Frequency Domain Distributed OFDM Source Detection

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***Abstract*—We consider distributed detection of an orthogonal frequency-division multiplexing (OFDM) random source using a cooperative set of sensors. Assuming that the observations of different sensors are independent, we derive/propose several frequency-domain detectors: the Neyman-Pearson detector for known SNRs and noise variances and three generalized likelihood ratio detectors for unknown SNRs and/or noise variances assuming that the transmit power is either uniformly allocated to all the subcarriers or not. Our theoretical analysis matches our simulation results and show that the proposed detectors, despite their lower computational complexity, outperform the state-of-the-art time-domain detectors in practical cases.**

I. Introduction

In distributed detection, multiple sensors cooperatively detect the presence or absence of a signal source. To this end, sensors transmit a summary of their observation to a Fusion Center (FC), where a global decision is made. In contrast, sensors in the centralized counterpart, transmit all the raw observations to the FC [1]. We assume that the observations of different sensors are independent, and consider distributed detection of an orthogonal frequency-division multiplexing (OFDM) source signal in such a system. Developing efficient detectors for OFDM systems using distributed sensors is of great importance. For instance, in cognitive radio network, it is crucial to efficiently detect the presence of the primary users that employ OFDM. As another example, detection of OFDM systems makes heterogeneous communication system possible, wherein several OFDM users such as LTE and WiFi can coexist. Here, we design efficient OFDM signal detectors with low complexity and evaluate the impact of the parameters of the source and sensors on the detection performance.

Several methods are proposed to obtain summaries for distributed detection. For instance, it is proposed to transmit the energy [2] or the likelihood ratio [3]–[5] of the received signal to the FC. Employing sub-optimal techniques, the FC then combines the reported summaries to make a global decision. To detect the OFDM signals, the inherent correlation of the OFDM symbols can be exploited. For instance, several time-domain detectors are proposed in [6], [7] that use computationally expensive algorithms to exploit such correlation. In this paper, we consider distributed detection of an OFDM source signal in frequency-domain with imperfect synchronization in two cases: 1) stationary channel: the channel responses remain unchanged over the entire detection interval, 2) non-stationary channel: the channel responses may vary over the detection interval.

In time-domain, the cyclic prefix in the OFDM signal creates cyclo-stationary feature in the signal. To use this feature, autocorrelation of the received signal can be used for detection. The time-domain detectors in [6], [7] are computationally demanding since the distribution of OFDM symbols with imperfect synchronization in time-domain is rather complex. It is proven in [8] that the distribution of OFDM symbols in frequency-domain converges to a normal distribution as the number of subcarriers increases. This result is general and does not depend on the existence, length, and location of the cyclic prefix in the OFDM symbols. Using this result, we derive detectors that are robust to the synchronization mismatches (in time and frequency) and have lower computational complexity compared to the time-domain detectors.

In this paper, we first derive the Neyman-Pearson (NP) detector Λ_1 assuming known system parameters. In some cases, the noise variance can be accurately estimated and is known to the sensors in advance. For these cases, we propose two new generalized likelihood ratio detectors (GLRDs): Λ_2 and Λ_3, where Λ_2 assumes that the unknown transmit power is uniformly distributed over all the subcarriers, whereas Λ_3 makes no such an assumption. When the SNRs and noise variances are unknown, the GLRD Λ_4 can be employed. Our novel asymptotical analysis accurately evaluates the performance of Λ_4 as the number of temporal samples is large enough in practice. We show that our proposed frequency-domain detectors have lower computational complexity compared to time-domain detectors and outperform some state-of-the-art time-domain detectors in practical cases.

The Discrete Fourier Transform (DFT) of a vector $x \in \mathbb{C}^K$ is denoted by $X = \mathcal{F}x$, where $[X]_k = \sum_{n=0}^{K-1} x_n e^{-\frac{2\pi i}{K}kn}, k = 0, \ldots, K-1$ is the kth element of X. The inverse DFT (IDFT) of X is denoted by $x = \mathcal{F}^{-1}X$, where $[x]_n = \frac{1}{K}\sum_{k=0}^{K-1} X_n e^{\frac{2\pi i}{K}kn}, n = 0, \ldots, K-1$. The maximum likelihood (ML) estimate of a parameter θ is also denoted by $\hat{\theta}$.

