Preprint

This is the submitted version of a paper published in *IEEE Transactions on Instrumentation and Measurement*.

Citation for the original published paper (version of record):

*IEEE Transactions on Instrumentation and Measurement*, 62(12): 3351-3360
http://dx.doi.org/10.1109/TIM.2013.2265607

Access to the published version may require subscription.

N.B. When citing this work, cite the original published paper.

Permanent link to this version:
http://urn.kb.se/resolve?urn=urn:nbn:se:hig:diva-15966
Cognitive Radios: Discriminant Analysis for Automatic Signal Detection in Measured Power Spectra

1 Lee Gonzales Fuentes, 2 Kurt Barbé, 1,2 Wendy Van Moer and 1 Niclas Björsell

1 University of Gävle, Kungsbackavägen 47, 801 76 Gävle, Sweden
2 Vrije Universiteit Brussel, Dept. ELEC-MESA, Pleinlaan 2, B-1050 Brussels, Belgium
Email: lee_gzs_fts@yahoo.com

Abstract—Signal detection of primary users for cognitive radios enables spectrum use agility. In normal operation conditions, the sensed spectrum is non-flat i.e. the power spectrum is not constant. A novel method proposed the segmentation of the measured spectra into regions where the flatness condition is approximately valid. As a result, an automatic detection of the significant spectral components together with an estimate of the magnitude of the spectral component and a measure of the quality of classification became available. In this paper, we optimize the methodology for signal detection for cognitive radios such that the probability that a spectral component was incorrectly classified is minimized. Simulation and measurement results show the advantages of the presented technique in different types of measured spectra.

Keywords—Discriminant analysis; spectrum sensing; signal detection; cognitive radio; power spectrum; spectral component; rice distribution; statistics.

I. INTRODUCTION

The efficient use of a natural resource like the radio electromagnetic spectrum can be achieved by means of cognitive radio. Cognitive radio is an intelligent wireless communication system that is cognizant of its radio frequency environment, learns from it and adapts its transmission or reception parameters to the different variations of its surrounding. It dynamically monitors the unused spectrum, exploiting it by unlicensed users or transferring it when requested by licensed users such that interference between users is prevented [a]. This “sensing” feature of cognitive radio is fundamental for an efficient management of the spectrum. Some methods are suggested for this purpose i.e. geo-location database and spectrum sensing. Spectrum sensing enables the cognitive radio to adapt to the environment by identifying the unused portions of spectrum and transmit in these spectrum holes. Cognitive radio should therefore determine if a signal from a user is locally present in a determined frequency band. Hence, the spectrum sensing problem can be reduced to the signal detection of a primary transmitter. A simple approach is the visual analysis of the signal spectrum. If the signal-to-noise ratio (SNR) is high enough, it is possible to determine the presence of a signal component since a signal line leaps out of the noise floor. However, some factors can turn this into a difficult task: low SNR, fading and multipath in wireless communication, and noise power uncertainty [1], [2].

Some spectrum sensing techniques are already available. The Energy Detection (ED) method [3] does not need any information of the signal to be detected, but requires a good estimate of the noise power [4]. Hence, it is very vulnerable to noise uncertainty. Some improvement can be achieved by means of energy and autocorrelation statistics, where no knowledge of the signal and noise are required but an increment on the channel gain is needed [5]. To overcome these shortcomings, test-statistic based methods: the Covariance (CV) method [6], [7] and the Maximum-Minimum Eigenvalue (MME) detection [12] are blind algorithms insensitive to noise. MME assumes an infinite number of samples and requires knowledge the number of primary users [9], [10]. A latest method [11] is based on Random Vandermonde Matrices (RVM), which presents a better performance than the previous methods even for a finite number of measurement samples. These sensing techniques present some specific applications and limitations [12], and generally required information either on the noise power or the signal characteristics.

