Blind Spectrum Sensing for Cognitive Radio Based on Model Selection

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Abstract— **Cognitive radio devices will be able to seek and dynamically use frequency bands for network access. This will be done by autonomous detection of vacant sub-bands in the radio spectrum. In this paper[1], we propose a new method for blind detection of vacant sub-bands over the spectrum band. The proposed method exploits model selection tools like Akaike information criterion (AIC) and Akaike weights to sense holes in the spectrum band. Specifically, we assume that the noise of the radio spectrum band can still be adequately modeled using Gaussian distribution. We then compute and analyze Akaike weights in order to decide if the distribution of the received signal fits the noise distribution or not. Our theoretical result are validated using experimental measurements captured by Eurécom RF Agile Platform. Simulations show promising performance results of the proposed technique in terms of sensing vacant sub-bands in the spectrum.**

Keywords—Cognitive radio, Spectrum Sensing, Model Selection, Akaike weights.

I. Introduction

Recent results published by Federal Communications Commission (FCC), see [1], concluded that spectrum utilization depends strongly on time and place. In this setting, it was also concluded that allocated bands are sometimes under utilized. Traditional approach to spectrum management is very inflexible in the sense that frequency bands are exclusively licensed to users and each system has to operate within a limited frequency band. However, with most of the spectrum being already allocated, it is becoming exceedingly hard to find vacant bands to either deploy new services or to enhance the existing ones. This spectrum limitation has had profound impacts on the research directions of wireless communications community.

Cognitive radio has been proposed as the means to promote efficient utilization of the spectrum by exploiting the existence of spectrum holes [2]. The spectrum use is concentrated on certain portions of the spectrum while a significant amount of the spectrum remains unused. These holes can be classified into three types [3]:

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.

In this paper we focus on sensing white spaces.

Spectrum sensing has been identified as a key enabling cognitive radio to not interfere with primary users, by detecting in reliable way primary users signals. Thus classical sensing techniques 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 [4] and feature detection [5]. 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 energy. 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.

In this paper, we propose a new method to sense vacant frequency sub-bands over the spectrum band for cognitive radio communications. The idea of the proposed technique is based on scanning the frequency band to locate white spaces (spectrum holes) in the spectrum. The vacant sub-bands can then be used of cognitive radio communication without affecting primary system quality of service (QoS). The technique exploits model selection tools like Akaike information criterion (AIC) [6] and Akaike weights [7]. AIC was recently used in the literature to estimate the number of significant eigenvalues of the covariance matrix of a given observation vector in [8]. The main goal within our contribution is to exploit Akaike weights information in order to decide if the distribution of the received signal fits the noise distribution. Specifically, the proposed technique compute the Akaike weights and, depending on these results, we can conclude on the nature of the sensed sub-band.

The remainder of the paper is organized as follows. In Section II, we revisit the AIC model selection tool and present

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the problem statement. In Section III, we give a brief review of model selection using AIC: the AIC is presented and the Akaike weights are derived. The detection approach based in model selection is developed in Section IV. Finally, we present some simulation results of the proposed technique in Section V. Section VI concludes the paper.

II. Problem Statement

Our goal is to detect vacant sub-band over the spectrum band exploiting the Akaike Infirmation Criterion (AIC). It is well known that ambient noise can be modeled using Gaussian distribution. Thus, we propose to analyze Akaike weights information in order to determine the position of vacant band in the spectrum of the received signal. This section gives a short review of the basic ideas.

It is assumed that the samples of the received signal are distributed according to an original probability density function f, called the operating model. The operating model is usually unknown, since only a finite number of observations is available. Therefore, approximating probability model must be specified using the observed data, in order to estimate the operating model. The approximating model is denoted as g_θ, where the subscript θ indicates the U-dimensional parameter vector, which in turn specifies the probability density function.