We introduce the system model in Section II and investigate the NP detector in Section III. In Section IV-A assuming uniform transmit power, we derive the GLRD for unknown SNRs and known noise variance. We study GLRDs for two cases: 1) known noise variances, and 2) unknown SNRs and noise variances in Section IV-B and Section IV-C respectively. In Section V, we numerically evaluate the proposed detectors. We give our concluding remarks in Section VI.

II. System Model

We assume M sensors aim to cooperatively detect the presence of an OFDM source employing K subcarriers. We assume that the sensors are not synchronized and observe independent pieces of the same source in independent additive

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white normal noise. This can be guaranteed if 1) the carrier frequency mismatch of the involved sensors are considerably less than the bandwidth of one subcarrier, i.e., they observe the same channel with no perfect synchronization, 2) the sampling times of the sensors are not synchronized, however, their sampling frequencies are (almost) identical, and 3) the sampling times of the sensors are such that the source observations from different sensors can be treated as independent.

Let $\{h_{m,n}(l)\}_{l=0}^{L_c-1}$ denote the channel impulse response between the source and $m \in \{0,\dots,M-1\}$th sensor over the $n \in \{0,\dots,N-1\}$th time interval, where L_c is the channel length. We assume that each sensor observes N discrete-time sequences with length K from the same OFDM source. Let $S_{n,k}$ denote the frequency-domain OFDM transmitted symbol at the kth subcarrier during the nth interval. The transmitter computes the IDFT of the symbols, i.e., $\{\mathcal{F}^{-1}S_{n,k}\}$, adds the cyclic prefix, and then transmits the result through the channel. We assume that the sensors are not synchronized and the mth sensor records the nth time interval of its received signal with some unknown delay, and some small offsets in carrier frequency and sampling rate. Therefore, the observed sequence may contain samples from the nth and $n+1$st sets of OFDM symbols. The sensors then take DFT of the K samples of the recorded sequence to obtain $\{Y_{m,n,k}\}$. For a perfectly synchronized system it is known that $Y_{m,n,k} = H_{m,n,k}S_{n,k} + W_{m,n,k}$, where $W_{m,n,k}$ is a zero-mean complex normal noise with variance σ_m^2, i.e., $f(\{W_{m,n,k}\}) = \prod_{m,n,k} \frac{1}{\pi\sigma_m^2} \exp - \frac{|W_{m,n,k}|^2}{\sigma_m^2}$, and $H_{m,n,k} = \sum_{l=0}^{L_c-1} e^{-\frac{j2\pi kl}{K}} h_{m,n}(l)$ is the channel gain at frequency k. However for a unsynchronized system, with received signal delay and time and frequency offsets, it is proven in [8] that $\{Y_{m,n,k}\}_{k=0}^{K-1}$ are uncorrelated and converge in distribution to normal random variables as K increases. Thus, we model the unconditional distribution of $\{Y_{m,n,k}\}_{k=0}^{K-1}$ as a set of independent normal random variables with zero mean and variances of $P_k |H_{m,n,k}|^2 + \sigma_m^2$. Obviously, it is not accurate to approximate the conditional distribution of $\{Y_{m,n,k}\}$ given the synchronization parameters and channel conditions with a normal pdf.

