Wideband Spectrum Sensing for Cognitive Radios in Weakly Correlated Non-Gaussian Noise

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***Abstract*—Wideband signals can be subjected to various types of non-Gaussian and impulsive noise. Such non-Gaussian noise may cause degradation in the detection performance of conventional wideband signal detection methods, such as the periodogram-based approach. In addition, the signal detection probability can be further reduced due to possible correlation among the noise samples. Under such non-Gaussian noise conditions, we formulate a wideband signal detection method for cognitive radios (CR's) based on a locally-optimal (LO) Neyman-Pearson (NP) detector by assuming a weakly correlated noise model with known parameters. The corresponding decision statistic is expressed in the frequency-domain, allowing to detect the spectral activities within the sensed band of interest. The proposed detector is shown to reduce the impact of correlated non-Gaussian noise on the detection performance. We compute the receiver operating characteristic (ROC) of the proposed wideband LO-NP detector and show its superior performance, compared to existing wideband detectors under correlated noise conditions.**

***Index Terms*—Cognitive radio, correlated noise, locally optimal detector, signal detection, wideband spectrum sensing.**

I. Introduction

Cognitive radios (CR's) are considered as intelligent radio devices that are able to achieve efficient utilization of the RF spectrum [1], [2]. In the context of dynamic spectrum access (DSA), CR's are assumed to operate as secondary wireless users that detect the spectral holes and communicate over the unused portions of the spectrum [2]. To this end, a CR must be equipped with wideband spectrum sensing abilities, allowing it to exploit more spectral opportunities in order to achieve high transmission rates [3]. A CR sensing a wide frequency band not only has to detect the active signals, but it should also identify their center frequencies within the sensed frequency band [4]. Thus, spectral estimation is considered as a major component in wideband signal detection [5].

In contrast with narrowband signal detection, wideband signal detectors can be subjected to multiple electromagnetic interference sources that may be operating in the sensed wideband of interest [5]. Such heterogeneous electromagnetic activity was shown to be non-Gaussian, making the common Gaussian noise assumption not valid for wideband spectrum sensing [5], [6]. In particular, the conventional periodogram-based signal detection approach was shown to be unsuitable for the non-Gaussian noise case [5], [7]–[9]. Under such non-Gaussian noise conditions, non-linear detectors can be used to reduce the impact of non-Gaussian and impulsive noise on the detection performance [9], [10]. Non-linear detectors are commonly obtained using locally-optimal (LO) detection methods [5], [9]–[12].

In addition to the non-Gaussian nature of noise in wideband systems, it was shown that noise may exhibit temporal correlation in many practical applications [13], [14]. Thus, the common independent noise assumption may not be valid in practice, which requires detection approaches that take into account possible correlation among noise samples. Such dependent noise environments have been considered in [15] where an LO detector was proposed to detect wireless signals in the presence of weakly correlated noise. The proposed detector of [15], however, is not suitable for wideband signal detection since it was formulated based on a time-domain detection rule, which does not reflect the ongoing spectral activities of the various signals within the sensed wideband. On the other hand, a wideband signal detector was proposed in [5] by assuming non-Gaussian noise environments. However, the proposed detector of [5] was only limited to the independent noise case.

In this paper, however, we propose a novel approach for wideband signal detection by assuming a non-Gaussian weakly correlated moving-average (MA) noise model, similar to [15]–[17]. The assumed noise model has been introduced by Portnoy [18], [19] in the context of robust parameter estimation [15], [16] and provides a simple, yet useful, representation for random sequences that exhibit weak dependence among samples [16]. This MA representation can model the situation in which terms depending on second or higher order of the averaging weights can be negligible, with the degree of dependence being parameterized by the averaging weights [16], [17]. We formulate our signal detection problem as a composite hypothesis testing based on the LO Neyman-Pearson (NP) criterion, similar to [5]. The LO-NP approach is convenient for blind signal detection since it does not require complete knowledge of the signal distribution [5]. Furthermore, LO detectors are suitable for low signal-to-noise ratio (SNR) regime [9].

