SPACE-TIME-FREQUENCY CANDIDATE METHODS FOR SPECTRUM SENSING

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ABSTRACT

The basic idea behind Cognitive Radio (CR) is to allow unlicensed users to utilize licensed frequency bands when they do not interfere to the primary (licensed) users. Thus, an important requirement of CR systems is to sense the spectrum in order to obtain awareness about the spectrum usage. In this paper, a new spectral estimation procedure for monitoring the radio spectrum which exploits frequency, time and angle diversity is presented. The procedure is a feature-based method able to detect predetermined spectral shape, providing at the same time an estimate of its power level, an estimate of its frequency location and an estimate of its angle of arrival. The specific spectral shape is called the candidate spectrum and gives name to the different methods.

1. INTRODUCTION

In 2002, the Federal Communications Commission (FCC) proved two very important facts [1]: (i) the availability of unlicensed spectrum is getting scarse mainly due to the recent rapid growth of wireless devices and (ii) the licensed part of the radio spectrum is poorly utilized in the sense that many licensed bands are only used sporadically. The spectrum scarsity together with the inefficiency of the licensed spectrum have resulted in an innovative way of thinking known as Cognitive Radio (CR).

The idea of CR [2] is to solve the spectrum allocation problem by allowing spectrum sharing, i.e, allowing opportunistic unlicensed access to the unused licensed frequency bands insofar as the unlicensed users do not degrade the service of the original license holders. To protect the primary (licensed) systems from the opportunistic secondary users' interference, spectrum holes [3] should be reliably identified. The identification procedure of available spectrum is commonly known as spectrum sensing. Spectrum sensing involves making observations of the radio frequency spectrum and reporting on the availability of unused spectrum for use by the CR users.

Recently, the idea of CR has evoked much enthusiasm. Particularly, there has been much work on designing sensing algorithms. There are several sensing methods proposed in the literature. Focussing on each narrow band, existing spectrum sensing techniques are widely categorized in two families: blind sensing and feature-based sensing techniques. One of the most popular blind detection strategy is energy detector (ED) [4]. However, ED is unable to discriminate between the sources of received energy. On the other hand, the most famous feature-based method is the matched filter. If the full structure of the primary signal is known (together with time and carrier synchronization), the optimal detector is matched filter detector. Unfortunately, the complete knowledge of the primary signal is not usually available. If only some features of the primary signal are known, feature-based detectors such cyclostationary detector [5] are more suitable. A survey of the most common spectrum sensing techniques, both non-feature and feature-based detectors, has been published in [6].

The conventional spectrum sensing algorithms usually exploit two dimensions of the spectrum space: frequency and time. In other words, they look for bands of frequencies that are not being used at a particular time. Fortunately, there are other dimensions that need to be explored further for spectrum opportunity. With the recent developments of beamforming technology, a new dimension emerges: the angle dimension. If a primary user is transmitting in a specific direction, the secondary user can transmit in other directions without interfering on the primary user. Thus, the spatial diversity brings extra spectrum opportunities [7].

Here, a new spectral estimation procedure for monitoring the radio spectrum which exploits frequency, time and angle dimension is presented. The procedure is a feature-based method able to detect predetermined spectral shape, providing at the same time an estimate of its power level, an estimate of its frequency location and an estimate of its angle of arrival. The specific spectral shape is called the candidate spectrum and gives name to the different methods. This paper extends previous results presented in [8], where only the frequency and power of the primary user were identified.

The reminder of this paper is organized as follows: In Section II the system model is provided. In Section III the 2D candidate method general idea is described and three different candidate methods are proposed. Finally, Section IV studies the performance of the proposed procedures and Section V states the conclusions.

2. SYSTEM MODEL

Before presenting the Candidate spectrum sensing techniques, we first briefly present the system model for the open spectrum scenario. The space-time-frequency spectrum sensing will be computed using multiple snapshots of measurements from a uniformly spaced linear array (ULA). Given the source $s(t)$, which denotes the desired signal from now on, the complex baseband snapshot of the received RF signal with respect to the center frequency of the RF band under

This work was partially supported by the Catalan Government under grant 2009 SGR 891, by the Spanish Government under project TEC2008-06327- C03 (MULTI-ADAPTIVE), by the European Cooperation in Science and Technology under project COST Action IC0902 and by the European Commission under project NEWCOM++ (ICT-FP7-216715).

