SPECTRUM LABELING FOR COGNITIVE RADIO SYSTEMS: CANDIDATE SPECTRAL ESTIMATION

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ABSTRACT

A key challenge of the air interface of the cognitive radio is an accurate detection of weak signals of licensed users over a wide spectrum range. This paper describes a method for first detecting and next locating in frequency a given primary user, even when a non-candidate interference is located at the same frequency. The range of SNR that is covered proves that the estimate is efficient for realistic scenarios. In addition, the good performance is kept even for very short data records (50 symbols of the candidate signal). The proposed technique shows much better performance than energy detectors and less complexity than cyclo-stationary based ones.

Index Terms— Cognitive radio, spectrum sensing, spectrum analysis.

1. INTRODUCTION

Spectrum is considered to be a scarce resource since all frequencies below 3 GHz have been completely allocated to specific users. However, actual measurements show that most of the allocated spectrum is vastly underutilized at any specific location and time. This fact gives opportunity to unlicensed devices to be secondary users of the spectrum and use the frequency bands only if the official user of the spectrum (primary system) is not using them. In other words, cognitive radios have been proposed as a way to reuse this underutilized spectrum [1][2][3][4]. Under an open spectrum vision, the operator premises must detect spectrum vacancies from their primary users in order to offer these vacancies, in terms of bandwidth and time, to potential bidders. To achieve this reuse while guaranteeing non-interference with the primary user, either operator premises or cognitive radios must detect very weak primary signals.

This work proposes a technique for accurate detection of weak signals of licensed users; thus, allowing a proper labeling of the spectrum by distinguishing them from secondary or interfering users. Within the framework of major spectral estimation methods, including frequency detectors and parametric spectral estimation procedures, the authors have proposed in [6] a new procedure for high resolution spectral density estimation. This paper summarizes and extends previous results for either detection or both detection and frequency location of a given modulation included in a given data record. The procedure aims at agilely detect the presence of a candidate signal just from its autocorrelation function, which depends only on the basic pulse used by the modulation transport. The most interesting feature of the final spectrum labeling technique is the robustness in presence of other interference.

First, this paper formulates the problem in Section 2. Next, Section 3 proposes a low complexity candidate detector, which is independent of the frequency location of the candidate. If a primary user has been detected, then the results are refined by incorporating frequency location information, which is summarized in Section 4. The performance of the obtained power level estimate is shown in terms of probability of detection versus false alarm. Finally, conclusions come in Section 5.

2. PROBLEM STATEMENT

In this paper we focus on detecting the presence of a licensed user or candidate signal just from its autocorrelation function (acf) or matrix $\underline{\underline{R}}_C$, which depends only on the basic pulse used by the modulation transport.

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More specifically, let us assume that the licensed user is sensed without knowing the power level neither the carrier frequency. The power level is not known since this level depends on the location of the sensing equipment. The carrier frequency is also unknown when the cognitive radio searches among different licensed bands and it is agile to move among them. The licensed user is assumed to use a known power spectral density, which mostly depends on the baud rate and the symbol shape. This candidate spectrum implies a spectral occupancy defined by S(w) for zero carrier frequency or base band, $\left(-2\pi B\right) \le w \le \left(2\pi B\right)$. From this candidate spectrum, the corresponding autocorrelation function is obtained, and the QxQ Toeplitz matrix $\underline{\underline{R}}_C$ is derived in accordance with the order of the spectral estimation procedure (i.e. Q). Note that the greater the record length or order Q the better is the performance of the procedure, but, at the same time, it increases the number of samples (i.e. the length of analysis) that is required to detect the presence or absence of the licensed user. Note that the record length multiplied by the number of samples per symbol results in the length of analysis. To simplify the notation, we let $\underline{\underline{R}}_C$, and also any other correlation matrix of interest along the work, denote either the theoretical correlation matrix or its estimate $\hat{\underline{\underline{R}}}_C$. Even so, the reader should keep in mind that in applications $\underline{\underline{R}}_C$ is always $\hat{\underline{\underline{R}}}_C$.