The problem of discerning signal from noise in an observed spectrum is also tackled by harmonic or periodic components detection methods. Most of these methods are parametric and assume a statistical model of the signal [5]-[9], [14]-[17]. The multitaper method (MTM) is one nonparametric spectral estimator that uses an orthonormal sequence of Slepian tapers or windows and their corresponding eigenspectra values. MTM is nearly optimal and computationally feasible, particularly for small sample measurements [b], [c]. However, its complexity increases as the number of tapers increases. Filter banks have been used to simplify MTM [d]. Recent studies indicate that the quality of the method is controlled by the number of tapers, threshold, and signal and noise power [e]. Aside of the detection of the spectral lines, no information on either the probability of misclassification of the frequency lines or the estimate of the magnitude of the spectral component is provided.

An automatic harmonic detection method [18] based on a statistical test has been developed. This technique automatically detects harmonics and has three major advantages over the existing methods.

1) The method requires no user interaction and minimal postulated noise assumptions.
2) The probability of false alarm is obtained.
3) The estimate of the magnitude of every detected harmonic component is computed for a probabilistic validation of the classification.
The method presented in [18] is shown to be optimal for flat spectra only [19]. However, it can be extended towards nonflat spectra for signal detection in cognitive radios [20]. This is obtained, by segmenting the spectrum and applying the method to each segment. The segmentation clearly has some advantages:

1. The presence or absence of a signal regardless of the shape of the spectrum can be detected.
2. Reduction in the misclassification probabilities can be achieved by recomputing the validation process of the regrouped frequency lines with high probabilities of misclassification.
3. The width of the segment can be updated to minimize the misclassification probabilities.

The quality of the segmentation algorithm depends on the proper selection of the boundaries of every segment. In this paper, the probabilities of misclassification results will be used to update the boundaries of the original segments such that the automatic signal detection is recomputed and the misclassification probabilities are reduced. Hence, the detection algorithm can become useful for signal detection for cognitive radio applications due to the advantages above other methods.

The paper is organized as follows: Section II provides a concise description of the automatic method as well as its advantages and disadvantages. The segmentation technique for nonflat spectra is explained in Section III. In Section IV, the advantages and disadvantages. The segmentation technique is used for signal detection. Section V illustrates the proposed algorithms on simulation examples. Section VI illustrates the performance of the method on measurement examples. Section VII proposes an update for the segment bounds. In the final section, conclusions are given.

II. DISCRIMINANT ANALYSIS METHOD

In this section, the discriminant analysis algorithm described in [18] is summarized since it forms the basis of the extended method that is proposed in this paper. Furthermore, the advantages and the disadvantages of this technique are elaborated on.

A. Signal assumptions

Let \( x(t) \) be a continuous time signal such that

\[
x(t) = g(t) + n(t),
\]

where \( g(t) \) is a periodic multisine signal with \( K \) arbitrary tones, and \( n(t) \) is a noise process such that its power spectral density \( S_n(j\omega) \) and its variance \( \sigma_n^2 \) exist.

The signal \( x(t) \) is digitized and the resulting signal \( x_d(n) \) with \( n = 0, \ldots, N-1 \). The magnitude of the signal \( A_x(k) = |X_d(k)| \), where \( X_d(k) \) is the discrete Fourier coefficient of the signal \( x_d(n) \) at frequency bin \( k \).

The amplitude measurement \( A_x(k) \) can be represented by:

\[
A_x(k) = |G_d(k) + N_d(k)|
\]

where \( G_d(k) \) and \( N_d(k) \) are the discrete Fourier coefficients at frequency bin \( k \) of the signal and noise, respectively. The variable \( N_d(k) \) is complex circular Gaussian distributed with zero mean and variance \( S_n(j\omega_k) \). Thus, \( A_x(k) \) is distributed according to the Rice probability density function

\[
Rice(|G_d(k)|, \sqrt{S_n(j\omega_k)}).
\]

A random variable \( Z \) is Rice distributed \( Z \sim Rice(\nu, \sigma^2) \) if

\[
Z = \sqrt{X^2 + Y^2} \sim N(\nu \cos \theta, \sigma^2) \quad \text{and} \quad Y \sim N(\nu \cos \theta, \sigma^2)
\]

are two independent normal distributions where \( \nu \) is the amplitude of the signal, \( \sigma^2 \) is the variance of the signal and \( \theta \) is a real number.