The resulting LO decision statistic is expressed in frequency-domain, leading to a novel signal detection approach that extends the signal detector of [5] to the dependent noise case. This allows to analyze the impact of noise correlation in such wideband non-Gaussian environments. This generalization could be achieved thanks to the assumed weakly correlated noise model of [18] whose probability density

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function (pdf) can be expressed in a product form, similar to independent noise distributions. The proposed wideband signal detection method was shown to outperform the detection probability of existing wideband detectors in the presence of weakly correlated non-Gaussian noise. In addition, high detection rates could be achieved in the low signal-to-ratio (SNR) regime, as expected in LO detection methods.

The remainder of this paper is organized as follows: In Section II, we formulate the LO-NP detection problem. We derive the LO-NP detection rule in Section III based on a weakly correlated noise model. Simulation results are shown in Section IV and we conclude the paper in Section V.

II. System Model

We consider a wideband CR that is sensing a certain wide frequency band of interest. The detected signal is denoted as $\mathbf{Y} = [Y_1, \cdots, Y_N]^T$ such that:

$$\mathbf{Y} = \theta\mathbf{S} + \mathbf{W}, \tag{1}$$

where $\mathbf{W} = [W_1, \cdots, W_N]^T \sim f_{\mathbf{W}}(\mathbf{w})$ is the noise vector, $\mathbf{S} = [S_1, \cdots, S_N]^T \sim f_{\mathbf{S}}(\mathbf{s})$ is the signal vector and $\theta \geq 0$ [5]. The signal detection problem can thus be formulated as the following composite hypothesis testing:

$$\begin{array}{rcll} \theta \in \Theta_0 & = & \{0\} & \text{under } \mathcal{H}_0 \\ \theta \in \Theta_1 & = & (0, \infty) & \text{under } \mathcal{H}_1 \end{array},$$

where $\mathcal{H}_0$ and $\mathcal{H}_1$ correspond, respectively, to the signal absent and present hypotheses [9]. We denote the mean and covariance matrix of the signal $\mathbf{S}$ by $\bar{\mathbf{s}}$ and $\Sigma_{\mathbf{S}}$, respectively.

The likelihood function of the above hypothesis testing problem can be expressed as:

$$L(\mathbf{y}, \theta) = \frac{\mathbb{E}\{f_{\mathbf{W}}(\mathbf{y} - \theta\mathbf{S})\}}{f_{\mathbf{W}}(\mathbf{y})}, \tag{2}$$

where $\mathbf{S}$ is a random vector with unknown distribution $f_{\mathbf{S}}(\mathbf{s})$. Thus, the decision statistic in (2) cannot be evaluated analytically due to the unknown distribution $f_{\mathbf{S}}$. However, similar to [5], we can obtain a second-order LO-NP test that is independent of $f_{\mathbf{S}}$. The second-order LO-NP decision statistic can thus be computed as [5], [20]:

$$T_2^{(LO)}(\mathbf{y}) = \left.\frac{\partial^2}{\partial\theta^2} L(\mathbf{y}, \theta)\right|_{\theta=0} = \frac{\mathrm{Tr}\left(\mathbf{F}''_{\mathbf{W}}(\mathbf{y})\left(\Sigma_{\mathbf{S}} + \bar{\mathbf{s}}\bar{\mathbf{s}}^T\right)\right)}{f_{\mathbf{W}}(\mathbf{y})}, \tag{3}$$

where $\mathbb{E}\{\mathbf{S}\} = \bar{\mathbf{s}}$, $\mathbf{F}''_{\mathbf{W}}(\mathbf{w}) = \frac{\partial}{\partial \mathbf{w}}\mathbf{f}'_{\mathbf{W}}(\mathbf{w})$ being the Hessian matrix of $f_{\mathbf{W}}(\mathbf{w})$, $\mathbf{f}'_{\mathbf{W}}(\mathbf{w}) = \frac{\partial f_{\mathbf{W}}(\mathbf{w})}{\partial \mathbf{w}}$ the gradient vector of $f_{\mathbf{W}}(\mathbf{w})$, and assuming that $\mathbb{E}\left\{\mathbf{S}\mathbf{S}^T\right\} = \Sigma_{\mathbf{S}} + \bar{\mathbf{s}}\bar{\mathbf{s}}^T$ [5], [20]. If $\bar{\mathbf{s}} = \mathbf{0}$, then $\mathbb{E}\left\{\mathbf{S}\mathbf{S}^T\right\} = \Sigma_{\mathbf{S}}$, and the decision statistic $T_2^{(LO)}(\mathbf{y})$ depends on the second order statistics of the signal $\mathbf{S}$, without requiring complete knowledge of the signal distribution $f_{\mathbf{S}}$.