E. Lagunas was supported by the Catalan Government under grant FI-DGR 2011.

scrutiny at a given time n can be written as,

$$\mathbf{x}_n = a_s(n)\mathbf{s}_s + \mathbf{n}_n \tag{1}$$

where $\mathbf{n}_n$ contains the noise plus the interference contribution. The snapshot $\mathbf{x}_n$ has length N_a, being N_a the number of sensors. The amplitude of the source is indicated with $a_s(n)$ and vector $\mathbf{s}_s$, known as steering vector, is defined as $\mathbf{s}_s = \begin{bmatrix} 1 & e^{jw_s \frac{d}{c}\sin(\theta_s)} & \ldots & e^{jw_s(N_a-1)\frac{d}{c}\sin(\theta_s)} \end{bmatrix}^T$. Here, d is the distance between two consecutive array elements, c is the speed of the light, θ_s is the angle of arrival of the desired user and w_s denotes the baseband frequency of the source with respect to the center frequency of the band under scrutiny w_0. Note that (1) assumes the narrowband model, i.e, negligible group delay.

With the aim of compact notation we consider a vector $\mathbf{X}_n$ formed by the concatenation of the Q snapshots acquired. Thus, the vector $\mathbf{X}_n$ has length QN_a. The data autocorrelation matrix is estimated from N_f independent data records. The sample base band correlation is,

$$\hat{\mathbf{R}} = \frac{1}{N_f}\sum_{n=1}^{N_f} \mathbf{X}_n {\mathbf{X}_n}^H \tag{2}$$

3. 2D CANDIDATE SPECTRUM SENSING: ANGLE AND FREQUENCY SCANNING

This section is divided in three parts: (i) definition of the candidate spectrum and autocorrelation matrix; (ii) introduction of the similarity function and (iii) derivation of three 2D Candidate spectrum sensing techniques.

3.1 The Candidate Spectrum and Autocorrelation Matrix

The goal of the 2D Candidate method is to detect the frequency, power and angle of arrival of the candidate (licensed) user, whose power spectral shape is the only prior knowledge we have. The candidate spectral shape (that is how the desired power spectral shape is called henceforth) mostly depends on the energy spectrum of the modulation pulse $p(t)$ and the baud rate $r = 1/T$. From the candidate spectrum, the corresponding candidate autocorrelation function defined in base band ($\mathbf{R}_b$) can be easily obtained.

In this paper we focus on detecting the presence of a licensed user from the featured-based detector perspective. More specifically, the problem is solved by tuning the detector to the spectral shape of the primary user. In order to explore the frequency dimension, the candidate autocorrelation $\mathbf{R}_b$ is modulated by a rank-one matrix formed by the scanning frequency vector at the sensed frequency w as follows,

$$\mathbf{R}_c = \left[\mathbf{R}_b \odot \mathbf{e}\mathbf{e}^H\right] \tag{3}$$

where $\odot$ denotes the elementwise product of two matrices, $\mathbf{e} = \begin{bmatrix} 1 & e^{jw} & \ldots & e^{j(Q-1)w} \end{bmatrix}^T$. Note that in (3) the dependency on w has been removed to clarify notation. The resulting matrix has dimension $Q \times Q$.

An extended candidate correlation matrix based on $\mathbf{R}_c$ must be built to cope with the angle of arrival dependency. The candidate correlation matrix can be obtained as follows,

$$\mathbf{R}_{cm} = \mathbf{S}\mathbf{R}_c\mathbf{S}^H \tag{4}$$

where matrix $\mathbf{S}$ is defined as $\mathbf{S} = \mathbf{I}_Q \otimes \mathbf{s}_d$, with $\mathbf{I}_Q$ being the identity matrix of dimension Q, $\mathbf{s}_d = \begin{bmatrix} 1 & e^{jw_0\frac{d}{c}\sin(\theta)} & \ldots & e^{jw_0(N_a-1)\frac{d}{c}\sin(\theta)} \end{bmatrix}^T$ and $\otimes$ denoting the kronecker product. Here, w_0 indicates the central frequency of the RF band under scrutiny. Again, the dependency on the angle θ in (4) has been removed to clarify notation. The dimensions of the general candidate correlation matrix are $\mathbf{R}_{cm} \in \mathbb{C}^{QN_a \times QN_a}$.