B. Automatic detection

The automatic detection algorithm can be divided in three major parts: the discriminant analysis, the estimation of the magnitudes of the signal and noise power and the probabilistic validation of the detected spectral lines.

1. Discriminant Analysis

The main philosophy of discriminant analysis is to partition the data in two groups such that the groups are maximally separated under the constraint that the variance within every group is as small as possible. Expressing this objective in a statistical testing framework results in Fisher’s quadratic discriminant [18], [21], such that

\[
T^2 = \frac{(A_x^I - A_x^J)^2}{\sigma_I^2(|I|-1) + \sigma_J^2(|J|-1)}(|I| + |J| - 2),
\]

where \( A_x^I \) and \( A_x^J \) represent the mean amplitude of the classified signal lines and noise lines, respectively. The variables \( |I| \) and \( |J| \) represent the respective number of classified signal and noise lines. Finally, \( \sigma_I^2 \) and \( \sigma_J^2 \) are the respective variances of the amplitudes of the classified signal and noise lines. The objective of the discriminant analysis is to maximize (4). Therefore, the set of frequency bins of the signal lines \( I \) and of the noise lines \( J \) should be chosen in such a way that the numerator or distance between the group means is maximized, and the denominator or distance within the group variances is minimized. A binary grid search is used to come to the correct discrimination height.

2. Estimation of signal and noise power magnitudes

In this paragraph, the method of moment (MoM) estimator for the noise power and signal component magnitudes is derived [20].

Assuming that the noise spectrum is white, the estimate of the noise power for noise frequency lines \( k \in J \) is

\[
\hat{S}_n(j\omega_k) = \frac{1}{|J|} \sum_{k \in J} (A_x(k))^2.
\]

The maximum likelihood for the signal component is not available. The MoM estimator in [18] is used to estimate the signal magnitude for \( k \in I \)

\[
|\hat{G}_d(k)| = \sqrt{A_x^I(k) - \hat{S}_n(j\omega_k)}.
\]

3. Probabilistic validation of the detected spectral lines
In order to assess the quality of the classification, the probability of false classification is computed by studying the probability distribution of the amplitude measurements $A_x(k)$.

To formally introduce the probability of misclassification, we denote $A_x(k)$ to be the random variable describing the amplitude measurement at frequency $k$ which follows a Rice distribution with parameters $(\theta_d(k), \frac{1}{2} S_n(j \omega_k))$ for signal lines and $(0, \frac{1}{2} S_n(j \omega_k))$ for noise lines.

Hence, $\mathbb{P}(A_x(k) > A_x(k)|k \notin I)$ is the probability that $A_x(k)$ can be larger than the measurement $A_x(k)$, even when $k$ is a noise line. $\mathbb{P}(A_x(k) < A_x(k)|k \notin I)$ is the probability that $A_x(k)$ can be smaller than the measurement $A_x(k)$, even when $k$ is a signal line. Based on the nature of $k$, the values in (5) and (6) are used to estimate the probabilities as follows

$$\hat{p}(k) = \begin{cases} 
1 - F_{\text{Rice}}(\frac{1}{2} S_n(j \omega_k))(A_x(k)) \\
F_{\text{Rice}}(\frac{1}{2} S_n(j \omega_k))(A_x(k)) 
\end{cases},$$

where $F_{\text{Rice}}$ denotes the cumulative distribution function of the Rice distribution.

Note that the discriminant analysis method described in this section has the following advantages.

1) It is fully automatic, with no user interaction.
2) It provides an estimate of the spectral component.
3) It provides a user-friendly and simple validation.

However, the presented technique only works under the assumption that the considered power spectrum of both signal and noise is flat, which cannot be assumed in practical applications e.g. normal operation conditions of cognitive radios.

### III. SEGMENTATION ALGORITHM

In this paragraph, we propose an extension of the discriminant analysis method (Section II) to nonflat spectra using visual analysis. This can be done by partitioning the spectra into small segments in which the power spectrum of the noise can be approximated as being flat. To assess this, we need to detect the frequency lines that are purely noise contributions. Doing so, the width of the region where the flatness condition holds can be determined.