Therefore, the second-order LO-NP detector can be formulated using the randomized decision rule $\tilde{\delta}_{LO}$ which represents the probability of choosing hypothesis $\mathcal{H}_1$, such that [5], [9]:

$$\tilde{\delta}_{LO}(\mathbf{y}) = \left\{\begin{array}{lll} 1 & \text{if } T_2^{(LO)}(\mathbf{y}) & > \eta \\ \gamma_{LO} & \text{if } T_2^{(LO)}(\mathbf{y}) & = \eta \\ 0 & \text{if } T_2^{(LO)}(\mathbf{y}) & < \eta \end{array}\right., \tag{4}$$

where $\eta \geq 0$ and $0 \leq \gamma_{LO} \leq 1$. In [5], a closed-form expression for $T_2^{(LO)}(\mathbf{y})$ was obtained in frequency-domain in function of the power spectral density (PSD) of the signal of interest. The resulting frequency-domain expression of $T_2^{(LO)}(\mathbf{y})$ in [5] was based on the fact that the joint distribution of independent noise samples can be written in product form, which restricted the formulation of [5] to the independent noise case. In this paper, however, the independent noise assumption is relaxed by considering a weakly correlated noise model whose pdf can still be expressed in product form.

III. Signal Detection under Weakly Correlated Moving Average (MA) Noise Model

In this section, we assume that the noise process in (1) follows a unilateral MA weakly correlated noise model, as in [15], where the correlated noise sequence $\{W_k\}_{k=1}^N$ is represented using the following recursive model [15]:

$$\begin{array}{rcl} W_1 & = & e_1 \\ W_k & = & e_k + \tau e_{k-1},\ k = 2, \cdots, N, \end{array} \tag{5}$$

where $\{e_k\}_{k=1}^N$ is an independent identically distributed (i.i.d.) noise sequence with a pdf $f_e(e)$ and $|\tau| < 1$ being the correlation parameter [15].

Given the above weakly correlated noise model, the joint pdf of $\mathbf{W}$ can be obtained in product form as [15]:

$$f_{\mathbf{W}}(\mathbf{w}) = f_{\mathbf{W}}(w_1, \cdots, w_N) = \prod_{k=1}^N f_e(z_k(\mathbf{w})), \tag{6}$$

where $z_k(\mathbf{w}) \triangleq \sum_{i=0}^{k-1}(-\tau)^i w_{k-i}$, for $k = 1, \cdots, N$. The product form expression of the noise pdf in (6) allows to simplify the expression of the LO decision statistic in (3), leading to a frequency-domain formulation. By using the expression of $f_{\mathbf{W}}(\mathbf{w})$ in (6), we can obtain a closed-form expression of the elements of the gradient $\mathbf{f}'_{\mathbf{W}}(\mathbf{w})$ as:

$$\begin{aligned} \frac{\partial}{\partial w_k} f_{\mathbf{W}}(\mathbf{w}) &= \frac{\partial}{\partial w_k}\prod_{i=1}^N f_e(z_i(\mathbf{w})) \\ &= \sum_{i=1}^N \frac{\partial f_e(z_i(\mathbf{w}))}{\partial w_k}\prod_{p=1, p\neq i}^N f_e(z_p(\mathbf{w})) \\ &= \sum_{i=k}^N \frac{\partial f_e(z_i(\mathbf{w}))}{\partial w_k}\prod_{p=1, p\neq i}^N f_e(z_p(\mathbf{w})) \end{aligned} \tag{7}$$

