_1)...y(t_N)]$. Assuming a family of models, select the model which best fits the data. Akaike's proposal is to select the model which minimizes the AIC criterion defined by [10]:

$$AIC = -2\log f(\mathbf{y}|\widehat{\theta}) + 2k \tag{5}$$

where $\widehat{\theta}$ is the maximum likelihood estimate of the parameter vector θ and k is the biais correction. Inspired by Akaike work, Schwartz and Rissanen have an approach quite different. Schwartz approached the problem by a bayesian arguments. However Rissanen based his work on information theoretic arguments. It turns out that in the large-sample limit, both Schwartz's and Rissanen's approach yield the same criterion, given by [10]:

$$MDL = -2\log f(\mathbf{y}|\widehat{\theta}) + \frac{k}{2}\log N \tag{6}$$

B. Sub-space based technique

In this section, we apply the information theoretic criteria to detect the number of DoF of a given observation vector. Our review of the basics of eigenvector technique follows Wax and Kailath [10]. As stated before, regarding the N observations $y(t_1), ..., y(t_N)$, we can not exactly estimate the values of the eigenvalues, thus making it difficult to determine the number of DoF. From our covariance matrix model given by equation (3) and (4), let us consider the following family of covariance matrices

$$\mathbf{R}^{(k)} = \Psi^{(k)} + \sigma^2\mathbf{I} \tag{7}$$

Where $\Psi^{(k)}$ denotes a semi-positive matrix of rank k, and σ^2 denotes an unknown scalar. Note that k ranges over the set of all possible number of DoF, i.e. $k = 0, 1, ..., N-1$. Using linear algebra, we can express $R^{(k)}$ as

$$\mathbf{R}^{(k)} = \sum_{i=1}^{k}(\lambda_i - \sigma^2)V_iV_i^H\sigma^2$$

where $\lambda_1, ..., \lambda_k$ and $\mathbf{V}_1, ..., \mathbf{V}_k$ are the eigenvalues and eigenvectors, respectively, of $\mathbf{R}^{(k)}$. The AIC and the MDL criteria are given by [10] and [11]:

$$AIC = -2\log\left(\frac{\prod_{i=k+1}^{p} l_i^{\frac{1}{p-k}}}{\frac{1}{p-k}\sum_{i=k+1} pl_i}\right)^{(p-k)N} + 2k(2p-k) \tag{8}$$

While the MDL criterion is given by

$$MDL = -\log\left(\frac{\prod_{i=k+1}^{p} l_i^{\frac{1}{p-k}}}{\frac{1}{p-k}\sum_{i=k+1}^{p} l_i}\right)^{(p-k)N} + \frac{k}{2}(2p-k)\log N \tag{9}$$

The number of significant eigenvalues is determined by the value that minimizes the AIC and/or the MDL. We plot, the computed number of DoF obtained by AIC and MDL criterion following equation (8) and (9) respectively.

Figure 2 depicts the behavior of the AIC and MDL curves as function of the eigenvalue index. Remember that the number of significant eigenvalues (or the DoF) is given by the index of the AIC, respectively MDL, following respectively, equation (8) and (9). As a matter of fact, we remark that two curves decrease with respect to the eigenvalue index until they reach a minimum value. This is due to the fact that, for first indexes, the signal is correlated and consequently the two curves decrease. On the other hand, when the TS is occupied

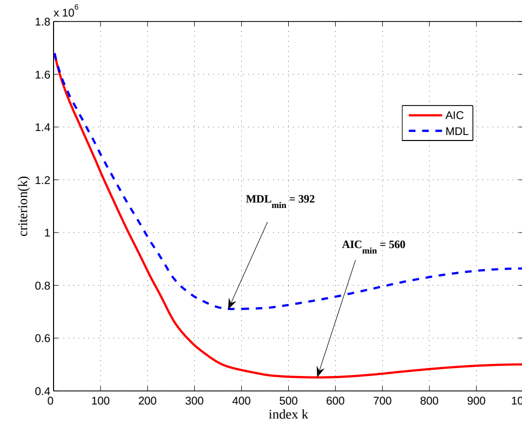

Fig. 2. The AIC and MDL of the UMTS Time Slot 1 (data).

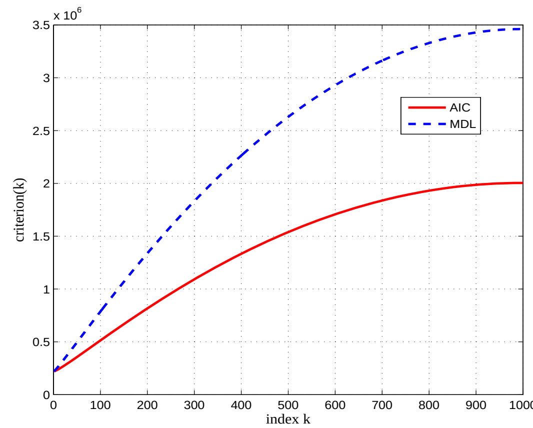

Fig. 3. The AIC and MDL of the UMTS Time Slot 3 (noise).