#### A. Initial detection method for signal and noise components

By a simple visual inspection, one can already have a rough idea of which parts of the spectrum contain signal, and which contain noise. A signal line typically has larger magnitude than its neighboring noise frequency lines. In the proposed detection algorithm, we consider a frequency line to be a potential signal line if the magnitude difference between this frequency line and its neighboring frequency lines is larger than a user-defined value $\delta_G$. Whereas a noise line is determined if the difference between the analyzed frequency line and its neighboring frequency lines is smaller than $\delta_G$. To implement the above idea, we apply the following equations to obtain these maximum and minimum magnitude values:

$$A_x(l) < A_x(k) - \delta_G,\quad (8)$$

where $k < l$. Every $A_x(k)$ satisfying (8) is a local maximum, and is denoted as $A_x^{\text{max}}(k)$. Every $A_x(k)$ satisfying (9) is a local minimum and is denoted as $A_x^{\text{min}}(k)$.

The result of this algorithm is illustrated in Fig. 1. The crosses represent the frequency lines $k$ with magnitude $A_x^{\text{max}}(k)$, these lines are possibly signal contributions. The circles represent the frequency lines $k$ with magnitude $A_x^{\text{min}}(k)$ and these lines are definitely noise contributions. The remaining frequency lines can be either noise or signal contributions.

#### B. Segmentation width

Based on the previously detected noise contributions with magnitude $A_x^{\text{min}}(k)$, the segments where the spectrum is locally flat are to be determined. Let $k_{\text{upper}}$ and $k_{\text{lower}}$ be the frequency lines where maximal magnitude and minimal magnitude are found when satisfying (10) and (11).

$$A_x^{\text{min}}(l) < A_x^{\text{min}}(k_{\text{upper}}) - \delta_{SG},\quad (10)$$

$$A_x^{\text{min}}(l) > A_x^{\text{min}}(k_{\text{lower}}) - \delta_{SG},\quad (11)$$

The frequency lines $k_{\text{upper}}$ and $k_{\text{lower}}$ are the positions at which the magnitude of the noise power presents abrupt changes. Consequently, these frequency lines determine the bounds of a segment within which the noise power does not significantly deviate.

The order in which these frequency lines appear define the right bound of a segment, while the left bound of the next segment is the right bound of the previous segment. An exception occurs for the frequency lines located at the beginning and end of the spectrum, for which the left and right bounds are respectively 1 and $N$. For instance, having i maximal values $k_{\text{upper}}$ and j minimal values $k_{\text{lower}}$, the bounds of the different segments can be determined as follows:
An illustrative example is presented in Fig. 2. The diamonds represent the magnitudes of the bounds of the segments with maximal magnitude and the squares represent the magnitudes of the bounds with minimal magnitude. Clearly, the main difficulty is to select the proper values for $\delta_G$ and $\delta_{SG}$. Although these values can be selected arbitrarily by the user, some interesting rules-of-thumb are proposed:

1) For SNR values higher than -5 dB. At high SNR, the Rice distribution of the amplitude of a disturbed signal can be approximated to Gaussian distribution. Visual analysis indicates us that most $A_x^{\text{max}}(k)$ and $A_x^{\text{min}}(k)$ are found to lie around two standard deviations of the mean of the power spectrum. Thus, $\delta_G$ would reflect the 95% confidence interval for Gaussian random variables. A starting value for $\delta_G$ is given by

$$\delta_G = |\mu + 2\sigma|,$$

where $\mu$ and $\sigma$ are the mean and the standard deviation of the magnitude of the discrete Fourier coefficient of the signal $A_x(k)$, respectively. Magnitude values that exceed at least $\delta_G$, assures an initial detection of signal and noise spectral lines. Whereas a starting value for $\delta_{SG}$ can be given by the standard deviation of the detected $A_x^{\text{min}}(k)$ values.