3.2 Similarity function

The proposed procedure is based on a spectral scan which reacts only when the candidate's spectral shape is present. Furthermore, a frequency scanning and an angle scanning can be viewed as a baseband autocorrelation function modulated at frequency w and moved to angle θ. Therefore, some similarity function is required to measure how much candidate spectrum power is contained in the given autocorrelation data matrix.

The corresponding model for the data autocorrelation matrix defined in (2) is given by,

$$\begin{aligned} \hat{\mathbf{R}} &= \gamma(w_s)\mathbf{S}\left[\mathbf{R}_b \odot \mathbf{e}(w_s)\mathbf{e}^H(w_s)\right]\mathbf{S}^H + \mathbf{R}_n \\ &= \gamma(w_s)\mathbf{S}\mathbf{R}_c\mathbf{S}^H + \mathbf{R}_n \\ &= \gamma(w_s)\mathbf{R}_{cm} + \mathbf{R}_n \end{aligned} \tag{5}$$

where $\mathbf{R}_n$ is the noise plus interference autocorrelation matrix and $\gamma(w_s)$ is the power level at frequency w_s. The interference is independent of the noise and candidate signal, and its spectral shape is different from that of the candidate.

Based on these assumptions, an estimate of the power level γ can be formulated as,

$$\min_{\gamma} \Psi\left(\hat{\mathbf{R}}, \gamma\mathbf{R}_{cm}\right) \tag{6}$$

where $\Psi(\cdot,\cdot)$ is a similarity function between the two matrices. The suitable similarity function must work in low SNR scenarios, it must be robust to the presence of strong interference that secondary users may cause, and must operate with a low number of data records to guarantee short sensing time. Note that the solution to (6) will be clearly a function of the steering frequency and a function of the steering angle.

The different estimates result from the proper choice of the aforementioned similarity function can be decided in two groups: (1) similarity functions based on the distance between the two matrices and (2) similarity fuctions based on the positive definite character of the difference ($\hat{\mathbf{R}} - \gamma\mathbf{R}_{cm}$).

3.3 2D Candidate Methods

Three different 1D candidate methods (only frequency scanning) were defined in [8]. The first one, a detector based on the traditional Euclidean metric (Frobenius norm of the difference between matrices), can be directly applied to the current 2D scanning (CANDIDATE-F). Thus, our problem can be written as,

$$\min_{\gamma} \left|\hat{\mathbf{R}} - \gamma\mathbf{R}_{cm}\right|_F \tag{7}$$

and the solution to (7) is given by,

$$\gamma_F = \frac{\mathrm{Trace}\left(\mathbf{R}_{cm}\hat{\mathbf{R}}\right)}{\mathrm{Trace}\left({\mathbf{R}_{cm}}^2\right)} \tag{8}$$

However, this estimate does not preserve the positive definite property of the difference.

The second alternative is a detector based on the geodesic distance (CANDIDATE-G) that best suits the space generated by hermitian matrices. The set of autocorrelation matrices is a convex cone because they are hermitian and positive semidefinite matrices. Therefore, a more proper distance for the space generated by the semidefinite positive matrices is the geodesic distance. However, the solution proposed in [8] has to be modified to cope with the 2D scanning. The geodesic distance between $\mathbf{R}_1$ and $\mathbf{R}_2$ is given by,

$$d_{geo}^2(\mathbf{R}_2, \mathbf{R}_1) = \sum_{q=1}^{Q} (Ln(\lambda_q))^2 \quad (9)$$

where

$$\mathbf{R}_1^{-1}\mathbf{R}_2\mathbf{e}_q = \lambda_q \mathbf{e}_q \text{ for } q = 1, \ldots, Q \quad (10)$$