(TS 1 and TS 12), we notice that the number of DoF is clearly smaller than the dimension of the covariance matrix $N = 1000$. In figure 3, we investigate the information-theoretic behavior when the TS is assumed to be idle. As expected, the two curves increase with respect to the eigenvalue index. In fact, as the TS is idle (noise), the number of DoF is always performed due to the fact that samples are uncorrelated.

On the other hand, by observing figure 2, the minima seem to lie in an extremely flat region of the function and the feeling is that the proposed approach is extremely sensitive. It would thus be interesting not to perform an optimization based on real-world measurements only, but also based on simulated data in order to analyze the robustness of the proposed approach in presence of increased levels of noise. Figure 4 depicts the behavior of the AIC and MDL curves for the 802.11b WiFi signal for different SNR and for N=1000. Notice here that the the proposed approach is more robust than for the UMTS signal especially for the AIC criterium.

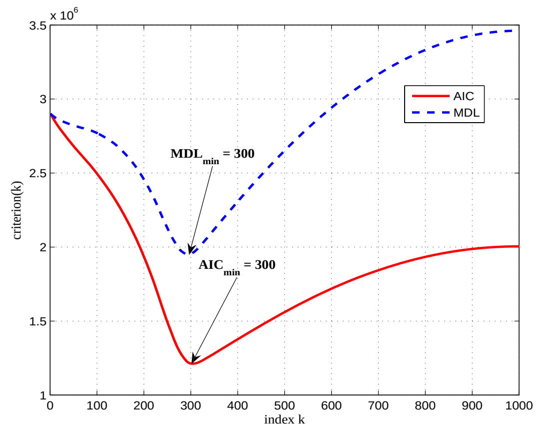

Fig. 4. The AIC and MDL of WiFi signal at 10 dB.

Moreover, we can pointed out that both AIC and the MDL criteria give the same number of significant eigenvalues for SNR = 10 dB. However, as for the case of the UMTS signal, we remark that in in the presence of increased levels of noise (i.e. when the SNR = 0 dB), the two curves increase as function of the eigenvalue index. Due to the lack of space, we will not present these consistencies here and the reader is referred to the reference [12].

IV. Empirical technique

In the previous section, we explored the information theoretic criteria to determine the number of significant eigenvalues of a given observation vector. Let us now use a different method based on an empirical approach. Our method is based on the eigenvalues decomposition following equation (7). Since our UMTS frame is divided into 15 slots, we compute the covariance matrix for each slot. We determine the empirical CDF of the eigenvalues of each slot, and based on these CDFs, we can find the number of the significants eigenvalues that capture a certain level of the signal energy. The number of the significant eigenvalues that capture 85% and 98% of the total energy for each slot of the signal is captured by the figure 5. As expected, we see that the numbers of significant eigenvalues for the 1^{st} and the 12^{th} TS are clearly lower than for the other idle TS even by capturing 80% of the energy. Notice here that the proposed empirical strategy is consistent even for lower energy thresholds. This result is very interesting since by only determining the number of DoF which capture a fraction of the energy, a cognitive user can deduce the nature of the sensed signal.

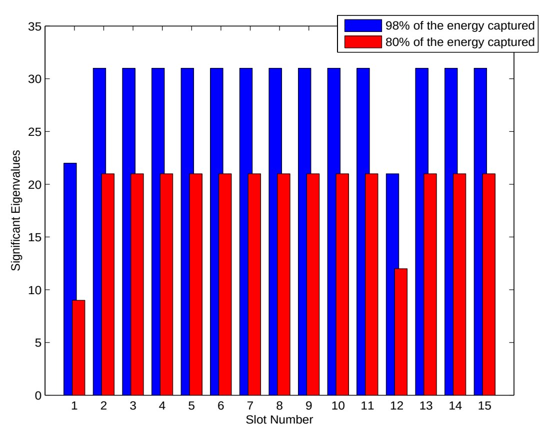

Fig. 5. Number of the significant eigenvalues per Slot.

V. Conclusion

In this paper, we proposed a new sensing technique based on a sub-space approach. We investigated Information-Theoretic Criteria (AIC and MDL) and the empirical technique with respect to UMTS real-world measurements as well as to simulated WiFi signals in order to analyze the robustness of the proposed approach in presence of increased levels of noise. We analyze their respective potential to sense idle part of the spectrum and it was shown that the proposed sub-space technique presents very promising issues within the framework of blind sensing. As a future work, it is of major interest to generalize the problem to study the performances of such an approach to heterogeneous networks in a wide-band context [12].

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