2) For SNR values lower than -5dB. The previous definitions for $\delta_G$ and $\delta_{SG}$ can result in larger values that do not always detect enough initial spectral lines and hence make not feasible to find the bounds of the segments. However, these values can be used as initial values, and then decreased them in such a way that the chosen $\delta_G$ allows detecting a sufficient number of initial spectral lines. For $\delta_{SG}$, one can try lower or higher values than the standard deviation of the

$A_x^{\text{min}}(k)$ values. A trade-off between the $\delta_G$ and $\delta_{SG}$ is present, where increments on $\delta_G$ allow decrements on $\delta_{SG}$.

IV. SIGNAL DETECTION

In this section, the segmentation technique is used for signal detection. The idea is to apply the method described in Section II, as detailed in [18], to each of the detected segments.

In Fig. 3, the signal detection method is illustrated. The gray curve is the spectrum analyzer amplitude measurement. Once applied the segmentation algorithm to the measured amplitude, as seen in Fig. 1 and Fig. 2, each segment receives a different discrimination height. The horizontal black lines represent the discrimination heights. Within each segment, the frequencies with measured amplitude below the discrimination height are classified as being noise lines while the frequencies with measured amplitude above the discrimination height are classified as signal lines. The dark black curve is the smooth discrimination curve over the full frequency band of interest. This curve is obtained when a polynomial is fitted to the centers of every discrimination height, which are identified as black circles over the different segments. Data fitting using a polynomial regression model is used for this purpose [23].

Given $N$ data points on frequency lines $k$, and the discrimination height $h$ function, the discrimination height variable is modeled as a linear combination of the variable $k$.

Regression estimates the model parameters $\alpha$ and some uncontrolled errors $\epsilon$ are present. A $p$-order of the polynomial model can be synthesized as

$$h(k) = \sum_{i=0}^{p-1} \alpha_i (k)^i + \epsilon(k).$$

The estimate of the polynomial coefficients is given by

$$\hat{\alpha} = (X^T X)^{-1} X^T h.$$  \hspace{1cm} (14)
The frequency lines with amplitude values close to the discrimination height are susceptible to be misclassified and therefore, to present higher misclassification probabilities. This suggests that the classification process was not correct for those frequency lines and consequently, that the segment bounds were not chosen properly. Given that, these frequency lines are moved to the other group and the validation process is recomputed with (7). The misclassification probabilities for the signal lines ranged from 0 to 0.43, while the noise lines received misclassification probabilities ranged from 0 to 0.49. Regrouping of the frequency lines balances the misclassification probabilities at the expense of worsening the misclassification probability of one of the groups.

For instance, a detected noise line at a frequency of 0.6197 radians/sample presents a misclassification probability of 0.56 as seen in Fig. 5. This suggests that this frequency line was wrongly classified as a noise line and hence, it is moved to the signal line group receiving a misclassification probability of 0 as illustrated in Fig. 6, which demonstrates this frequency line was a misdetected signal line. An interesting observation is that, even when the method wrongly classifies some frequency lines either as a signal or noise line, the validation process is able to recognize this by assigning considerably high probability values to those frequency lines.

B. Uniform signal amplitude under colored noise

Following the representation given in (1), the signal $g(t)$ is a multisine with uniform amplitude spectrum and 8 tones. The noise sequence $n(t)$ is a zero-mean colored noise, which is obtained using a Butterworth low pass filter at a normalized frequency of 0.5. In Fig. 7, the segmentation technique for signal detection of the disturbed signal with an SNR of -10dB is performed as described in Section III. $\delta_G$ and $\delta_{SG}$ are computed as described in Section III-B.3, as a result $\delta_G = 14.43$ and $\delta_{SG} = 16.02$ are computed. The standard deviation of the $A^\min(k)$ values is large due to the shape of the spectra, where for the frequency lines higher than the cut-off frequency, the magnitude can reach very low values in contrast with the