In order to explore the carrier frequency and the power level, the candidate correlation $\underline{\underline{R}}_C$ is scaled by a factor γ and modulated by a rank-one matrix formed by the steering vector at the sensed carrier frequency. The candidate modulated correlation $\underline{\underline{R}}_{CM}$ is shown in (1)

$$\underline{\underline{R}}_{CM} = \gamma.\left[\left(\underline{S}.\underline{S}^H\right) \odot \underline{\underline{R}}_C\right] \qquad (1)$$

where $\odot$ denotes the component-by-component or Schur product, $\underline{S} = \left[1 \quad \exp(jw) \quad ... \quad \exp(j(Q-1).w\right]^T$ is the steering frequency vector and w is the frequency where the estimate of the spectral density of the input signal is going to be produced. Note that $\left(\underline{S}.\underline{S}^H\right)$ can be considered as basic modulated candidate (i.e. $\underline{\underline{R}}_C$ is equal to a matrix with all its entries equal to one) and $\underline{\underline{R}}_{CM}$ the generalized one.

Let the sensing node get data samples $\{x(n)\}$ and compute the QxQ correlation matrix that is associated with $\{x(n)\}$

$$\underline{\underline{R}} = E\left[\underline{x}_n \, \underline{x}_n^H\right] \qquad (2)$$

where $\underline{x}_n = \left[x(n) \; x(n-1) \cdots x(n-Q+1)\right]^T$ and $(.)^H$ denotes the conjugate transpose. The data correlation matrix $\underline{\underline{R}}$ contains the candidate modulated correlation $\underline{\underline{R}}_{CM}$ together with AWGN of power σ^2 and interference. Under the assumption that the signals are uncorrelated with one another, $\underline{\underline{R}}$ can be written as:

$$\underline{\underline{R}} = \underline{\underline{R}}_{CM} + \underline{\underline{R}}_I + \sigma^2 \underline{\underline{I}} \qquad (3)$$

where $\underline{\underline{R}}_I$ is de interference correlation matrix.

The problem to solve consists in finding the candidate autocorrelation $\underline{\underline{R}}_C$ from the data autocorrelation $\underline{\underline{R}}$. The spectral shape or candidate spectrum is assumed to be known in shape and bandwidth *B*, but the power level γ and the frequency location *w* remain unknown. The proposed procedure detects the licensed user activity even when it is far below the interference level and in the same frequency band. Moderate data length and low filter order is required. Invoking the additive decomposition of $\underline{\underline{R}}$ in (3) we can estimate the spatial power γ and frequency location *w* by resorting to a correlation matrix subtraction or fitting framework. In other words, given a data autocorrelation matrix $\underline{\underline{R}}$, to find out the frequency and power in $\underline{\underline{R}}_{CM}$, referred hereafter as the candidate, that better fits $\underline{\underline{R}}$.

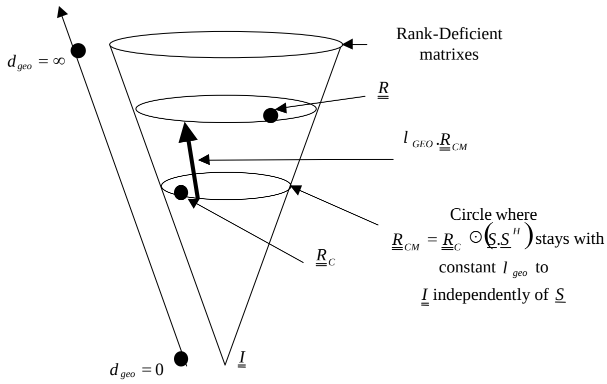

Figure 1. Illustration of geodesic distances in the cone of the positive definite correlation matrixes.

3. CANDIDATE DETECTION WITH THE GEODESIC DISTANCE

The problem of finding a modulated candidate autocorrelation $\underline{\underline{R}}_{CM}$ that fits best in the data autocorrelation can be formulated in terms of distance between these two autocorrelation matrixes. In order to formulate the distance, instead of using the traditional Euclidean metric as in [6], an interesting detector of the candidate can be formulated from the geodesic distance between the candidate (1) and the data matrix $\underline{\underline{R}}$, which is a suitable metric for hermitian matrixes [5]. Assuming $\lambda(q)$ (q=1...Q) are the generalized eigenvalues of the pair $\left(\underline{\underline{R}}, \gamma \underline{\underline{R}}_{CM}\right)$, i.e. $\underline{\underline{R}}.\underline{a}_q = \gamma.\lambda(q).\underline{\underline{R}}_{CM}.\underline{a}_q = l(q).\underline{\underline{R}}_{CM}.\underline{a}_q$, *then*