In information theory, the Kullback-Leibler distance describes the discrepancy between the two probability functions f and g_θ and is given by [6]:

$$\begin{aligned} D(f\|g_\theta) &= E\{\log f_X(X)\} - E\{\log g_\theta(X)\} \\ &= -h(X) - \int f_X(x)\log g_\theta(x)dx \end{aligned} \quad (1)$$

where the random variable X is distributed according to the original but unknown probability density function f, and $h(.)$ denotes differential entropy. This distance measure is not directly applicable, since the original probability density function f is not known. It is known, however, that the Kullback-Leibler distance is nonnegative, i.e., $D(f\|g_\theta) \geq 0$. This implies that the Kullback-Leibler discrepancy,

$$-\int f_X(x)\log g_\theta(x)dx = h(X) + D(f\|g_\theta) \quad (2)$$

approaches the differential entropy of X from above for increasing quality of the model g_θ. The differential entropy of X is reached if and only if $f = g_\theta$. Applying the weak law of large numbers, this expression (2) can be approximated by averaging the log-likelihood values given the model over N independent observations $x_1, x_2, ..., x_N$ according to:

$$-\int f_X(x)\log g_\theta(x)dx \approx -\frac{1}{N}\sum_{n=1}^{N} g_\theta(x_n) \quad (3)$$

The Kullback-Leibler discrepancy (2) depends on the estimated vector θ, which itself is a function of the actual observations $x_1, x_2, ..., x_N$. If another set of observations $\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_N$ is used, a different Kullback-Leibler discrepancy would be obtained. The expected Kullback-Leibler discrepancy is given by:

$$-E_\theta\left\{\int f_X(x)\log g_\theta(x)dx\right\} \quad (4)$$

where the expectation is taken with respect to the distribution of the estimated parameter vector θ. This expression (4) cannot be computed, but estimated.

III. Model Selection Using Akaike Information Criterion

The information theoretic criteria was first introduced by Akaike in [6] for model selection. Assuming a candidate model, the idea is to decide if the distribution of the observed signal fits the candidate model. The AIC criterion is an approximately unbiased estimator for (4) and is given by:

$$\text{AIC} \;=\; -2\sum_{n=1}^{N}\log g_{\hat{\theta}}(x_n) + 2U \quad (5)$$

The parameter vector θ for each family should be estimated using the minimum discrepancy estimator $\hat{\theta}$, which minimizes the empirical discrepancy. This is the discrepancy between the approximating model and the model obtained by regarding the observations as the whole population. The maximum likelihood estimator is the minimum discrepancy estimator for the Kullback-Leibler discrepancy.

Consider a probability distribution parameterized by an unknown parameter θ, associated with either a known probability density function or a known probability mass function, denoted as f_θ. As a function of θ with $x_1, x_2, ..., x_N$ fixed, the likelihood function is:

$$L(\theta) = f_\theta(x_1, x_2, ..., x_N) \quad (6)$$

The method of maximum likelihood estimates θ by finding the value of θ that maximizes $L(\theta)$. The maximum likelihood estimator (MLE) of θ is given by:

$$\hat{\theta} = \arg_\theta \max L(\theta) \quad (7)$$

Commonly, one assumes that the data drawn from a particular distribution are i.i.d. with unknown parameters. This considerably simplifies the problem because the likelihood can then be written as a product of N univariate probability densities:

$$L(\theta) = \prod_{n=1}^{N} f(x_n \mid \theta) \quad (8)$$

and since maxima are unaffected by monotone transformations, one can take the logarithm of this expression to turn it into a sum:

$$L^*(\theta) = \sum_{n=1}^{N}\log f(x_n \mid \theta) \quad (9)$$

Consequently, the expression of the maximum likelihood in our case is:

$$\hat{\theta} \;=\; \arg_\theta \max \frac{1}{N}\sum_{n=1}^{N}\log g_\theta(x_n) \quad (10)$$

The maximum of this expression can then be found numerically using various optimization algorithms. This contrasts with seeking an unbiased estimator of θ, which may not necessarily yield the MLE but which will yield a value that (on average) will neither tend to over-estimate nor under-estimate the true value of θ. The maximum likelihood estimator may not be unique, or indeed may not even exist.

Akaike weights can be computed using (5), in order to decide if the distribution of the received signal fits the noise distribution or not. The Akaike weights can be interpreted as estimate for the probabilities that the corresponding candidate distribution show the best modeling fit. It provides another measure of the strength of evidence for this model, and is given by:

$$\mathrm{W}_j = \frac{e^{\frac{1}{2}\Phi_j}}{\sum_{i=1}^{N} e^{\frac{1}{2}\Phi_i}} \tag{11}$$

where Φ_j denotes the AIC differences defined by:

$$\Phi_j = \mathrm{AIC}_j - \min_i\ \mathrm{AIC}_i \tag{12}$$

where $\min_i\ \mathrm{AIC}_i$ denotes the minimum AIC value over all analysis windows. The Akaike weights allow us not only to decide if the distribution of the received signal fits the Gaussian distribution, but also provide information about the relative approximation quality of this distribution.