where the lower index terms ($i < k$) in (7) are eliminated since

$$\frac{\partial z_i(\mathbf{w})}{\partial w_k} = \left\{\begin{array}{cl} 0 & \text{if} \quad i < k \\ (-\tau)^{i-k} & \text{if} \quad i \geq k \end{array}\right.,$$

with $z_i(\mathbf{w})$ being independent of w_k for $i < k$. Hence,

$$\frac{\partial f_e\left(z_i(\mathbf{w})\right)}{\partial w_k} = \frac{\partial z_i(\mathbf{w})}{\partial w_k} f'_e\left(z_i(\mathbf{w})\right),$$

where $f'_e(x) = \frac{df_e(x)}{dx}$. Replacing the expression of $\frac{\partial f_e(z_i(\mathbf{w}))}{\partial w_k}$ in (7), we obtain the gradient vector components as:

$$\begin{aligned}\frac{\partial}{\partial w_k} f_{\mathbf{W}}(\mathbf{w}) &= \sum_{i=k}^{N} (-\tau)^{i-k} f'_e(z_i(\mathbf{w})) \prod_{p=1, p\neq i}^{N} f_e(z_p(\mathbf{w})) \\ &= \sum_{i=k}^{N} (-\tau)^{i-k} \frac{f'_e(z_i(\mathbf{w}))}{f_e(z_i(\mathbf{w}))} \prod_{p=1}^{N} f_e(z_p(\mathbf{w})) \\ &= f_{\mathbf{W}}(\mathbf{w}) \sum_{i=k}^{N} (-\tau)^{i-k} g(z_i(\mathbf{w})) \\ &= f_{\mathbf{W}}(\mathbf{w}) \tilde{g}_k(\mathbf{w}),\end{aligned}$$

where $\tilde{g}_k(\mathbf{w}) \triangleq \sum_{i=k}^{N} (-\tau)^{i-k} g(z_i(\mathbf{w}))$ and $g(x) \triangleq \frac{f'_e(x)}{f_e(x)}$. We can also obtain the elements of the Hessian matrix $\mathbf{F}''_{\mathbf{W}}(\mathbf{w})$ as:

$$\begin{aligned}\frac{\partial^2 f_{\mathbf{W}}(\mathbf{w})}{\partial w_j \partial w_k} &= \frac{\partial}{\partial w_j} \left[f_{\mathbf{W}}(\mathbf{w}) \tilde{g}_k(\mathbf{w}) \right] \\ &= \tilde{g}_k(\mathbf{w}) \frac{\partial f_{\mathbf{W}}(\mathbf{w})}{\partial w_j} + f_{\mathbf{W}}(\mathbf{w}) \frac{\partial \tilde{g}_k(\mathbf{w})}{\partial w_j} \\ &= f_{\mathbf{W}}(\mathbf{w}) \left[\tilde{g}_k(\mathbf{w}) \tilde{g}_j(\mathbf{w}) + \tilde{h}_{j,k}(\mathbf{w}) \right], \quad (8)\end{aligned}$$

where we denote $\tilde{h}_{j,k}(\mathbf{w}) \triangleq \frac{\partial \tilde{g}_k(\mathbf{w})}{\partial w_j}$. It can be shown that $\tilde{h}_{j,k}(\mathbf{w})$ can be expressed as:

$$\tilde{h}_{j,k}(\mathbf{w}) = \frac{\partial \tilde{g}_k(\mathbf{w})}{\partial w_j} = \sum_{i=\max\{k,j\}}^{N} (-\tau)^{2i-k-j} g'(z_i(\mathbf{w})),$$

where $g'(x) = \frac{dg(x)}{dx}$. Using (8), and assuming $\bar{\mathbf{s}} = \mathbf{0}$, we can evaluate the expression of the second order LO decision statistic in (3) as:

$$T_2^{(LO)}(\mathbf{y}) = \sum_{m=1}^{N} \sum_{n=1}^{N} \rho_{m,n}^{(s)} \left[\tilde{g}_m(\mathbf{y}) \tilde{g}_n(\mathbf{y}) + \tilde{h}_{m,n}(\mathbf{y}) \right].$$