In Fig. 4, the segmentation technique is used for signal detection of a disturbed signal presenting an SNR of -15 dB. $\delta_G$ and $\delta_{SG}$ are computed as described in Section III-B.3, as a result $\delta_G = 15.12$ and $\delta_{SG} = 0.97$. Since not enough initial values are found to run the algorithm, $\delta_G$ is reduced. Therefore, the initial detection of signal and noise spectral lines is performed using (8) and (9) with $\delta_G = 8$. The reduction of $\delta_G$ allows increments of $\delta_{SG}$. Next, the bound segments are found with (10) and (11) when $\delta_{SG} = 1.5$ is chosen. The signal detection is performed as described in Section II, and a different discriminant height is assigned to each segment. Polynomial fitting is performed as described in Section IV, resulting in a discrimination curve of degree $p=7$.

Next, the estimators (5) and (6) are computed to estimate the noise power and signal magnitude. The magnitude estimate $\delta_G(k)$ is ranging from -10.55 to -3.32 dBm the visual observations. However, the noise estimate $\delta_{SG}(j\omega_k)$ presents values of -68 dBm, which seems to correspond to an underestimate.

Hence, the validation process was performed. The misclassification probabilities are calculated with (7). The method detects 108 signal lines, in which 7 lines were correctly classified and received misclassification probabilities of 0, while the other 101 lines received probabilities around 0.07. The remaining frequency lines are classified as noise lines and present misclassification probabilities ranged from 0 to 0.63.

V. NUMERICAL EXAMPLES

This section provides some simulation examples where the performance of the technique will be evaluated for different SNR ranging from 0 to -21 dB as required by the IEEE standard for cognitive radios [24].

A. Different amplitude under white noise

The signal satisfies the representation given in (1), where $g(t)$ is a multisine with different amplitude spectrum and 8 tones arbitrarily chosen, while $n(t)$ is a zero-mean white Gaussian noise sequence.

The frequency lines with amplitude values close to the discrimination height are susceptible to be misclassified and therefore, to present higher misclassification probabilities. This suggests that the classification process was not correct for those frequency lines and consequently, that the segment bounds were not chosen properly. Given that, these frequency lines are moved to the other group and the validation process is recomputed with (7). The misclassification probabilities for the signal lines ranged from 0 to 0.43, while the noise lines received misclassification probabilities ranged from 0 to 0.49. Regrouping of the frequency lines balances the misclassification probabilities at the expense of worsening the misclassification probability of one of the groups.

For instance, a detected noise line at a frequency of 0.6197 radians/sample presents a misclassification probability of 0.56
According to the discriminant analysis philosophy, the objective is to separate the groups in order to minimize the misclassification probabilities. When the segmentation algorithm is used for signal detection, the validation step suggests that the segmentation was incorrect for some frequency lines. However, the fact that by regrouping the frequency lines, the misclassification probabilities are altered indicates that the width of the segment can be manipulated.
when the values of $\delta_G$ and $\delta_{SG}$ are updated using the probabilistic validation results. This can improve the performance of the method and hence, reduce the misclassification probabilities.

VI. MEASUREMENT EXAMPLES

In the measurement examples, signals with different spectrum shape are measured. The computer-generated signals are sent to a signal generator in its time-domain version using a carrier frequency $f_c = 1.5GHz$. The amplitude of the signal was measured with a signal analyzer using a bandwidth $B_W = 100MHz$ and 100001 number of sweep points. The measured amplitude is sent back to a computer, where the signal detection method is applied to the data. The examples present multisine signals with 8 tones disturbed either by white or colored noise sequences. This controlled laboratory experiment will allow us to evaluate the proposed technique.

A. Multisine with different amplitude under white noise

The multisine shown in Fig. 3 is measured. The values of $\delta_G$ and $\delta_{SG}$ are computed as described in Section III-B.3, as a result $\delta_G = 24.43$ and $\delta_{SG} = 1.94$. However, a reduction for $\delta_G$ is needed to assure sufficient initial values. $\delta_G = 10$ is found to compute (9) and (10). The initial detection of signal and noise spectral components is performed. The segment bounds are found with (11) and (12) using $\delta_{SG} = 1$. Since this is a data-driven method, these values differ from the ones of the simulation examples, since the amount of data is higher.

