NEW SPECTRAL ESTIMATION BASED ON FILTERBANK FOR SPECTRUM SENSING

Miguel A. Lagunas Hernández[1], *Miguel A. Rojas* [*1],*Petre Stoica* [†2]

[1]Centre Tecnòlogic de Telecomunicacions de Catalunya, Barcelona, Spain
[2]Uppsala University, Dept. of Information Technology, Uppsala, Sweden
Email: m.a.lagunas@cttc.es, marojas@cttc.es, ps@it.uu.se

ABSTRACT

The advance of cognitive radio (CR) technology put in evidence the need of new spectral estimation methods for proper labeling of licensed and un-licensed users. We present a new spectral estimation procedure for monitoring the radio spectrum. The estimate is derived from a different view point of traditional filter bank approach. The resulting method is able to detect a predetermined spectral shape forming part or contributing to a given data record, providing at the same time an estimate of its power level and its frequency location. We prove that traditional filter-bank spectral estimation reduces to a particular case of our procedure. The specific spectral shape to detect is named hereafter as the candidate spectrum. The major motivation for this procedure was the proper spectrum labeling of licensed users in cognitive radio scenarios. The performance of the spectral monitoring procedure is demonstrated in the detection of a BPSK primary user in a wireless scenario containing DVB-T emissions.

Index Terms— Spectral Estimation, Cognitive Radio, Filter Bank, Spectrum Labeling, Candidate Spectrum

1. INTRODUCTION

The advance of cognitive radio technology put in evidence that some of the radio spectrum regulation rules did not evolve at the same velocity that radio technology. In fact, it is well recognized that the radio spectrum is over-licensed but not over-used. This means that currently the radio spectrum is under utilized, mainly taking into account the available technology. There are many field tests and measurements that show low usage of radio spectrum of certain frequency bands and geographical regions. In 2002 studies of Federal Communications Commission (FCC) reported that the variation in the utilization of licensed spectrum ranges from 15% to 85% [1]. In consequence, the radio spectrum is under utilized by primary users, as an example this is the case for the TV broadcast band [2]. The concept of open spectrum (not free spectrum) consists in opening the unused spectrum to secondary users. A potential market model would be the deployment by existing or new operators of spectral monitoring equipment which broadcast to potential secondary users the spectral vacancies in terms of time available and frequency ranges. When a secondary user agrees to use the available spectrum with the operator, it starts transmission with some economic compensation for the operator for opening its spectrum to secondary users. Regardless this model is accepted or not, there is no way to avoid the proper spectrum monitoring and labelling of primary users in any vision of a CR scenario[3]. Furthermore, we believe that, together with cross-layer technologies to match the frequency vacancies to the CR applications, spectral estimation tools have to be revisited to detect spectral signatures rather than mere spectral occupancy.

Convinced that spectral signature estimation is one of the major problems to be faced in a CR deployment, we report a new spectral estimation, named as candidate spectrum, which is able to detect and label specific spectral signatures [4]. The procedure is based on the filter bank approach for spectral estimation , proving that traditional spectral estimation can be encompassed as candidate spectral estimation when the candidate, i.e. the signature we are interested in, consists in an un-modulated carrier. The resulting procedure is able to detect and label power and central frequency location of any spectral signature (candidate) in presence of wireless noise, and co-channel interference with different modulation format or signature.

This paper is organized as follows. In section 2, it is revisited the filter bank method for spectral estimation and explores the possibility of changing the traditional single frequency scanning by a spectral shape. Derivation of the new spectral estimation method is described in section 3. Section 4 describes different spectrum sensing techniques to detected spectrum environment. Section 5 describes briefly the application of cognitive radio to detect a primary user using BPSK modulation in presence of DVB-T users using OFDM/QAM modulation. Additionally, section 5 presents some simulation results to evaluate the reported spectral estimation method. Finally, in section 6, we present our conclusions.