By assuming that the signal $\mathbf{S}$ is wide-sense stationary (WSS), we can express the elements of the covariance matrix $\Sigma_{\mathbf{S}}$ as $\rho_{m,n}^{(s)} = \int_{-1/2}^{1/2} \phi_s(F) e^{j2\pi(m-n)F} dF$, where $\phi_s(F)$ is the PSD of the signal of interest, similar to [5]. Thus, we can express $T_2^{(LO)}(\mathbf{y})$ as:

$$\begin{aligned}T_2^{(LO)}(\mathbf{y}) &= \int_{-1/2}^{1/2} \phi_s(F) \left[\left| \sum_{n=0}^{N-1} \tilde{g}_{n+1}(\mathbf{y}) e^{-j2\pi nF} \right|^2 + \right. \\ &+ \left. \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} \tilde{h}_{m+1,n+1}(\mathbf{y}) e^{j2\pi(m-n)F} \right] dF \\ &= \int_{-1/2}^{1/2} \phi_s(F) \left[|G(F)|^2 + H(F) \right] dF, \quad (9)\end{aligned}$$

where we denote:

$$G(F) \triangleq \sum_{n=0}^{N-1} \tilde{g}_{n+1}(\mathbf{y}) e^{-j2\pi nF},$$

and

$$H(F) \triangleq \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} \tilde{h}_{m+1,n+1}(\mathbf{y}) e^{j2\pi(m-n)F}.$$

Thus, it is clear from (9) that the second order LO decision statistic of WSS signals with unknown probability distributions and in the presence of correlated noise (with arbitrary distribution) can be obtained by correlating the assumed PSD of the signal of interest ($\phi_s(F)$) with $\hat{\phi}(F)$ where:

$$\hat{\phi}(F) \triangleq H(F) + |G(F)|^2.$$

In practice, however, the proposed wideband detection method does not require complete knowledge of the PSD $\phi_s(F)$. That is, if the PSD is assumed to be an impulse function $\phi_s(F) = \delta(F - f)$ with an unknown parameter f, the decision statistic in (9) will simplify to $T_2^{(LO)}(\mathbf{y}) = \hat{\phi}(f) = T_2^{(LO)}(f)$ [5]. Hence, the wideband detection rule reduces to finding the active frequencies $\hat{f} = \left\{ f : \hat{\phi}(f) > \eta \right\}$, where η is a certain detection threshold. This is equivalent to applying a threshold test to the function $\hat{\phi}(F)$. In our wideband signal detection framework, we denote $\frac{1}{N}\hat{\phi}(F)$ to be the *correlated noise-based periodogram* of the received signal, given a certain weakly correlated noise distribution.

IV. Simulation Results

In our simulations, we consider two binary phase-shift keying (BPSK) signals centered at $f_c = 20MHz$ and $30MHz$, with respective bandwidths of $2MHz$ and $4MHz$. The received signal is sampled at a sampling rate of $f_s = 80MHz$. The signal is subject to the additive weakly correlated noise model of (5) with an underlying Gaussian-Laplace mixture noise sequence $\{e_k\}$, where $\tau = 0.3$ and the Laplace mixing parameter is $\epsilon = 0.2$ [5], [11], [12]. The Laplace noise pdf is denoted as $\frac{1}{2\mu} e^{-|x|/\mu}$, with $\mu = \frac{1}{\lambda} = 2$. The Gaussian noise component has a zero mean and a variance $\sigma^2 = 1$.

In Fig. 1, we compute the proposed correlated noise-based periodogram $\frac{1}{N}\hat{\phi}(F)$ of the detected signal, and compare it to the independent noise-based periodogram of [5], the SVM-FFT periodogram of [21] and the conventional periodogram $\frac{1}{N}|Y(F)|^2$, (where $Y(F)$ is the discrete Fourier transform of $\mathbf{y}$, with $F \in \{0, \frac{1}{N}, \cdots, \frac{N-1}{N}\}$) [22]. These results show that the proposed spectral estimation function can significantly reduce the noise fluctuations in the periodogram, leading to a better detection performance, compared to the other methods.