Next, the signal detection is applied to every segment as shown in Fig. 8. The horizontal black lines are the different discrimination heights of every segment, according to the segmentation and signal detection algorithms. The black circles are the center of the discrimination heights to which a discrimination curve of degree $p=2$ is fitted and it is distinguished as a bold dark curve.

The estimators (5) and (6) are computed to estimate the noise power and signal magnitudes. The signal amplitude estimate $\tilde{G}_d(k)$ is ranging from -47.99 to -35.81 dBm. The noise power estimate $\tilde{S}_n(j\omega_k)$ for the different segments ranges from -62.88 to -38.54 dBm.

Finally, the probabilistic validation is performed. The misclassification probabilities are estimated using (7). In total, 4747 lines were classified as noise lines and the probabilities ranged from 0 to 0.63. The method detects 254 signal lines, from which 8 are correctly detected as signal lines presenting a misclassification probability of 0 while the other 246 detected signal lines received probabilities around 0.1609.

B. Uniform signal amplitude under colored noise

In this example, the amplitude of the signal is uniform. The noise sequence is colored using a shaping Butterworth filter with a cutoff frequency of 0.75. The values of $\delta_G$ and $\delta_{SG}$ are computed as described in Section III-B.3, as a result $\delta_G = 23.27$ and $\delta_{SG} = 7.44$. An initial detection of signal and noise components is performed using $\delta_G = 6$ to compute (8) and (9). The boundaries of the segments are determined with (10) and (11) and $\delta_{SG} = 4$. Next, the signal detection is applied to every segment of the measured amplitude spectrum and polynomial fitting results in a discrimination curve of $p=2$, as shown in Fig. 9. The same legend from Fig. 8 holds.

Using (5) and (6), the signal amplitude estimate $\tilde{G}_d(k)$ ranges from -47.97 to -35.27 dBm, while the noise estimate $\tilde{S}_n(j\omega_k)$ ranges from -96.42 to -41.13 dBm. The validation process is performed. The misclassification probabilities are calculated with (7). The method detects 132 as signal lines, from which 8 are correctly classified as signal lines and received misclassification probabilities of 0 while the remaining detected signal lines received a misclassification probability values that reach up to 0.15. The remaining frequency lines were classified as noise lines and received misclassification probabilities from 0 to 0.63. After regrouping of frequency lines, the signal lines received probability values of 0.43 and the noise lines received probability values of 0.49.

In this particular example, the frequency lines higher than the cut-off frequency present a decreasing noise floor which
makes the signal lines more visible. Therefore, the algorithm can find a good position for the discrimination height cutting between the noise floor and the signal lines. This is acknowledged by the lower misclassification probabilities assigned to these frequency lines.

A measure of the quality of the classification can also be given in terms of risk of misclassification, where the quality of the detection and hence, of the segmentation algorithm are evaluated by measuring the magnitude of misclassification probability of every frequency line in the full band of interest. It became obvious during the validation process that some frequency lines whose amplitude lies close to the discrimination height present a high risk of being misclassified in either group. These frequency lines present amplitudes that are low enough to be considered as noise lines but also high enough to be considered as signal lines. This duality is reflected in the misclassification probability values assigned to them. Consequently, the amplitudes of the frequency lines with sufficient distance from the discrimination height will present low misclassification probabilities and therefore a small risk of being incorrectly classified whether as noise or signal lines.

For this purpose, the spectrum is sliced into different regions that cover the different levels of risk. The risk of being falsely classified as being either noise or signal line is illustrated in Fig. 10 and Fig. 11 from the measurement examples showed in Fig. 8 and Fig. 9. In a light gray color are the frequency lines with very low risk $\hat{\pi}(k)<10\%$, in gray color are the frequency lines with low risk $10\%<\hat{\pi}(k)<30\%$, in dark gray color are the frequency lines with considerable risk $30\%<\hat{\pi}(k)<50\%$, and in black color the frequencies with high risk $\hat{\pi}(k)>50\%$ of being incorrectly classified.