Identifying $\mathbf{R}_1 = \gamma\mathbf{R}_{cm}$ and $\mathbf{R}_2 = \hat{\mathbf{R}}$ and minimizing (9), the power level estimate and the resulting minimum geodesic distance can be derived (11).

$$\gamma_G = \left(\prod_{m=1}^{Q} \lambda_m\right)^{\frac{1}{Q}} \quad (11a)$$

$$d_{geo,min}^2 = \sum_{m=1}^{Q} |\ln(l_m)|^2 = \sum_{m=1}^{Q} |\ln(\lambda_m/\gamma_G)|^2 \quad (11b)$$

where λ_m ($m = 1, \ldots, Q$) denotes the Q generalized eigenvalues of the pair ($\hat{\mathbf{R}}$,$\mathbf{R}_{cm}$) (12a). As you may note, due to the extension to the angle dimension, matrix $\mathbf{R}_{cm}$ is rank deficient, i.e, the rank of $\mathbf{R}_{cm}$ is Q while its dimension is $QN_a \times QN_a$.

$$\hat{\mathbf{R}}\mathbf{e}_q = \lambda_q \mathbf{R}_{cm}\mathbf{e}_q \text{ for } q = 1, \ldots, Q \quad (12a)$$

$$\frac{1}{\gamma}\mathbf{R}_{cm}^{-1}\hat{\mathbf{R}}\mathbf{e}_m = l_m \mathbf{e}_m \text{ for } m = 1, \ldots, Q \quad (12b)$$

Interestingly, the power level estimate γ_G does not depend on the frequency w of the candidate. Thus, the power level estimate does not require frequency scanning resulting in a low complexity estimation. The frequency location and the direction of arrival are obtained plotting the inverse of the minimum geodesic distance (11b) versus frequency and angle.

Finally, a third power level estimate (CANDIDATE-M) can be derived by forcing a positive definite difference between the data autocorrelation matrix and the candidate matrix. This methods is based again on the eigenvalues decomposition and thus, is required to be adapt to the rank deficient candidate matrix $\mathbf{R}_{cm}$. The problem can be formulated as,

$$\begin{aligned} &\max_{\gamma \geq 0} \quad \gamma \\ &\text{s.t.} \quad \hat{\mathbf{R}} - \gamma\mathbf{R}_{cm} \succ 0 \end{aligned} \quad (13)$$

and the solution is the minimum eigenvalue of ($\mathbf{R}_{cm}^{-1}\hat{\mathbf{R}}$), that is,

$$\gamma_M = \lambda_{min}\left(\hat{\mathbf{R}}, \mathbf{R}_{cm}\right) \quad (14)$$

where the generalized eigenvalue of the pair ($\hat{\mathbf{R}}$,$\mathbf{R}_{cm}$) has to be solved to obtain γ_M. Please note the implicit frequency and angle scanning in $\mathbf{R}_{cm}$.

Table 1: Scenario Characteristics

	Desired User	Interference
Modulation	BPSK	Pure Tone
Frequency w_s (MHz)	2	3
DOA (degrees)	30	60
SNR (dB)	10	10

4. SIMULATIONS

This section is divided in two parts. The first part concentrates on the general performance of the three Candidate methods proposed in the previous section. In the first section scenarios with high SNR are used for the sake of figure clarity. The second part gives the ROC (Receiver Operating Characteristic) results for low SNR scenarios.

4.1 High SNR Scenario

The general performance of the three candidate methods proposed before will be discussed in this section. The scenario for this study considers a desired user with binary phase shift keying (BPSK) using a rectangular pulse shape (with 4 samples per symbol) and an interference. For simplicity and as baseline, we assume that the interference is a pure tone. In practise, the interference signal is due to the presence of a secondary user, which is rarely going to use the same modulation or physical support as the primary user. The scenario characteristics have been summarized in Table 1.