III. Optimal Detector for Known Parameters

In this section, we derive the optimal NP detector assuming that subband SNRs and noise variance are all known. The performance of the optimum detector for this case is an upper bound for any other system, and therefore is used to assess other detectors. The NP detector compares the ratio of the probability density functions (pdfs) of the observations $\{Y_{m,n,k}\}$ under two hypotheses with some threshold. As discussed in Section II, we assume that $Y_{m,n,k}$ has zero mean complex normal distribution with variance σ_m^2 and $\theta_{m,n,k} = \sigma_m^2 + |H_{m,n,k}|^2 P_k$, under $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively, i.e.,

$$\begin{cases} f(\{Y_{m,n,k}\}|\mathcal{H}_1) = \prod_{m,n,k} \dfrac{\exp(-\frac{|Y_{m,n,k}|^2}{\theta_{m,n,k}})}{\pi\theta_{m,n,k}}, \\ f(\{Y_{m,n,k}\}|\mathcal{H}_0) = \prod_{m,n,k} \dfrac{\exp(-\frac{|Y_{m,n,k}|^2}{\sigma_m^2})}{\pi\sigma_m^2}. \end{cases} \tag{1}$$

where $\mathcal{H}_0$ and $\mathcal{H}_1$ denote the absence and the presence of the source signal respectively. It is easy to show that $\frac{f(\{Y_{m,n,k}\}|\mathcal{H}_1)}{f(\{Y_{m,n,k}\}|\mathcal{H}_0)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \bar{\eta}_1$ can be rewritten as

$$\Lambda_1 \triangleq \sum_{m,n,k} w_{m,n,k} \frac{U_{m,n,k}}{\sigma_m^2} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_1, \tag{2}$$

where $U_{m,n,k} = |Y_{m,n,k}|^2$, $\eta_1 = \log(\bar{\eta}_1) + \sum_{m,n,k} \log(\frac{\theta_{m,n,k}}{\sigma_m^2})$, and $w_{m,n,k} = 1 - \frac{\sigma_m^2}{\theta_{m,n,k}}$.

The detector Λ_1 first spatially normalizes the observations by dividing their norm by σ_m^2. The assigned weight $w_{m,n,k}$ to the normalized value is the ratio of the signal component of the subband energy, i.e., $|H_{m,n,k}|^2 P_k$, to the total subband energy, $\theta_{m,n,k}$. In addition, $w_{m,n,k} \in [0,1]$ is an increasing function of the subband SNR (defined as $\frac{|H_{m,n,k}|^2 P_k}{\sigma_m^2}$), i.e., $\lim_{\text{SNR}\to 0} w_{m,n,k} = 0$ and $\lim_{\text{SNR}\to\infty} w_{m,n,k} = 1$.

Since the number of operations required to evaluate (2) is dominated by a DFT (requiring an order of $KN\log_2 K$ operations), Λ_1 requires an order of $KN\log_2 K$ operations at each participating sensor, which is fewer than that of the time-domain NP detector proposed in [6], which requires an order of K^3N^2 operations.

Under the stationary channel model, the channel impulse response $h_{m,n}(l)$ remains static during the spectrum sensing interval. This is in contrast to the non-stationary channel model where the channel impulse response is constant only over the duration of one observation interval, but varies from interval to interval. Thus for the stationary channel model, the DFT of the channel impulse response in (2) is constant over the spectrum sensing interval and can be approximated as $H_{m,n,k} \approx H_{m,k}$, i.e., $w_{m,n,k} \approx w_{m,k}$, and $\theta_{m,n,k} \approx \theta_{m,k}$.

IV. Generalized Likelihood Ratio Detectors

A. GLRD: Uniform Power Distribution and Unknown SNRs

We previously assumed that the subband SNRs and noise variance are known. However in some cases the environment has a fast changing dynamic and it is unreasonable to assume the availability of the channel knowledge at the sensors. Moreover, due to the fast dynamic of the channel, the OFDM source cannot adapt to the channel variations and therefore allocates its transmit power uniformly to the different subchannels. Here, we address the detection of such an OFDM source, where the transmit power of subbands P_k are assumed equal yet unknown. Without loss of generality, let the channel gains $H_{m,n,k}$ absorb the subband transmit power, i.e., $P_k = 1$. Hence, to obtain the GLRD, we only need to find the ML estimator (MLE) of $|H_{m,n,k}|^2$ by maximizing the pdf of the observations $f(\{Y_{m,n,k}\}|\mathcal{H}_1)$ in (1) with respect to $|H_{m,n,k}|^2$. Note that since $h_m(n,l) = 0$ for $l \geq L_c$, the projection of the IDFT of $\{|H_{m,n,k}|^2\}$ is zero on some components, i.e., $[\mathcal{F}^{-1}|H_{m,n,k}|^2]_l = 0, L_c \leq l \leq K - L_c$. Hence, $\widehat{|H_{m,n,k}|^2}$ is the solution to the following non-convex optimization problem:

$$\begin{cases} \min\limits_{|H_{m,n,k}|^2} \exp\Big(\sum\limits_{m,n,k} \frac{U_{m,n,k}}{\sigma_m^2 + |H_{m,n,k}|^2} + \log(\sigma_m^2 + |H_{m,n,k}|^2)\Big) \\ \big[\mathcal{F}^{-1}|H_{m,n,k}|^2\big]_l = 0, \quad L_c \leq l \leq K - L_c. \end{cases} \tag{3}$$

Since there is no tractable solution to (3), we propose the following method to obtain an approximate solution. We notice that the solution to (3), when the constraints are relaxed, is given by $\max(U_{m,n,k} - \sigma_m^2, 0)$. As such, we can use the following method to find such an approximate solution:

1) Take IDFT of $\max(U_{m,n,k} - \sigma_m^2, 0)$ and retain the first L_c and last $L_c - 1$ elements, i.e.,

$$\hat{\rho}_{m,n}(l) = \begin{cases} 0, & L_c \leq l \leq K - L_c \\ [\mathcal{F}^{-1}\max(U_{m,n,k} - \sigma_m^2, 0)]_l, & \text{else.} \end{cases} \quad (4)$$

2) Take DFT of $\hat{\rho}_{m,n}(l)$ and use $|[\mathcal{F}\hat{\rho}_{m,n}(l)]|$ as a feasible initial estimate of $|H_{m,n,k}|^2$.

We approximate the solution of (3) with $|\widehat{H_{m,n,k}}|^2 \approx |[\mathcal{F}\hat{\rho}_{m,n}(l)]_k|$. Substituting this approximation in $\frac{f(\{Y_{m,n,k}\}|\mathcal{H}_1)}{f(\{Y_{m,n,k}\}|\mathcal{H}_0)} \gtrless_{\mathcal{H}_0}^{\mathcal{H}_1} \bar{\eta}_2$, with $\bar{\eta}_2$ being the detection threshold, we propose the following sub-optimal GLRD:

$$\Lambda_2 \triangleq \sum_{m,n,k} \frac{|[\mathcal{F}\hat{\rho}_{m,n}(l)]_k|}{\sigma_m^2 + |[\mathcal{F}\hat{\rho}_{m,n}(l)]_k|} \frac{U_{m,n,k}}{\sigma_m^2} - \log(1 + \frac{|[\mathcal{F}\hat{\rho}_{m,n}(l)]_k|}{\sigma_m^2}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_2, \quad (5)$$

where $\eta_2 = \log(\bar{\eta}_2)$.

Using (5), each sensor only needs to know the noise variances σ_m^2 and performs an order of $NK \log_2 K$ operations (due to the dominant contribution of DFT in the complexity). This detector exploits the additional a-priori knowledge of uniform transmit powers. However, this exploitation involves extra cost for the computation of $|[\mathcal{F}\hat{\rho}_{m,n}(l)]|$ using (4).

Under the stationary channel mode, relaxing the constraints, the solution to (3) is given by $\max(\frac{1}{N}U_{m,k} - \sigma_m^2, 0)$, where $U_{m,k} = \sum_n U_{m,n,k}$. In this condition, the same procedure, as described above, provides a feasible starting point when the term $U_{m,n,k}$ is replaced with $\frac{U_{m,k}}{N}$ in (4).