$$d_{geo}^2\left(\underline{\underline{R}},\gamma.\underline{\underline{R}}_{CM}\right)=\sum_{q=1}^{Q}\left|Ln\left(\lambda(q)\right)\right|^2=\sum_{q=1}^{Q}\left|Ln\left(l(q)\right)-Ln(\gamma)\right|^2$$
$$if\ l_{GEO}=\left(\prod_{q=1}^{Q} l(q)\right)^{1/Q}$$
$$\min_{\gamma} d_{geo}^2\left(\underline{\underline{R}},\gamma.\underline{\underline{R}}_{CM}\right)\Rightarrow\gamma=\frac{1}{Q}\sum_{q} Ln(l(q))=l_{GEO}=\left(\det\left(\underline{\underline{R}}_C^{-1}\underline{\underline{R}}\right)\right)^{1/Q}\quad\forall\underline{S} \tag{4}$$

By derivation of d_{geo}^2 with respect to γ, it is obtained that the geodesic distance $d_{geo}^2\left(\underline{\underline{R}},\gamma\underline{\underline{R}}_{CM}\right)$ is minimized when the power level of the candidate γ is equal to the geometric mean of the eigenvalues of the pair $\left(\underline{\underline{R}},\underline{\underline{R}}_{CM}\right)$, l_{GEO}. Furthermore, as it is illustrated in Figure 1, the geometric mean of the eigenvalues is independent of the modulation. In other words, the geometric mean of the pair $\left(\underline{\underline{R}},\underline{\underline{R}}_{CM}\right)$ is equal to the one corresponding to the pair $\left(\underline{\underline{R}},\underline{\underline{R}}_{C}\right)$. Using this property, independently of the frequency location of the candidate, the geometric mean of the eigenvalues indicates how much we need to multiply the candidate in order to get close, in geodesic distance, to the data matrix. In summary, computing the determinant of $\underline{\underline{R}}_C^{-1}\underline{\underline{R}}$ implements a detector of the presence of the candidate in the given data. The detection is independent of the frequency location of the candidate, which represents a valuable advantage of the detector in terms of complexity.

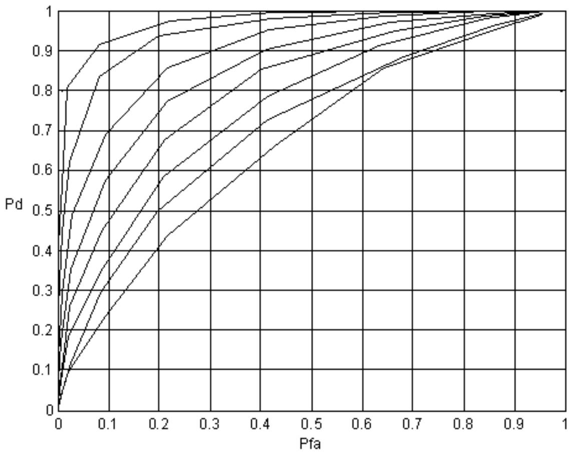

Figure 2. Performance of the so-called geodesic detector for a BPSK candidate. Pd versus Pfa. SNR of the candidate ranging from –13 dB up to –6 dB (1dB step).

Figure 2 evaluates the performance of the detection variable l_{GEO} in equation (4) by computing its probability of False Alarm vs. probability of Detection. In the scenario of Figure 2, the candidate spectrum is a BPSK modulation with rectangular pulse shape, at a baud rate of 4 samples per symbol. The SNR of the candidate is varied from –13dB up to -6dB (i.e. 1dB step). The probability of detection versus probability of false alarm is shown in Figure 2. The order of analysis is Q=8 and the samples per record were 200 samples.

As it can be seen from this figure, the performance of the detector is quite good, mainly taking into account its low complexity and its independence from the frequency location of the candidate. Once a licensed user has been detected, then its frequency location is necessary. Next section describes a technique for candidate frequency location that presents robustness to the presence of other interference signals.