*Work supported by the Mexican Government under grant PROMEP
†Work supported in part by the Swedish Research Council

2. REVISITING FILTER-BANK SPECTRAL ESTIMATION

In order to find the fundamental basis for the new spectral estimation is necessary to revisit the filter-bank approach for spectral estimation [5]. Basically, the mentioned approach is based on a dedicated filter design, which steered to a given frequency, aims to minimize spectral leakage from the rest of frequencies. The estimate is given by the measured output power of the filter (power level), divided by the bandwidth of the analysis filter (power density). The minimum leakage objective together with the steering constrain is usually formulated as (1).

$$\underline{A}^H.\underline{\underline{R}}.\underline{A}\Big|_{min}, \text{ subject to } \underline{A}^H\underline{S}=1 \tag{1}$$

Where $\underline{S} = \begin{bmatrix} 1 & e(jw) & \dots & e(j(Q-1))w \end{bmatrix}^H$ is the steering frequency vector with w equal to $(2\pi f)$, $\underline{A}$ contains the FIR Q filter coefficients and $\underline{\underline{R}}$ is the correlation matrix of the input signal.

As concerns with the constraint, it is clear that the response of cero dB at the steering frequency refers to the magnitude only and not necessarily over the filter phase, that does not impact in the resulting power level estimate. When setting the magnitude constrain only, (1) is reformulated as (2).

$$\underline{A}^H.\underline{\underline{R}}.\underline{A}\Big|_{min}, \text{ subject to } \underline{A}^H\left[\underline{S}.\underline{S}^H\right]\underline{A}=1 \tag{2}$$

The solution of (2) is given by the solution of (3), where λ is the Lagrange multiplier.

$$\left(\underline{\underline{R}}-\lambda\underline{S}.\underline{S}^H\right)\underline{A}=\underline{0} \tag{3}$$

Clearly λ represents how much power we can remove from data at the steering frequency, such that the remaining matrix preserves its positive definite character. This value, for a rank-one subtraction can be derived directly and reduces to be λ_{min} of the generalized eigenvalue problem. The unitary null eigenvector is also easy to derive. Both, eigenvector and λ_{min} are:

$$\underline{A}=\frac{\underline{\underline{R}}^{-1}\underline{S}}{\left(\underline{S}^H\underline{\underline{R}}^{-2}S\right)^{0.5}} \quad \lambda=\frac{1}{\underline{S}^H\underline{\underline{R}}^{-1}\underline{S}} \tag{4}$$

Note that the power level estimate coincides with the one derived from the use of the magnitude and phase constrain. And that when adjusting the unitary eigenvector to the constrain the filter also reduces to the same that in the traditional method. In summary nothing has changed, just it is a different view but much richer than the traditional one as we will see. In fact, (3) suggest a re-formulation of the non-parametric spectral estimation problem. The problem can be viewed as follows: First, the power level estimate is just how much power we can remove of a single line contribution to the data autocorrelation matrix, yet preserving its positive definite character. Second, the analysis bandwidth can be defined as the bandwidth of the filter producing the same power either introducing the single line or the data autocorrelation matrix. This is the eigenvector of (5).

$$\underline{\underline{R}}.\underline{A}=\lambda\underline{S}.\underline{S}^H\underline{A} \tag{5}$$

The noise bandwidth of the eigenvector will be:

$$B_N=\frac{\underline{A}^H.\underline{A}}{\underline{A}^H\left(\underline{S}.\underline{S}^H\right).\underline{A}}=\frac{1}{\underline{A}^H\left(\underline{S}.\underline{S}^H\right).\underline{A}} \tag{6}$$

Finally, the spectral density will be estimated by the power level λ divided by B_N.

$$\hat{s}(w)=[\underline{A}.\left(\underline{S}.\underline{S}^H\right).\underline{A}]\lambda \tag{7}$$

In summary, this complicated manner of looking to a well known and solved, problem resumes as: Compute λ_{min} in (3) for power level estimate and the corresponding eigenvector; then use (7) for spectral density. The motivation for this complex view of filter-bank spectral estimation is appreciated in the next section.