B. GLRD: Non-uniform Power Distribution and Unknown SNRs

In contrast to the Section IV-A, here we assume the channel variations are slow and therefore the OFDM source employs bit-loading techniques (e.g. [9]) and adapt the transmit powers according to the channel. As such, we derive the GLRD assuming that $\{|H_{m,n,k}|^2 P_k\}$ are unknown while $\{\sigma_m^2\}$ are known. To this end, we need the MLE of $\theta_{m,n,k}$, i.e., $\widehat{\theta}_{m,n,k}$, which is found by maximizing $f(\{Y_{m,n,k}\}|\mathcal{H}_1)$ with respect to $\theta_{m,n,k}$ as $\widehat{\theta}_{m,n,k} = \max(U_{m,n,k}, \sigma_m^2)$. Substituting $\widehat{\theta}_{m,n,k}$ in the likelihood ratio $\frac{f(\{Y_{m,n,k}\}|\mathcal{H}_1)}{f(\{Y_{m,n,k}\}|\mathcal{H}_0)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \bar{\eta}_3$, with $\bar{\eta}_3$ being the detection threshold, and simplifying the result, we obtain the following GLRD for the non-stationary channel model:

$$\Lambda_3 \triangleq \sum_{m,n,k} g\big(\frac{U_{m,n,k}}{\sigma_m^2}\big) u\big(\frac{U_{m,n,k}}{\sigma_m^2} - 1\big) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_3, \quad (6)$$

where $\eta_3 = \log \bar{\eta}_3$, $u(.)$ is the step function, and $g(x) = x - 1 - \log(x)$.

Under the stationary channel model, the MLE of $\theta_{m,k}$ is given by $\widehat{\theta}_{m,k} = \max(\frac{U_{m,k}}{N}, \sigma_m^2)$. Thus, the GLRD in (6) is still applicable. However, $U_{m,n,k}$ must be replaced with $\frac{U_{m,k}}{N}$.

For the GLRD in (6), each sensor needs to know its noise variance. In this setting, each sensor first censors less informative observations with insignificant energy, i.e., those for which $\frac{U_{m,n,k}}{\sigma_m^2} < 1$, (or $\frac{U_{m,k}}{N\sigma_m^2} < 1$ under the stationary model) and only takes into account the observations that favor the hypothesis $\mathcal{H}_1$. Then, using the function $g(x) = x - 1 - \log(x)$, sensors performs a transform on the local energies and forwards the summation $\sum_{n,k} g\big(\frac{U_{m,n,k}}{\sigma_m^2}\big) u\big(\frac{U_{m,n,k}}{\sigma_m^2} - 1\big)$. This detector requires each participating sensor to performs only an order of $KN \log_2 K$ operations (due to the dominant contribution of DFT in the complexity), which is fewer than that of the suboptimal time-domain detector proposed in [6] which requires an order of NK^2 operations.

C. GLRD: Unknown SNRs and Noise Variances

So far, the noise variance was assumed known. In some situations, the noise spectrum may vary with time and therefore it must be estimated based on the acquired samples. Here, we treat the noise variance as unknown and derive a GLRD. This GLRD does not need to know which sub-carriers are modulated or what their amplitudes are. To estimate the unknown, we maximize the pdfs in (1) with respect to $\theta_{m,n,k}$. Thus we have

$$\mathcal{H}_0 : \widehat{\sigma_m^2} = \frac{\sum_{n,k} U_{m,n,k}}{NK}, \quad \mathcal{H}_1 : \widehat{\theta}_{m,n,k} = U_{m,n,k}. \quad (7)$$

Substituting (7) respectively in $f(\{Y_{m,n,k}\}|\mathcal{H}_0)$ and $f(\{Y_{m,n,k}\}|\mathcal{H}_1)$, we obtain the following GLRD:

$$\Lambda_4 \triangleq \sum_m \Omega(U_{m,1,1}, \ldots, U_{m,N,K}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_4. \quad (8)$$

where $\Omega(x_1, \ldots, x_p) = \log(\frac{x_1 + \ldots + x_p}{p}) - \frac{\log x_1 + \ldots + \log x_p}{p}$, referred to as the homogeneity index of $(x_1, \ldots, x_p)$, and η_4 is the detection threshold. To use Λ_4 for the stationary channel model and under $\mathcal{H}_1$, it can be shown that $\widehat{\theta}_{m,n,k} = \frac{U_{m,k}}{N}$. Thus, the term $U_{m,n,k}$ must be replaced by $\frac{U_{m,k}}{N}$.