IV. Blind Detection Approach Based on Model Selection

In this section, we present a new approach to detect the idle sub-bands based on the applications of the Akaike weights introduced by Akaike in [6] and [7].

We consider that the ambient noise can be modeled using Gaussian distribution and its norm can be modeled using Rayleigh distribution. In particular, we scan the spectrum band of the received signal with the mean of frequency sliding window. We then compute Akaike weights of the band of interest. Finally, we fix a threshold in order to decide on the nature of the received signal. The flow chart of the proposed algorithm is shown in Fig. 1, which can be implemented in four steps:

1) Distribution Parameters estimation:

In the first step of the algorithm, we choose the size of the observed window in order to estimate parameters $\hat{\theta}$ over this window using (10). As an exemple, the window is set to 200 kHz for GSM signals, which is equal to the GSM bandwidth.

2) Computing AIC and Akaike weights:

In the second step, we compute the value of AIC and then Akaike weights using (11). Once we get the corresponding Akaike weights, we shift the window by one sample till the end of the band.

3) Bandwidth Division:

The third step gives 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). We then divide the spectrum with respect to the reference sub-band as shown in Fig. 2.

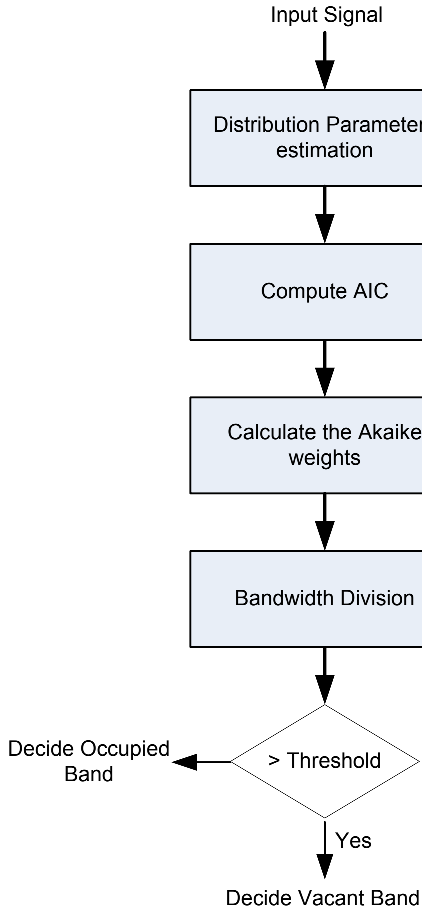

Fig. 1. The flow chart of the blind spectrum sensing algorithm based on model selection using Akaike weights

4) Threshold Decision:

Finally, we fix a threshold of Akaike weights measurements. 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).

V. Simulation Results

The proposed blind detection approach is evaluated using Eurécom RF Agile Platform [9]. It covers an RF band from 200 MHz to 7.5 GHz, with a maximum bandwidth of 20 MHz. It is able to receive and transmit almost all the existing commercial Radio Access Technologies. Concerning the transmitted power, the target is comparable to existing GSM terminals (+21 dBm). On the receiver side, the noise figure is from 8 to 12 dB, depending on the frequency band. The RF equipment include up to 4 antennas and 4 RF chains. In addition, it allows for experimenting with system on-chip architectures for wireless communications.

