Blind Spectrum Sensing for Cognitive Radio Based on Signal Space Dimension Estimation

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***Abstract*—Based on information theoretic tools, a new spectrum sensing method is proposed in this paper to detect vacant sub-bands in the radio spectrum[1]. Specifically, based on the subspace analysis of the received signal, we present a new method to detect the signal presence in a blind way. We have shown that the analysis of signal dimension can assist blind spectrum sensing procedure. Indeed, we have shown that the slope change, from positive to negative trend, of the signal space dimension curve is representative of the transition from a vacant band to an occupied band (and vice versa). In fact, the number of significant eigenvalues is determined by the value that minimizes the Akaike's Information Criterion (AIC) and is directly related to the presence/absance of data in the signal. The validation of this new method is based on experimental measurements captured by Eurécom RF Agile Platform operating from 200 MHz to 7.5 GHz. Simulations show good results in terms of spectrum holes detection.**

***Index Terms*—Cognitive radio, sensing, signal space dimension, subspace analysis, Akaike's information criterion (AIC).**

I. Introduction

A cognitive radio (CR) is a radio that is able to sense the spectral environment over a wide spectrum band and exploit this information to opportunistically provide wireless links that best meet the user communications requirements [1]. Since CRs are considered as lower priority or secondary users of spectrum allocated to a primary user, a fundamental requirement is to avoid interference to potential primary users in their vicinity. On the other hand, primary user networks have no requirement to change their infrastructure for spectrum sharing with cognitive networks. Therefore, CRs should be able to independently detect primary user presence through continuous spectrum sensing.

Spectrum sensing is one of the essential mechanisms of CR that has attracted great attention from researchers recently. It is done in order to locate the unused spectrum segments in a targeted spectrum pool and use these segments optimally without harmful interference to the licensed user. The search for the unused spaces can be based on different spectrum sensing methods [2]. For spectrum sensing, three signal processing techniques are commonly used: matched filtering [3], energy detection [4] and cyclostationary feature detection [5]. Matched filtering is an optimal way for signal detection in communication systems. However, it requires prior knowledge on the licensed user signal which may not be available. Energy detection is often used to determine the presence of signals without prior knowledge. However, in the most general case no prior information is available so that energy detection is the only possibility left. Energy detection compares the received energy in a certain frequency band to a usually predefined threshold. However, there are limitations for the energy detection: First, the decision threshold is subject to changing signal to noise ratios. Second, it can not distinguish interference from a user signal and it is not effective for signals whose signal power has been spread over wideband. Therefore, the power detection is not adequate for spectrum sensing. The cyclostationary feature detection is used to extract signal features in the background of noise. This technique is a promising option for the spectrum sensing of CR, especially in the situation where energy detection is not so effective.

Moreover, recent work conducted at Eurécom [6] [7] suggested to use the Akaike information criterion (AIC) [8] and minimum description length (MDL) [9] as a promising technique in the context of CR sensing. It was presented 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 this signal. In this paper however, we adopt the same framework to detect vacant sub-bands in the radio spectrum. The AIC criterion was investigated in order to sense the signal presence over the spectrum bandwidth. We focus on analyze the number of significant eigenvalues determined by the value which minimizes the AIC criterion and conclude on the nature of the sensed sub-bands. Based on these results, we propose the new method to detect vacant sub-bands in the radio spectrum using sliding window technique and exploiting the AIC criterion. Specifically, we will show that the number of significant eigenvalues is directly related to the presence/absance of data in the signal. Simulations show that the proposed technique allows spectrum sensing in a blind manner in both time and frequency domains. We also compare our analytical expressions with empirical simulations based on experimental measurements of Eurécom RF Agile Platform. The proposed detector is performed in comparison with cyclostationary detector and energy detector.

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The remaining of the paper is organized as follows. In Section II we briefly present the model structure adopted throughout this work and we analyze the number of significant eigenvalues. Section III describes the spectrum sensing method based on sliding window technique and presents simulation results. Performance evaluation and advantages are described in Section IV and a comparison of the proposed detector with that of cyclostationary detector and energy detector is given. Finally, Section V presents the conclusions of this study.