In order to evaluate the detection performance of our proposed wideband detection method, we compute the probability of detection $Pr\{T_2^{(LO)}(\mathbf{y}) > \eta | \mathcal{H}_1\} = Pr\{\hat{\phi}(f) > \eta | \mathcal{H}_1\}$, where hypothesis $\mathcal{H}_1$ denotes the existence of a certain active frequency component at f, and assuming $\phi_s(F) = \delta(F - f)$, as discussed in Section III. By varying f over the normalized frequency range $f \in [-\frac{1}{2}, \frac{1}{2}]$, we can test for the existence of spectral activities at any frequency $f \in [-\frac{1}{2}, \frac{1}{2}]$, as required in wideband spectrum sensing [4].

In this simulation, we use Monte-Carlo methods to compute the detection probability $P_D = Pr\{\hat{\phi}(f) > \eta | \mathcal{H}_1\}$, where $\mathcal{H}_1$ corresponds to an active frequency component at $f = 20MHz/f_s$. The resulting detection probability can be generalized to any active frequency component in $f \in [-\frac{1}{2}, \frac{1}{2}]$. As shown in Fig. 2, the proposed correlated noise-based detector can achieve a higher detection performance, compared

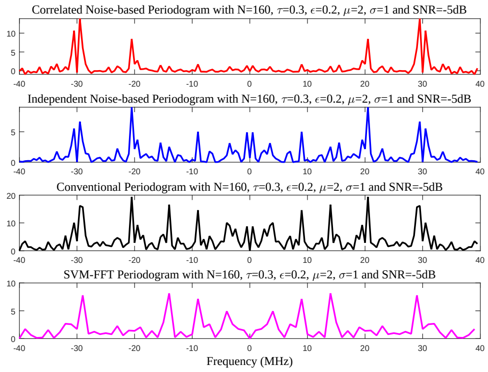

Fig. 1. Comparison among the correlated and independent noise-based periodograms, the SVM-FFT and the conventional periodogram in the presence of weakly correlated noise with SNR=-5dB and $N = 160$ samples.

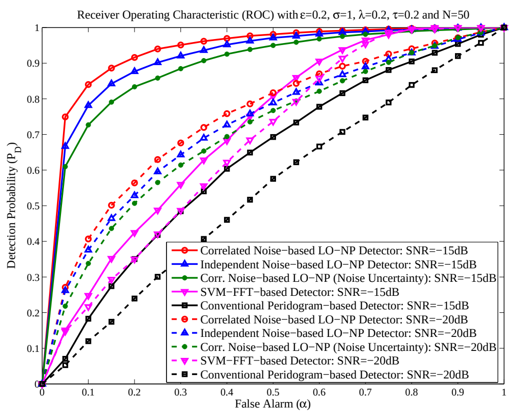

Fig. 2. Receiver operating characteristics of the correlated and independent noise-based signal detectors, the SVM-FFT and the conventional periodogram-based detectors in the presence of weakly correlated non-Gaussian noise.

to the independent noise-based detector, the SVM-FFT and the periodogram-based detector.

Finally, we analyze the robustness of the correlated noise-based detector by assuming that the actual value of the noise parameter σ deviates from its assumed value of $\sigma = 1$ to a value of $\sigma = 2$. As shown in Fig. 2, the detection performance of the proposed detector is slightly reduced under these conditions, which shows the robustness of the proposed detector under such noise uncertainty.

V. Conclusion

In this paper, we have proposed a wideband signal detection method for CR's in the presence of weakly correlated noise. The proposed method allows to reduce the impact of noise correlation in non-Gaussian noise environments. The proposed detector is based on an LO-NP detection rule and was expressed in frequency-domain, making it suitable for wideband spectrum sensing applications. The resulting frequency-domain detection rule could be obtained easily due to the factorization property of the weakly dependent noise distribution. We computed the ROC of the proposed detection method and showed its superior performance in the presence of correlated non-Gaussian noise environments, compared to similar wideband detection methods.

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