4. COMPLETE SPECTRUM LABELLING

The Capon's estimate can be formulated as a spectral subtraction problem [6], which basically reduces to find the minimum eigenvalue of (5)

$$\left(\underline{\underline{R}}-\lambda.\left[\left(\underline{S}.\underline{S}^H\right)\odot\underline{\underline{R}}_c\right]\right)\underline{A}=\underline{0} \tag{5}$$

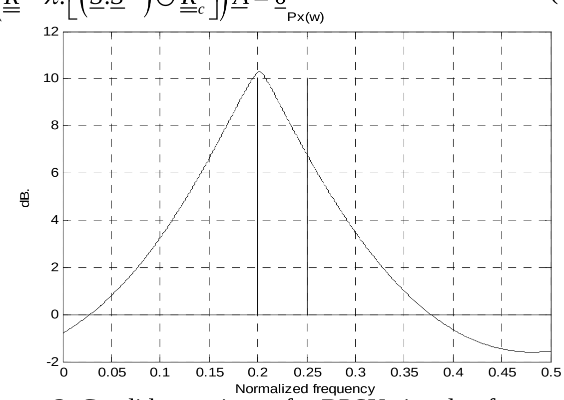

Figure 3. Candidate estimate for BPSK signal at frequency 0.2 with SNR 10 dB in presence of an unmodulated interference located at 0.25 with the same power level

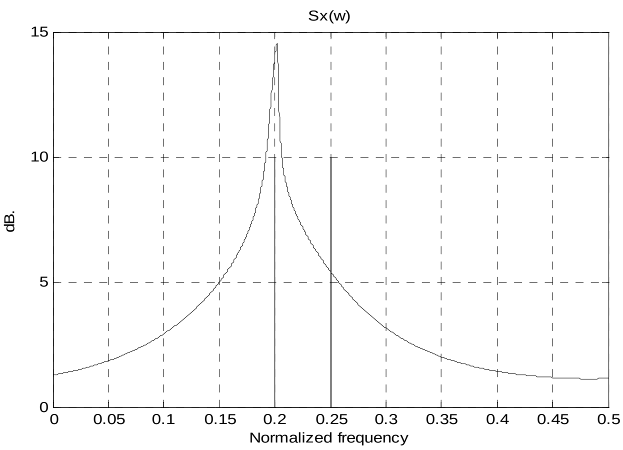

Figure 4. Power density for the power level estimate of the previous Figure 3.

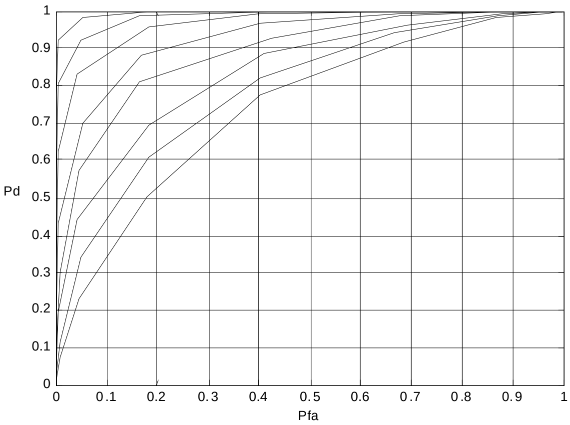

Figure 5. Detection characteristics for a M_QAM candidate. SNR from –13 up to –6 dB (e.g. 1 dB step). Power level estimate at actual frequency of 0.2. The length of the data records was 200 samples and the order of the estimate Q=8

The concept of candidate spectral density can be developed in terms of the filter A, i.e. the eigenvector associated to the minimum eigenvalue. In (6) the filter measures at its output a power level equal to $\underline{A}^H.\underline{\underline{R}}.\underline{A}$, which, thanks to the frequency response of the filter, is proportional to the output power when the candidate spectrum is the only contribution to the input spectrum

$$\underline{A}^H.\underline{\underline{R}}.\underline{A} = \lambda.\underline{A}^H\left[\left(\underline{S}.\underline{S}^H\right)\odot \underline{\underline{R}}_C\right]\underline{A} = \lambda.\underline{A}^H.\underline{\underline{R}}_{CM}.\underline{A} \quad (6)$$