It is proven in [8] that the probabilities of false alarm P_{fa} and misdetection P_{md} of Λ_4 as $NK \to \infty$ can be expressed as follows:

$$P_{\text{fa},\Lambda_4} \approx Q\Big(\frac{\overline{\eta_4}}{\sqrt{\frac{\alpha M \psi'(\alpha) - M}{NK}}}\Big), \quad (9)$$

$$P_{\text{md},\Lambda_4} \approx 1 - Q\Big(\frac{\overline{\eta_4} - \sum_m \Omega(\theta_{m,1,1}, \ldots, \theta_{m,N,K})}{\sqrt{\frac{\alpha M \psi'(\alpha) - M}{NK} - \frac{M}{NK} + \sum_m \alpha^{-1} \frac{\sum_{n,k} \theta_{m,n,k}^2}{(\sum_{n,k} \theta_{m,n,k})^2}}}\Big),$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{t^2}{2}} dt$, and $\overline{\eta_4} = \eta_4 - M(\log(P) - \psi(P))$. This results show that as $\sum_m \Omega(\theta_{m,1,1}, \ldots, \theta_{m,N,K})$ (the homogeneity index of the subband energies) increases, a better performance can be achieved. This happens only if $\theta_{m,n,k}$ are heterogenous, i.e., the source spectrum observed by sensors are non-flat. This detector compares the ratio of arithmetic to geometrical mean of the reported subband energies ($U_{m,n,k}$ or $\frac{U_{m,k}}{N}$) with a threshold. In fact, the ratio of geometrical mean to arithmetic mean is measure of spectral flatness, i.e., Λ_4 is always positive and quantifies how the observed signal resembles a white noise process. A smaller value for Λ_4 indicates that the energy is more uniformly distributed over all the subbands and the power spectrum is more flat. Otherwise, a large value of Λ_4 indicates that more power is concentrated in a number of bands than the other subbands. Note that under $\mathcal{H}_0$, the signal is a white noise process and has a flat spectrum. As a drawback, this detector fails in some cases (e.g. at low SNRs) where under $\mathcal{H}_1$, the spectrum is flat as it misinterprets the observation as white noise and favors $\mathcal{H}_0$. This implies that Λ_4 performs well only if the received power spectrum from the source is non-flat and but that of noise is.

Additionally, Λ_4 is a constant false alarm detector and does not require a-priori knowledge about the noise variance and the SNRs. For this detector, each sensor must carry out an order of $KN \log_2 K$ computations (due to the dominant contribution of DFT in the complexity) to obtain the real number $\Omega(U_{m,1,1}, \ldots, U_{m,N,K})$ and shall report it to the FC. The complexity of the time-domain GLR detector proposed in [6] is of order of NK^2 and is more than that of Λ_4.

V. Simulation Results and Discussion

We now evaluate the proposed detectors numerically. Figure 1 depicts the P_{md} versus the P_{fa} of Λ_1 to Λ_4 with $K = 32, M = 4, \sigma_m^2 = 0.4m$ and a cyclic-prefix $L_p = 8$ for two scenarios: 1) dashed line: $N = 10$ and and 2) solid line: $N = 20$. We assume that only half of the subbands are occupied with $P_k = 1$. In Figure 1, we also compare the performance of these detectors with two time-domain detectors proposed in [6, eq. (21)-(22)] denoted by Λ_5 and Λ_6. We observe that the performance of these detectors improves as the number of observation intervals N increases, i.e., the performance loss of the sub-optimal detectors can be compensated by increasing N. For instance, our simulation results show that Λ_2 for $N = 60$ outperforms the optimal detector Λ_1 with $N = 20$. Since our proposed detectors exploit the frequency features of the signal, they provide superior performance compared to the time-domain detectors in [6].