II. Formulation of the Problem

In this section, we describe the channel model that will be used throughout the paper and we formulate the AIC criterion. The radio channel measurement system used were conducted using Eurécom RF Agile Platform [10]. The RF 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 slots. Each time slot contains $T = 5120$ samples. The transmitted signal is convolved with a multi-path channel and a Gaussian noise is added. The received signal, denoted by the $q \times 1$ complex vector $\mathbf{x}$, can be modeled as:

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{n} \tag{1}$$

where $\mathbf{A}$ is a rank(p) $q \times p$ complex matrix whose columns are determined by the unknown parameters associated with each signal [11]. $\mathbf{s}$ is a $p \times 1$ complex vector and $\mathbf{n}$ is a complex, stationary, and Gaussian noise with zero mean and covariance matrix $E\{\mathbf{n}\mathbf{n}^H\} = \sigma_n^2 \mathbf{I}_n$. Our goal within this paper is to determine the value of q from N observation of $\mathbf{x}$. Because the noise is zero mean and independent of the signals, it follows that the covariance matrix of $\mathbf{x}(t)$ is given by:

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

where

$$\Psi = \mathbf{A}\mathbf{S}\mathbf{A}^H \tag{3}$$

with $\mathbf{S}$ denoting the covariance matrix of the signals, i.e., $\mathbf{S} = E\{\mathbf{s}\mathbf{s}^H\}$, and σ^2 denotes an unknown scalar. Furthermore, if q uncorrelated signals are present, the $p - q$ smallest eigenvalues of $\mathbf{R}$ are equal to the noise power σ_n^2. From our covariance matrix model given by equation (5), let us consider the following family of covariance matrix:

$$\mathbf{R}^{(k)} = \Psi^{(k)} + \sigma^2 \mathbf{I} \tag{4}$$

where $\Psi^{(k)}$ denotes a semi-positive matrix of rank k. Note that k ranges over the set of all possible number of DoF, i.e. $k = 0, 1, ..., p-1$. Using linear algebra, we can express $\mathbf{R}^{(k)}$ as: $\mathbf{R}^{(k)} = \sum_{i=1}^{k} (\lambda_i - \sigma^2) \mathbf{V}_i \mathbf{V}_i^H \sigma^2$, where $\lambda_1, ..., \lambda_k$ and $\mathbf{V}_1, ..., \mathbf{V}_k$ are the eigenvalues and eigenvectors, respectively, of $\mathbf{R}^{(k)}$.

The number of signals are determined from the estimated covariance matrix $\hat{\mathbf{R}}$ defined by:

$$\hat{\mathbf{R}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{x}(t_i) \mathbf{x}(t_i)^H \tag{5}$$

If $\hat{\lambda}_1, \hat{\lambda}_2, ..., \hat{\lambda}_q$ are the eigenvalues of $\hat{\mathbf{R}}$ in the decreasing order then [11] [9]:

$$\mathrm{AIC}(k) = -2 \log \left(\frac{\prod_{i=k+1}^{p} \hat{\lambda}_i^{\frac{1}{p-k}}}{\frac{1}{p-k} \sum_{i=k+1}^{p} \hat{\lambda}_i} \right)^{(p-k)N} + 2k(2p-k) \tag{6}$$

The number of DoF, possibly the number of significant eigenvalues, is determined as the value of $k \in \{0, 1, ..., p-1\}$ which minimizes the value of AIC.

The number of significant eigenvalues (SE) is determined by the value of p and q, and is given by [6] [7]:

$$SE = \begin{cases} p & \text{noise} \\ q & \text{signal} \end{cases} \tag{7}$$

where p is the dimension of the covariance matrix $\mathbf{R}^{(k)}$.

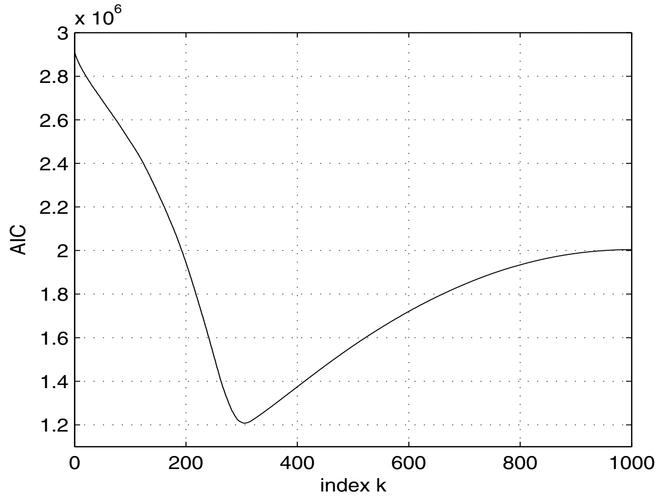

Fig. 1. Akaike Information Criterion of an occupied UMTS time slot: $SE = 300$.