Thus, the power level estimate can be viewed as the power output of the filter, normalized by the response to the candidate spectrum

$$\gamma = \frac{\underline{A}^H.\underline{\underline{R}}.\underline{A}}{\underline{A}^H.\underline{\underline{R}}_{CM}.\underline{A}} = \lambda \quad (7)$$

Since the filter is an eigenvector with norm equal to one, the noise bandwidth is $\frac{1}{\underline{A}^H.\underline{\underline{R}}_{CM}.\underline{A}}$

In summary, the spectral estimation procedure is summarized below in (8)

Define candidate autocorrelation matrix
at unit power level and baseband frequency $\underline{\underline{R}}_C$
Find the maximum eigenvalue and the eigenvector
asociated of $\lambda.\underline{\underline{R}}.\underline{e} = \underline{\underline{R}}_{CM}.\underline{e} = \left[\underline{S}.\underline{S}^H \odot \underline{\underline{R}}_C\right].\underline{e}$
Power level estimate $\hat{\gamma}\left(\underline{S}\right) = \lambda^{-1}$
Density estimate $\hat{s}_c\left(\underline{S}\right) = \lambda^{-1}.\left(\underline{e}^H\left[\underline{S}.\underline{S}^H \odot \underline{\underline{R}}_C\right].\underline{e}\right) = \underline{e}^H\,\underline{\underline{R}}.\underline{e}$
(8)

Figure 3 depicts the power density for a scenario where a 10 dB BPSK signal at normalized frequency of 0.2 shares the spectrum with an unmodulated carrier at 0.25 and 10 dB of

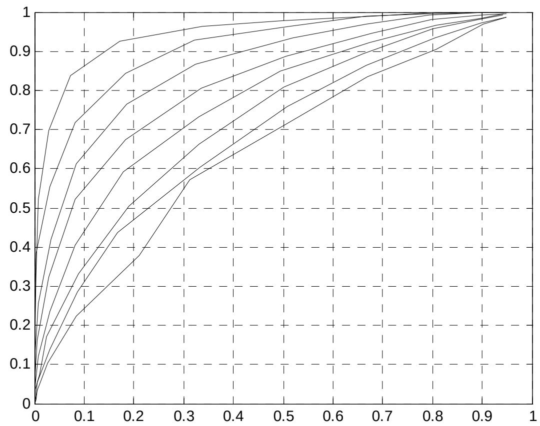

Figure 6. The performance degradation with respect to figure 5 due to the reduction of the length of the data record down to 80 samples.

SNR. It can be seen that the minimum eigenvalue plotted versus normalized frequency does not peak where the interference is present. At the same time the power level estimate at frequency 0.2 agrees with the actual power level of the candidate. The record length was 2000 samples, 4 samples per symbol of the BPSK candidate. The length of analysis was Q=8. Figure 4 shows the corresponding candidate spectral density of the power level estimate shown in the previous figure.

The rest of this section is devoted to show the performance of the power level estimate in (8) in terms of probability of detection, Pd, versus false alarm, Pfa. It is assumed that the carrier frequency of the candidate is known and equal to 0.2 in all the cases. Note that, when the central frequency is unknown, it can be determined with good accuracy either from the maximum of the power estimate, the enhanced power level estimates or the density estimates. In addition, the power level estimate behaves flat around the carrier frequency which represents robustness against small errors in frequency location of the candidate.

Figure 5 shows the probability of detection versus false alarm for a BPSK candidate of 4 samples per symbol and with SNR ranging from –13 dB up to –6 dB (i.e. 1dB step). The length of the data record is 200 samples and the order of the estimate is Q=8. Note that for the same scenario the performance of the minimum eigenvalue is superior to that shown by the geometric mean of the eigenvalues inspired in the geodesic distance (see in Figure 2 the performance of l_{GEO}). Figure 6 shows the degradation suffered by the detector when the length of the data record is reduced to 80 samples (i.e. equivalent to 20 symbols of the candidate). Increasing the length up to 2000 samples per record provides Pd equal to 0.99 with Pfa below 0.001 for SNR equal to –6 dB.