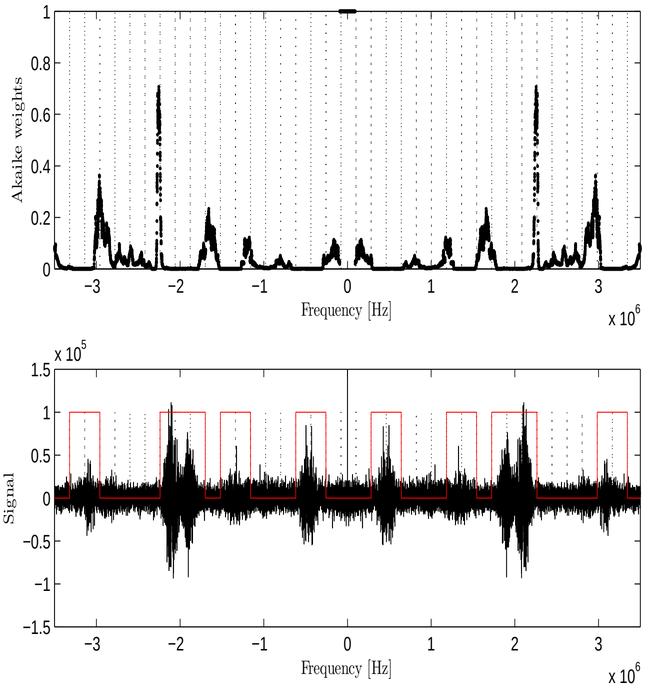

Fig. 2. Akaike weights for a baseband GSM signal at the carrier of 953 MHz.

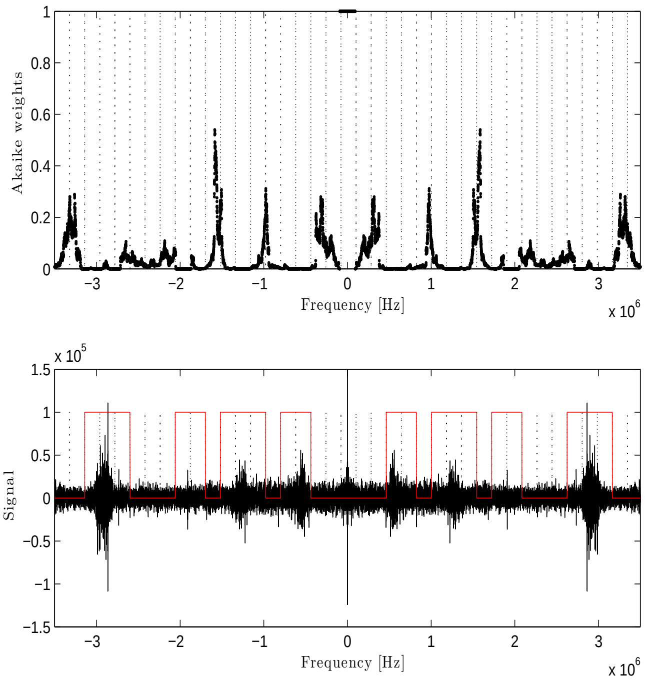

Fig. 3. Akaike weights for a baseband WiFi signal at the carrier of 2430 MHz.

At a first stage, we focus on GSM signals at carrier of 953 MHz with a bandwidth of 7680 MHz. We capture 10 realizations spaced by 1 ms and apply the proposed technique to evaluate the performance of the blind algorithm in terms of primary user detection signal. Time channel samples are stored in a vector of size N (with N equal to 20480). Parameters θ are estimated over 533 samples which correspond to the GSM bandwidth (equal to 200 kHz).

Fig. 2 depicts the Akaike weights obtained from the baseband GSM signal. It is clearly shown from Fig. 2 that vacant sub-band detection turns out to do a simple peak detection. Accordingly, we adopt this strategy in a first step and improve our algorithm by fixing a threshold of 1% below or above to decide whether the received signal is data or noise respectively.

At a second stage, we have also considered a WiFi signal at the carrier of 2430 MHz. The size of the window is around 500 kHz. Akaike weights with Gaussian distribution are presented in Fig. 3, for the baseband WiFi signal. The threshold is set 1%. Similarly to the case of GSM sensing, we obtain interesting results in terms of primary user signal detection. Fig. 3 shows also that, for Akaike weight value larger than the threshold, we can locate vacant sub-bands, and, for Akaike weights lower than the threshold, we decide the presence of data signal.

VI. Conclusion

Although the importance of blind sensing in the conception of cognitive radio devices, only few algorithm exist in the literature. In this paper, we propose a new detection method of vacant sub-band in the radio spectrum. The proposed algorithm using AIC and Akaike weights is based on model selection of the received signal distribution. The obtained performance results are promising, as has been shown by simulation. The proposed algorithm exhibits very interesting results in term of primary user signal detection in a perfectly blind way.

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