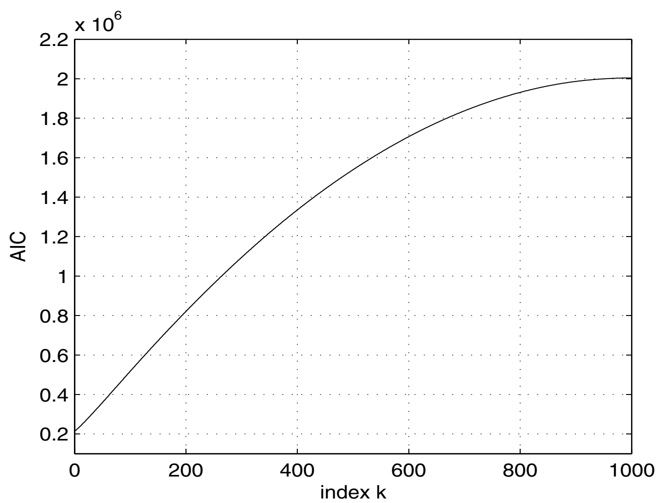

Fig. 2. Akaike Information Criterion of a vacant UMTS time slot: $SE = 1000$.

Fig. 1 and Fig. 2 depict the behavior of the AIC curves as function of the eigenvalues index for an occupied and vacant UMTS time slots of length 5120 samples, respectively. The dimension of the covariance matrix is equal to 1000. Based on (6), we determine the minimum AIC (AIC$_{min}$) and obtain the number of significant eigenvalues. We see clearly that the position of AIC$_{min}$ is located at $k = 300$ for the occupied UMTS time slot (see Fig. 1) and at $k = 0$ for the vacant UMTS time slot (see Fig. 2). According to (7), the number of significant eigenvalues in the first case is equal to $SE = q = 300$ and $SE = p = 1000$ for the second case.

III. Spectrum Sensing Method based on Sliding Window Technique

The discussion of the previous section suggests that the number of significant eigenvalues conclude on the nature of the sensed sub-bands. Based on these results, we propose in this section a new blind spectrum method. The proposed method is based on the sliding window technique. We select a sliding window size $T = 5120$ samples (smaller than the time slot) and slide the window over the UMTS-TDD frame to obtain AIC values for each analysis windows. A time-lag sliding window of $L = 100$ samples was used to scan all the signal. The size of the UMTS-TDD frame and the number of the sliding windows are denoted by N and $nw = \frac{N}{T}$, respectively.

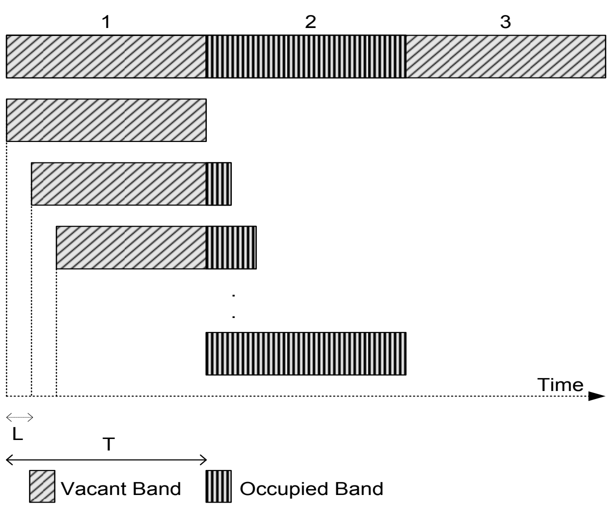

Fig. 3. Blind spectrum sensing method based on sliding window technique.