With respect to the impact of the order of the estimate in the resulting performance, we experienced that whenever the candidate matrix size is equal to or above the length of the pulse duration of the candidate, the performance depicted holds and it remains constant for orders above twice the pulse length. In these experiments, our rule set a length of Q=8, which corresponds to the minimum order for candidate with four samples per symbol. Increasing up to 16 the filter order do not show significant changes in performance regardless complexity increases.

The most interesting feature of the minimum eigenvalue estimate is the robustness that it shows in presence of other interferences. Next, Figure 7 shows the performance when the data signal contains an unmodulated interference. The record length is set to 200 samples and the order, set in accordance to the 4 samples per symbol of the candidate, was 8. The range of SNR was the same as before (-13 to -6 dB). Figure 8 shows the case when the interference is located at the same frequency than the candidate, 0.2. As it can be seen there is almost no difference with respect the case where interference was absent. This evidences the robustness of candidate estimate in front other interference sources different from the candidate.

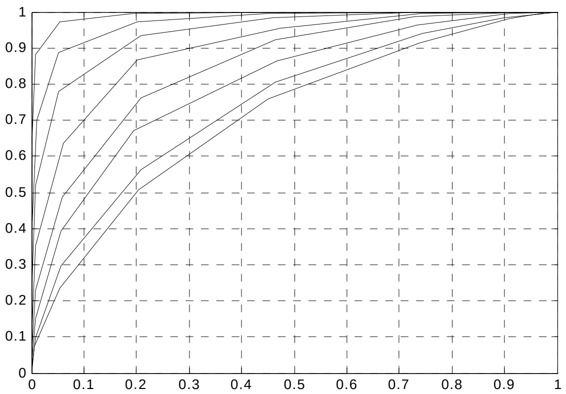

Figure 7. The same scenario as Figure 5 when an un-modulated interference is located at 0.25 with 10 dB. The parameters of the detector are the same that those used for the mentioned Figure 5.

5. CONCLUSIONS

From the previous section it is clear the good performance of the proposed procedure in order to detect the transmission of the candidate, even when a non-candidate interference is located at the same frequency. The range of SNR covered by the simulations proves that the estimate is efficient for realistic scenarios providing accurate detection even when the candidate is received below 10 dB. The performance is also good even for very short data records (50 symbols of the candidate signal). The proposed technique shows much better performance than energy detectors and less complexity than cyclo-stationary

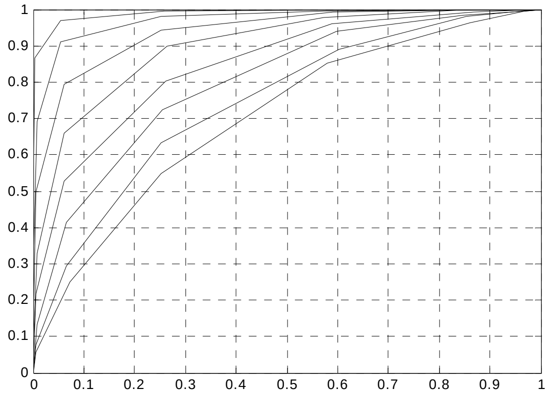

Figure 8. The same as figure 7 but with the un-modulated carrier located at the same frequency than the candidate, 0.2.

based ones. Concerning energy based detectors, note that they cannot perform well in the presence of interference close to the candidate frequency. With respect to cyclo-stationary based detectors, they are more complex and require more number of samples than the proposed techniques. More specifically, note that the correlation value that is computed in a cyclo-stationary based detector is between two different frequencies, which, of course, will be lower than the correlation at zero lag, i.e. the signal power level. In other words, since the candidate in (8) is detected by a peak almost equal to the actual power level this value will be higher or even much higher than the correlation between lines at different frequencies. It may be claimed that the background of candidate is the white noise level and in the cyclo-stationary spectrum is zero since the background noise is stationary. However, cycle processing requires very long records in order to show low background levels. In summary the convergence of cyclo-stationary spectrum requires long data records, which is no longer the case of candidate. Finally, when frequency location is not needed, the present work has also proposed a candidate detector based on the geodesic distance.

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