Figure 2 depicts the P_{md} versus P_{fa} of Λ_2 to Λ_6 for $K = 32, M = 4, \sigma_m^2 = 0.4m$ and a cyclic-prefix $L_p = 8$ and fixed total transmit power of $\sum P_k = 32$ for two cases where only 20 (solid line) or 8 (dashed line) subcarriers are employed for transmission. The case where only 8 subcarriers are employed represents an extremely non-flat spectrum. Therefore, we expect that the performance of Λ_2, which assumes uniform power allocation, significantly degrades as the homogeneity index of the source spectrum increases. In addition, Λ_3 which estimates subband SNRs, outperforms other sub-optimal detectors. In contrast, the performance of Λ_4 is improved as the homogeneity in of the source spectrum increases.

VI. Conclusion

We have considered distributed detection of an OFDM random source using multiple sensors. We have analyzed the optimal NP detector Λ_1 (for known SNRs and noise variances) and the GLRD Λ_4 (for unknown SNRs and noise variance) and proposed two new GLRDs Λ_2 and Λ_3 (assuming unknown SNRs or noise variances). We have derived the miss-detection and false alarm probabilities of Λ_4. Our theoretical analysis and simulation results have shown that the proposed frequency-domain detectors outperform the state-of-the-art time-domain detectors in applications such as cognitive radio.

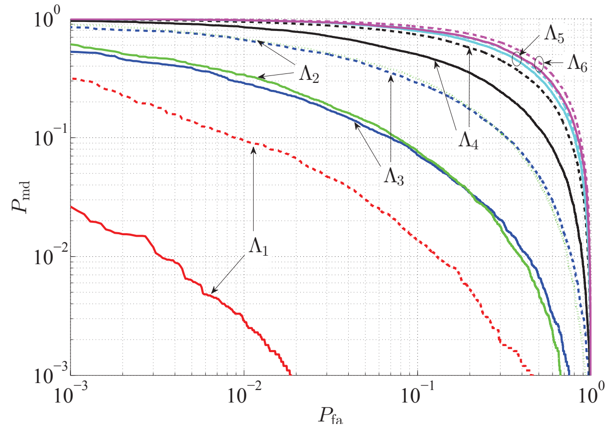

Fig. 1. P_{md} versus the P_{fa} of Λ_1 to Λ_6 with $K = 32, M = 4, \sigma_m^2 = 0.4m$ and a $L_p = 8$ for 1) dashed line: $N = 10$ and and 2) solid line: $N = 20$. We also assume that only half of the subbands are occupied with $P_k = 1$.

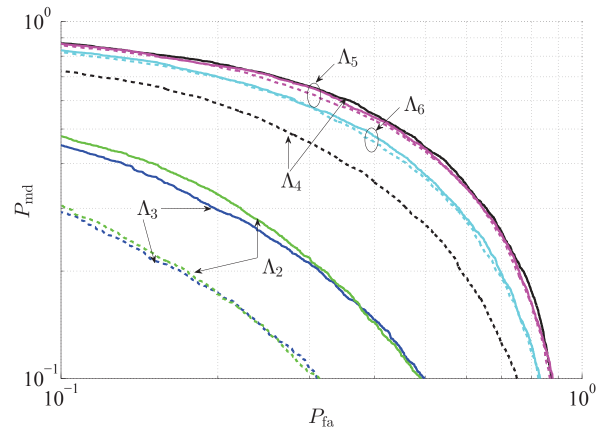

Fig. 2. Effect of spectrum flatness on the performance of Λ_2 to Λ_6 with $K = 32, M = 4, \sigma_m^2 = 0.4m$ and a $L_p = 8$ and fixed total transmit power of $\sum P_k = 32$ where only 20 (solid line) or 8 (dashed line) subcarriers are employed for transmission.

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