We illustrate in Fig. 3 the spectrum sensing method based on sliding window technique. As an example, we use in this figure a frame divided into 3 slots as follow: noise+data+noise, where the length of each TS is 5120 samples. In particular, we scan the spectrum band of the received signal with the mean of sliding window [12]. We then compute AIC value of the window of interest. Once we get the corresponding position of the minimum AIC$_{min}$ value, we shift the window by L samples till the end of the band.

Algorithm 1 Blind spectrum sensing algorithm

```
q ← 0
l ← 0
AIC_min ← AIC(0)

for n = 1 : nw do
    for k = 1 : p − 1 do
        if AIC(q) − AIC(k) > 0 then
            q ← k
        else break                          ▷ AIC is minimized
        end if
        if q = 0 then
            SE ← p
        else SE ← q
        end if
    end for
    if AIC(q) < AIC_min then
        AIC_min ← AIC(q)
        l ← n
    else break                     ▷ Detection of data signal
    end if
end for
```

The proposed blind spectrum sensing algorithm is described in the following pseudo code algorithm. We first initialize the position of AIC$_{min}$ to zero (i.e., $q = 0$) and the position of the minimum AIC$_{min}$ value over all analysis windows to zero (i.e., $l = 0$). For the first analysis window, we compute AIC(k) for $k = \{1, 2, ..., p - 1\}$: If AIC(q) − AIC(k) is negative then AIC value is minimized for $q = k$, else the position of AIC$_{min}$ will be incremented by one up to have AIC(q) − AIC(k) negative. We compare after that AIC$_{min}$ and AIC(q): If AIC(q) − AIC$_{min}$ is negative then the position of AIC$_{min}$ will be incremented by one and AIC$_{min}$ = AIC(q). We conclude that the position of AIC$_{min}$ is located at 0 if the analysis window contain a noise signal ($SE = p$), and at q for an occupied window ($SE = q$). Then, the analysis window will be shifted by $L = 100$ samples and we make the same approach for all analysis windows (i.e., $nw = \frac{N}{T}$) till the end of the band.

Simulations were carried out using a UMTS frame divided into 6 slots. The received signal in the time domain is shown in Fig. 4. It is clear that only the 2^{nd} and the 5^{th} time slot contain data. The remaining time slots are idle. First, we compute the covariance matrix for each analysis windows ruled by equation (5). We determine then the position of the value that minimizes the AIC of each window, and based on these values, we can find the number of the significants eigenvalues based on equation (7). The number of the significant eigenvalues for each analysis windows of the signal in the time domain is captured by Fig. 4. As expected, it is found that the numbers of significant eigenvalues for the vacant sub-bands are clearly higher than for the other sub-bands. It is worth noting in this context that the number of significant eigenvalues is directly related to the presence/absence of data in the signal.

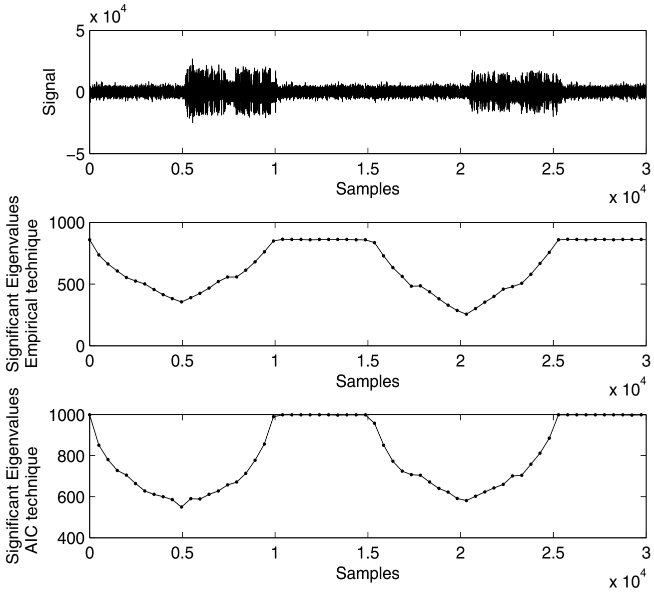

Fig. 4. Number of significant eigenvalues of an UMTS signal in the time domain.