3. CANDIDATE SPECTRAL ESTIMATION

Formula (3), as mentioned before, reveals that looking for a single carrier contribution in data autocorrelation matrix is just a problem of spectral subtraction. Furthermore, the concept of a basic candidate that its modulated from cero frequency to any other frequency can be formulated as, the basic zero frequency line with candidate correlation equal to $\underline{1}.\underline{1}^H$, where $\underline{1}$ denotes the vector of ones on every entry, which is modulated to the scanned frequency as (8), where $\odot$ indicates element wise product.

$$\underline{\underline{R}}_{SC}=\left(\underline{S}.\underline{S}^H\right)\odot\left(\underline{1}.\underline{1}^H\right)=\left(\underline{S}.\underline{S}^H\right)\odot\underline{\underline{R}}_C \tag{8}$$

In summary, the candidate we are looking for is the square matrix of ones, aiming to determine in which frequency it is located and what is its power level. At this moment we are ready to solve the CR problem. Let us assume that the licensed user is, for example, a BPSK modulation signal with four samples per symbol and rectangular pulse shape. The candidate correlation will be a Toeplitz matrix containing [1 0.75 0.5 0.25 0 0] as its first row. Then the power level estimate of this signature at a given frequency will be the minimum eigenvalue of (9).

$$\left(\underline{\underline{R}}-\lambda.\left(\underline{S}.\underline{S}^H\right)\odot\underline{\underline{R}}_C\right)\underline{A}=\underline{0} \tag{9}$$

Next, using the corresponding eigenvector, the density of the candidate will be (10).

$$\hat{s}_C(w)=\left[\underline{A}^H\left(\left(\underline{S}.\underline{S}^H\right)\odot\underline{\underline{R}}_C\right)\underline{A}\right]\lambda \tag{10}$$

Note that for the same symbol rate, any M-QAM signal, with rectangular pulse signaling, will be detected as candidate. When the symbol's rate (bauds) is not equal, the number of samples per symbol will change and, in consequence, it will not be recognized as the candidate which is at a rate, relative to our sampling rate, of four samples per symbol.

4. SPECTRUM SENSING ALTERNATIVES

The fundamental of CR technology is spectrum sensing method, whose function is to detect the current spectrum environment and to find the empty spectrum [6, 7]. Spectrum sensing is the process of periodically and dynamically detect primary users. Methods for spectrum sensing use to be based on energy detection and they are implemented by averaging frequency bins of an FFT, being blind to the modulation format that causes the measured energy [8]. At the same time, they show the low resolution associated with Fourier based methods. Other tool proposed for spectral monitoring is feature detection. These procedures exploit the periodicity inherent to most of the modulated signals. More specifically the ciclo-stationarity is the most used feature for spectrum labelling. These techniques are, let us say, less blind than the energy detection to the modulation format, but they suffer of low resolution. In addition, from preliminary simulations they seem to show lower robustness, in terms of detection versus false alarm, to SNR of the candidate, to short data records and to order selection. A similar alternative is to use high order moments for modulation detection but, again based in our limited experience, they seem to be blind to differentiate CR from primary users since they have low frequency resolution. At the same time, both cyclo-stationary as well as high order methods require long data lengths (long decision delay) for proper performance as modulation detectors. In summary, from out knowledge, none of the reported schemes for CR spectrum labelling have the ability of candidate spectrum to label power level and frequency location for an specific modulation format, in strong interferences and with low decisions delays.