The data record for the following plots is 1000 snapshots and Q=16. The array is composed of $N_a = 6$ antennas with an antenna separation equal to $\lambda/2$ resulting into a total array length of 37.5cm. Fig.1 and Fig.2 show the performance of the Candidate-F under the proposed scenario. It can be observed that the estimate γ_F presents low resolution and significant leakage when interferences are present. Thus, Candidate-F works like an energy detector and therefore is discarded in favor of the two other candidate methods.

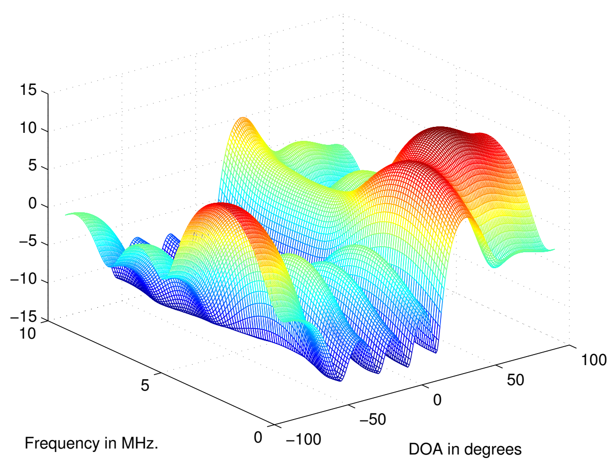

Figure 1: Candidate power level γ_F

In Fig.3 and Fig.4 is shown the perfomance of Candidate-M. The resulting estimate γ_M provides a clear estimate of the frequency and angle location, and produces a power level of

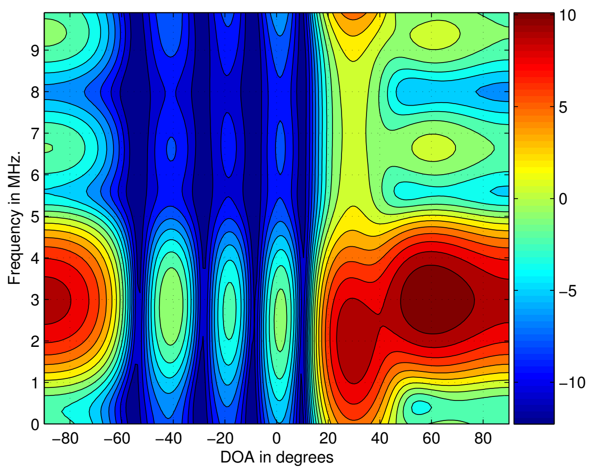

Figure 2: Contour lines of Candidate power level γ_F

8.74dB, which implies some bias. The interfering tone has disappeared due to the feature-based nature of the estimate.

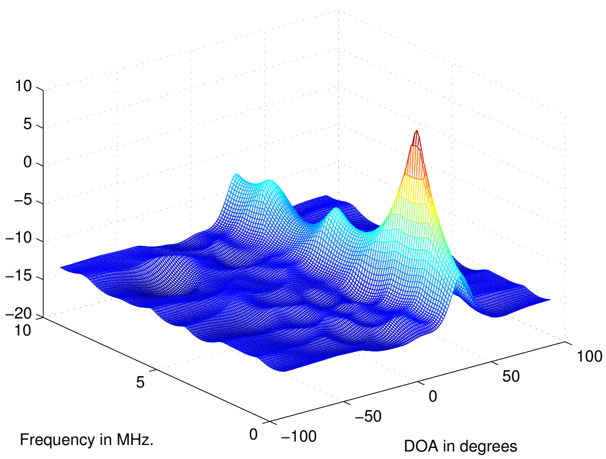

Figure 3: Candidate power level γ_M

Finally, the best power estimate in terms of resolution is given by γ_G which provides a power level of 9.99dB for the same scenario (see Fig.7). The independency of γ_G with respect to the carrier frequency could be observed in Fig.7, where the value of γ_G only depends on the angle of arrival. The inverse of the geodesic distance is shown in Fig.5 and in Fig.6. These plots show higher resolution compared with γ_M and an accurate estimation of the frequency and angle location. However, the range of $d_{geo,min}$ is 10dB while the range of γ_M is more than 20dB. This fact makes us think that Candidate-M may still work in scenarios with low SNR, where Candidate-G probably fails.