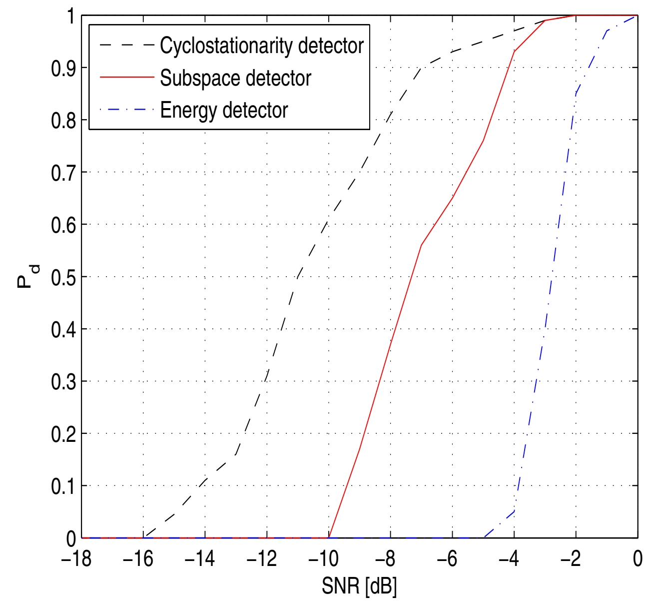

Fig. 5. Probability of detection vs. SNR for the proposed detector, energy detector and cyclostationary detector with $P_F = 0.05$.

We also compare our analytical expressions with empirical simulations based on experimental measurements captured by Eurecom RF Agile Platform. For the empirical simulations, we determine the empirical CDF of the eigenvalues of each window, and based on these CDFs, we can find the number of the significants eigenvalues that capture a certain level of the signal energy (in our case 98% of the total energy for each window). The comparison shows an excellent agreement between analysis and simulation in terms of detection of the presence of signal in the radio band.

IV. Performance Evaluation of the Spectrum Sensing Method

In order to evaluate the performance of the new spectrum sensing method, an OpenAirInterface at Eurecom is considered. The OpenAirInterface is an experimental real time hardware and software platform for air-interface experimentation. It consists of dual-RF CardBus/PCMCIA data acquisition cards called CardBus MIMO I. 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. The goal of spectrum sensing is to decide between the following two hypotheses,

$$\mathbf{x} = \begin{cases} \mathbf{n} & \mathrm{H}_0 \\ \mathbf{As} + \mathbf{n} & \mathrm{H}_1 \end{cases} \tag{8}$$

We decide a spectrum band to be unoccupied if there is only noise in it, as defined in H_0; on the other hand, once there exists primary user signal besides noise in a specific band, as defined in H_1, we say the band is occupied. Thus the probability of false alarm can be expressed as:

$$P_F = P(\mathrm{H}_1 \mid \mathrm{H}_0) = P(\mathbf{x} \text{ is present} \mid \mathrm{H}_0) \tag{9}$$

and the probability of detection is

$$\begin{aligned} P_D &= 1 - P_M = 1 - P(\mathrm{H}_0 \mid \mathrm{H}_1) \\ &= 1 - P(\mathbf{x} \text{ is absent} \mid \mathrm{H}_1) \end{aligned} \tag{10}$$

where P_M indicates the probability of missed detection.

Fig. 5 depicts the detection comparison of the proposed method with energy detector and cyclostationary detector. This figure shows the 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 detector. From the simulation results, we find that the proposed method generally works well under low SNR condition. For Fig. 5, we show that the proposed detector outperforms energy detector under the same interference condition. From this figure, we find that if knowledge of signal parameters is provided, the cyclostationary detector can still perform a high probability of detection. Hence, the proposed detector exhibits very interesting results in term of spectrum detection in a perfectly blind way.

V. Conclusion

Blind detection of telecommunication signals in a radio band is very helpful in CR environments; especially, when the second user does not have enough information about the primary user. In this paper, we proposed a new sensing technique based on signal space analysis. We investigated the relationship between the behavior of the slope of signal dimension curve and the transition from an occupied band to an adjacent free band (and vice versa). The validation of this new technique is done using measurements data captured by Eurécom Agile RF Platform in order to analyze the robustness of the proposed approach in presence of increased levels of noise. Comparison with both cyclostationarity and energy detection based techniques, has shown that the proposed detector has a good performance and a very promising issues within the framework of blind sensing.

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