5. A COGNITIVE RADIO APPLICATION

The application to be described, in order to show the potential of candidate spectrum labelling, is to detect unused TV channels. The wireless scenario contains one BPSK primary user and two DBV-T users having a power of 28 dB and a carrier frequency at 90 Mhz and 610 Mhz , using OFDM/QAM modulation see in Fig 1. The DVB-T users transmit the signal organized in frames. Each frame has a duration of T_s and consist of 68 OFDM symbols. Each symbol is constituted by a set of 1705 carriers in the 2K mode [9]. The transmitted signal is described by the following equation:

$$s(t) = Re\left\{e^{j2\pi f_c t}\sum_{m=0}^{\infty}\sum_{l=0}^{67}\sum_{k=K_{min}}^{K_{max}} c_{m,l,k} \times \psi_{m,l,k}\left(t\right)\right\} \tag{11}$$

where

$$\psi_{m,l,k}\left(t\right) = e^{j2\pi(t-\Delta)} \tag{12}$$

The primary user, we aim to detect, is transmitting a BPSK modulated signal with four samples per symbol at 350 Mhz with 26 dB of power and rectangular pulse shape. The channel is assumed non frequency selective, i.e. flat fading, otherwise the procedure have to be refined to cope with the channel effects on the candidate at the spectral monitoring station. The sample autocorrelation $\underline{\underline{\hat{R}}}_{xx}$ is computed using the forward and backward method formulated as (13)

$$\underline{\underline{\hat{R}}}_{xx} = \frac{1}{2\left(N-Q\right)}\sum_{n=Q+1}^{N}\left\{x(n)x^H(n) + \underline{\underline{J}}x^*(n)x^T(n)\underline{\underline{J}}\right\} \tag{13}$$

Where Q is the filter order ($Q = 8$), N is the number of samples ($N = 1705$), $\underline{\underline{\mathrm{J}}}$ is the exchange matrix whose cross diagonal elements are ones and all the others are zeros. Next diagram summarizes the candidate spectrum method.

Algorithm 1 New Spectral Estimation Method

Define Candidate Autocorrelation Matrix:
Set $\mathbf{R_c}$ at unit power level and baseband frequency

Find minimum eigenvalue and eigenvector associated of:
$\mathbf{Re} = \lambda\left[SS^H \odot \mathbf{R}_c\right]\mathbf{e}$

Compute power level:
$\hat{\gamma} = \lambda$

Compute Density Estimate:
$\hat{s_c} = \lambda\left(\mathbf{e}\left[SS^H \odot \mathbf{R}_c\right]\mathbf{e}\right)$

The estimates provided by the candidate spectrum technique are compared with the periodogram method, the traditional power level and the power density method

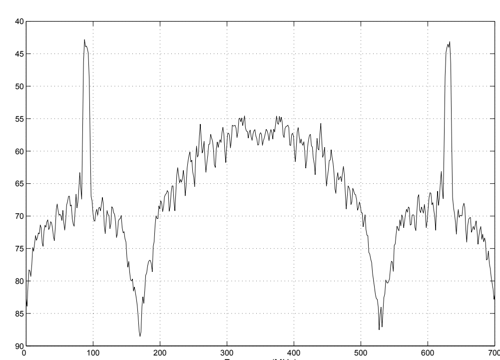

Fig. 1. Wireless scenario 90 Mhz and 610 Mhz DVB-T users and a 350 Mhz BPSK primary user (candidate)

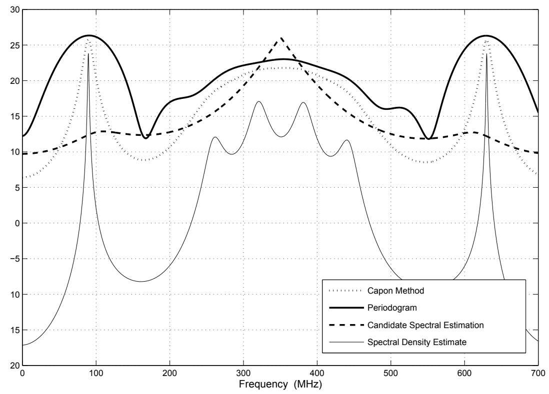

Fig. 2. Scenario of DVB-T users and BPSK candidate sensed with periodogram, Capon Method, Capon Method's spectral density and Candidate Spectral Estimation