4.2 Low SNR Scenario

This section evaluates the perfomance in low SNR scenarios by means of the ROC curves in order to illustrate the Candidate-M robustness mentioned in the previous section. Giving priority to interference robustness, we focus on the Candidate-M and Candidate-G in the following.

To evaluate the probability of false alarm versus the

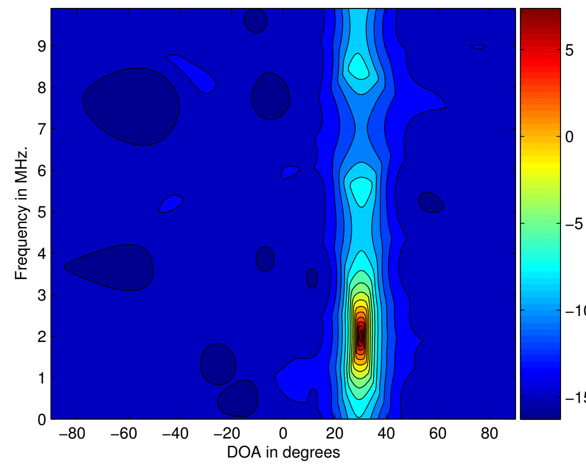

Figure 4: Contour lines of Candidate power level γ_M

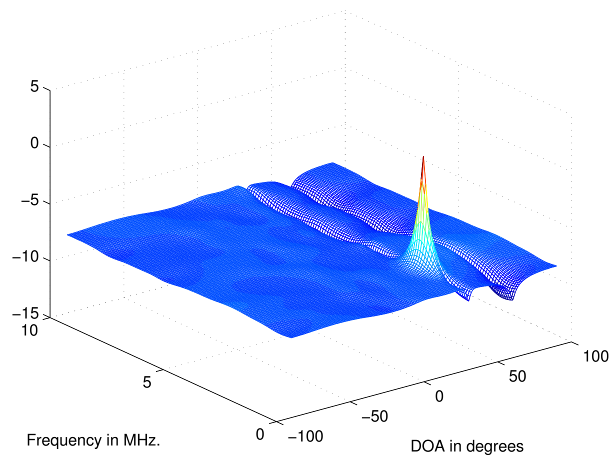

Figure 5: Candidate-G: inverse of $d_{geo,min}$

probability of detection we have run 500 simulations with N=200 and Q=8, each in the presence of the primary user (Hypothesis H1), and 500 records of the same length without the primary user (Hypothesis H0). The primary user is located at w_s equal to 2MHz and direction of arrival equal to 30 degrees. Again, the primary user is a BPSK and its SNR ranges from -14dB to -20dB. No interference is considered here. The superiority of γ_M is clear from Fig.8 and Fig.9 where the ROCs of Candidate-M and Candidate-G for very low SNR are displayed, respectively. The degree of robustness of the Candidate-M is observed as the resulting plots for Candidate-G are inferior with respect to those obtained by Candidate-M.

5. CONCLUSIONS

A new spectral feature detector for spectrum sensing in cognitive radio has been proposed in this paper. The basic strategy is to use the correlation matching with a predetermined spectral shape, which has to be known a priori. Unlike the first approach proposed in [8], the proposed procedures for monitoring the radio spectrum exploits three dimensions: frequency, time and angle. Thus, besides the advantages that give us conventional spectrum sensing algorithms, the new