VII. BOUNDARIES UPDATE USING PROBABILITIES OF MISCLASSIFICATION

In Section III, the segmentation algorithm is an attempt to define flat regions where the automatic signal detection method can be applied. The boundaries are determined at frequencies where the power spectrum is not constant i.e. where an abrupt change is perceived. In a disturbed signal, this can occur at many points in the spectra. The proper selection of the boundaries thus depends on the proper selection of the values $\delta_G$ and $\delta_{SG}$. How large these values are, determines the sensitivity of these two parameters to the changes in the spectrum, and present a direct impact in the correct performance of the automatic signal detection method. Generally, when the values of $\delta_G$ and $\delta_{SG}$ are too large, the method can miss some changing points and when too small it can detect many irrelevant changing points and hence, the computation becomes slower. From the simulation and measurement examples, the reduction of the misclassification probabilities of the detected noise lines becomes a challenge since the objective of the automatic signal detection method is to minimize the misclassification probabilities.

In order to reduce the misclassification probability values, this section proposes an iterative algorithm scanning for some missed changes within the previously defined segments. For this purpose, we can reuse the formulas given in (10) and (11) to search the missed changing points. Since the spectrum within the segment is approximately flat, $\delta_{SG}$ can be defined as the rule of thumb suggested with (12) so, new $k_{upper}$ and $k_{lower}$ frequency lines that present maximal and minimal amplitudes are chosen from the $A^\text{min}_S(k)$ values found within the initial segment bounds, as explained in Section III-B. The appearance of these new positions together with the previous ones generates newer segments and hence different discriminant heights. The median of the misclassification of the detected noise lines is computed. The process is repeated while a reduction on the misclassification probabilities is accomplished or stopped when the opposite occurs. When no $A^\text{min}_S(k)$ values are found between the bounds, the algorithm then reduces $\delta_G$ until the average of the misclassification probabilities is minimized.
Using the misclassification probabilities from the simulation example shown in Fig. 3, an update of the boundaries of the segments is performed and the signal detection method is applied to each new segment as seen in Fig. 12. The same legend from Fig. 3 holds. In total, 19 segments are obtained from which 12 were the initial segments and 7 are the new segments. The median of the misclassification probabilities for noise lines after the update was reduced to 0.39. A discrimination curve of degree $p=7$ is fitted to the centers of the discrimination heights.

The signal detection is performed after updating the boundaries of the simulation example shown in Fig. 5, and this can be seen in Fig. 13. In total, 14 segments are obtained from which 4 are initial segments and 10 are the new segments. The median of the misclassification for noise lines initially reached 0.63, and after the update of the boundaries it reduced to 0.49. A discrimination curve of degree $p=4$ is found.

In the measurement example shown in Fig. 9, the misclassification probability values presented in Section VI-B were used to perform the update of the boundaries as seen in Fig. 14. The number of segments increased from 6 to 28.

Decreasing $\delta_S$ did not give better results. The median of the misclassification probabilities decreased from 0.63 to 0.51. A discrimination curve of degree $p=3$ is needed.

In all the three cases, it is interesting to point out that in the presence of more segments both the discrimination heights and especially the discrimination curve adapts better to the shape of the noise floor. This is visually evident when the polynomial curve is found slightly above the noise floor, leaving the signal lines raise above it.

CONCLUSION

This paper proposes an extension of [18] to signal detection for nonflat spectra using a segmentation method [20] and an
iterative algorithm to update the segment boundaries such that the automatic signal detection method [18] can be used for spectrum sensing in cognitive radio and the misclassification probabilities are minimized. The only prior information needed is that within a frequency band, the discrimination method separates two groups: a signal and noise group. The advantage of the method over previous methods is minimal user interaction. No knowledge on the disturbing noise power is necessary which contrasts with the energy detection method. Furthermore, one does not need to specify in advance the number of primary users transmitting in the band of interest such that the proposed technique is fully blind.

ACKNOWLEDGEMENT

This work was funded in part by a post-doctoral fellowship of the foundation Flanders (FWO) and the research council of the VUB (OZR).

REFERENCES