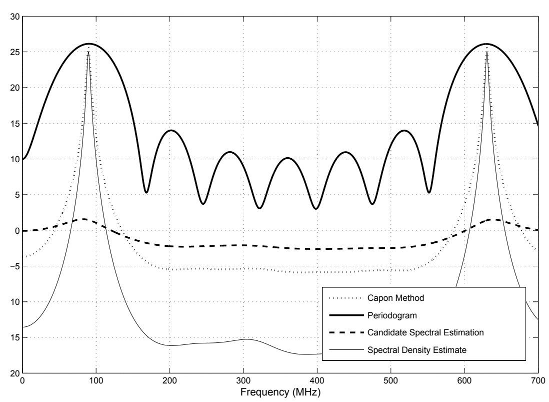

Fig. 3. Same scenario as figure 2 when BPSK candidate user vacate the radio spectrum

Figure 2 shows spectral estimates for the mentioned scenario using the followings methods: Periodogram, Capon , Candidate Spectral Estimation and power density. Observe that the proposed method only labels the BPSK primary user, i.e. the candidate, providing its power level with good accuracy (26 dB).

Figure 3 illustrates the case when the BPKS candidate user does not use the radio spectrum, since it is not active. The candidate estimate stays around the white noise level since no contribution of candidate is present at the receiver. Traditional procedures continue detecting energy regardless it does not correspond to the primary user. These preliminary results show that the candidate method is able to detect and label specific spectral shape

6. CONCLUSIONS

The candidate spectrum, has been introduced from revisiting the filter bank framework. Traditional estimates can be encompassed as the case where the candidate reduces to an unmodulated carrier. The performance of the candidate spectrum depends on the agreement between the candidate autocorrelation matrix and the actual one. This represents a problem for wireless scenarios experiencing selective fading. Further work, in addition to a solution to the selective fading problem, includes refinements to increase dynamic range on power level, estimation impact, further refinements in order to improve the detection versus false alarm performance, and wideband signal conditioning for the received signal.

As an example, we have shown that candidate spectral estimation can be used to detect the presence of BPSK primary user (candidate), regardless of the other two DVB-T transmission signals. In addition, the method provides the power level and frequency location of the BPSK transmission signal.

7. REFERENCES

[1] FCC, "Spectrum policy task force report," *ET Docket No. 02-155*, Nov. 2002.

[2] FCC, "Notice of proposed rule making: Unlicensed operation in the tv broadcast bands," *ET Docket No. 04-186*, May. 2004.

[3] S. Haykin, "Cognitive dynamic systems," *Proc. IEEE-ICASSP 2007*, vol. Paper IV, pp. 1369–1372, April 2007.

[4] M.A. Lagunas, Ana I. Perez, Petre Stoica, and Miguel A. Rojas, "The content of this article has been object of the request of a patent submitted on december 2007," .

[5] P. Stoica and R. Moses, "Spectral analysis of signals," *Pearson Prentice Hall*, 2005.

[6] J.Mitola, "Cognitive radio: An integrated agent architecture for software defined radio," *PhD thesis, KTH Royal Institute of Technology, Stockholm, Sweden*, 2000.

[7] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23(5), pp. 201–220, Feb. 2005.

[8] Tobias Renk, Clemens Kloeck, and Friedrich K. Jondral, "A cognitive approach to the detection of spectrum holes in wireless network," *Proc. IEEE-ICASSP*, vol. IV, 1984.

[9] ETSI TR, "Digital video broadcasting (dvb): Implementation guidelines for dvb terrestrial services," *Technical Report*, vol. 101 190 v1.2.1, 2004.