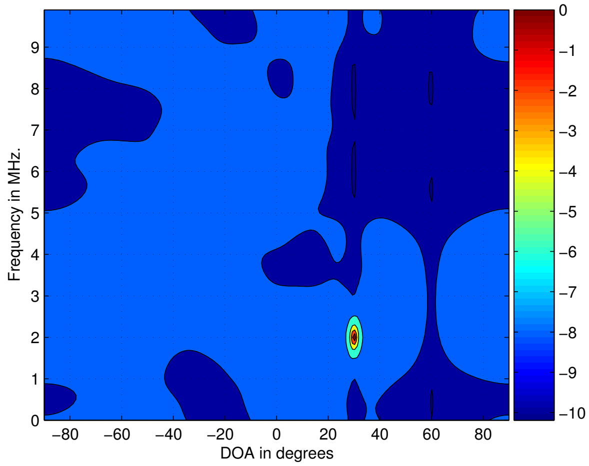

Figure 6: Contour lines of Candidate-G: inverse of $d_{geo,min}$

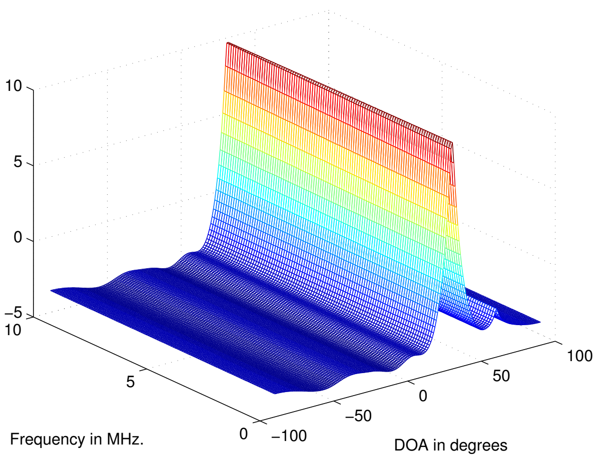

Figure 7: Candidate power level γ_G

method take advantage of the spatial diversity which brings extra spectrum opportunities.

The correlation matching framework developed here allows us to obtain three different methods. The first approach, named Candidate-F, shows low resolution and weaknesses to interference rejection. Candidate-M, provides better performance than Candidate-F but shows lower resolution than Candidate-G, which is based on the geodesic distance. However, Candidate-M shows high robustness to noise compared with Candidate-G.

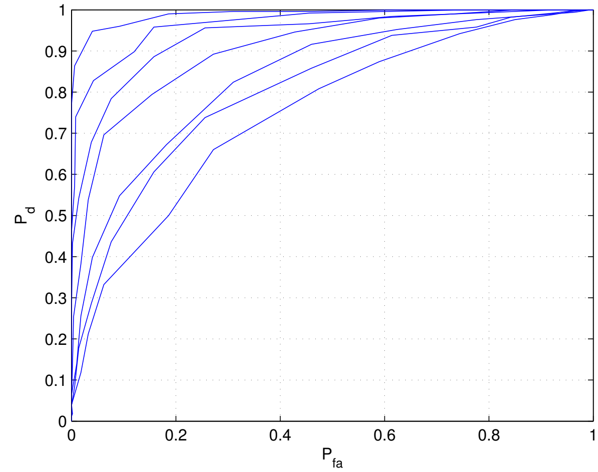

Figure 8: Evaluation of Candidate-M. SNR ranges from -20dB to -14dB.

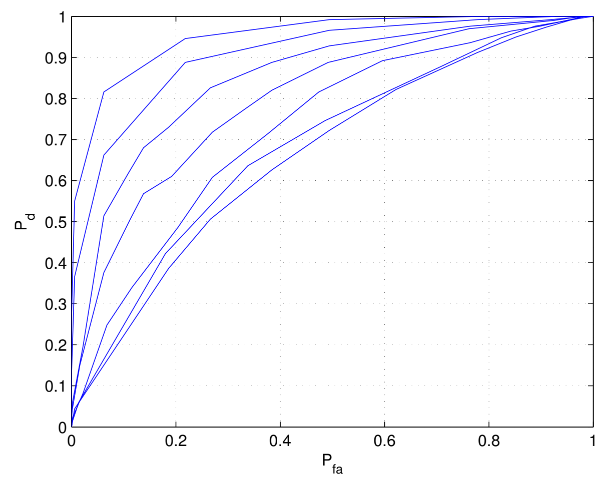

Figure 9: Evaluation of Candidate-G. SNR ranges from -20dB to -14dB.

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