On Energy Detection for MIMO Decision Fusion in Wireless Sensor Networks Over NLOS Fading

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***Abstract*—We analyze sufficiency and optimality of energy detection (ED) for decision fusion. The considered scenario assumes on-off keying (OOK), statistical channel state information and a fusion center (FC) equipped with multiple antennas. The fading is modeled through zero-mean Gaussian mixtures (GM) to deal with arbitrary *non-line-of-sight* (NLOS) environments. Theoretical findings are supported by numerical simulations.**

***Index Terms*—Decision fusion, energy detection, multiple-input multiple-output (MIMO), non-line-of-sight (NLOS) fading, wireless sensor network (WSN).**

NOTATION

Lower-case bold letters denote vectors, with a_n denoting the nth element of $\boldsymbol{a}$; upper-case bold letters denote matrices, with $A_{n,m}$ denoting the (n,m)th element of $\boldsymbol{A}$; $\boldsymbol{I}_N$ denotes the $N \times N$ identity matrix; $\boldsymbol{i}_N^{(n)}$ denotes the nth column of $\boldsymbol{I}_N$; $\mathbf{0}_N$ and $\mathbf{1}_N$ denote the N-length vectors whose elements are 0 and 1, respectively; $(\cdot)^t$, $(\cdot)^\dagger$, $\mathbb{E}\{\cdot\}$, and $\|\cdot\|$ denote transpose, conjugate-transpose, expectation, and Frobenius norm operators; $\Pr(\mathcal{A})$ denotes the probability of the event $\mathcal{A}$; $p(a)$ and $P_a(\cdot)$ denote the probability density function (PDF) and the complementary cumulative distribution function (CCDF), respectively, of the random variable (RV) a; $|a|$ denotes the modulus of a; $\mathcal{A}^n$ denotes the nth Cartesian power of the set $\mathcal{A}$; $\binom{\ell}{\boldsymbol{m}} = \frac{\ell!}{m_1!\ldots m_M!}$ is the multinomial coefficient; $\Gamma(a) = \int_0^\infty \xi^{a-1}\exp(-\xi)d\xi$ and $\Gamma(a;b) = \int_b^\infty \xi^{a-1}\exp(-\xi)d\xi$ denote the Gamma and upper incomplete Gamma functions, respectively; $\mathcal{N}_{\mathbb{C}}(\mathbf{0}_N;\boldsymbol{\Omega})$ denotes a circularly-symmetric complex Gaussian distribution with covariance matrix $\boldsymbol{\Omega}$; $\sim$ means "distributed as".

I. INTRODUCTION

DISTRIBUTED detection through a wireless sensor network (WSN) transmitting local decisions to a fusion center (FC) have been investigated assuming orthogonal (i.e., non-interfering) channels [1] and, recently, interfering fading channels [2], [3]. The latter case is motivated by the exploitation of array-processing techniques over the "virtual" multi-input multi-output (MIMO) channel. Both architectures have been recently applied to cognitive radio [4], [5].

To reduce the knowledge requirements at the FC and the computational complexity for the implementation of the decision rule, which can be demanding for the optimal rule based on the log-likelihood ratio (LLR) as well as for different suboptimal rules, energy detection (ED) was analyzed in [6] and proven to be optimal over Rayleigh fading in [7], [8].

In this letter we analyze possible optimality of MIMO decision fusion based on ED over a class of fading distributions modeled through a Gaussian mixture (GM) with zero-mean components. This class can model zero-mean unimodal symmetric fading distributions and it expands the Rayleigh fading scenario, analyzed in [8], to a large number of *non-line-of-sight* (NLOS) fading scenarios, then being suitable for more realistic channel distributions. ED for decision fusion with one single antenna at the FC over arbitrary GM fading has been recently investigated in [9] without focusing on optimality.

We show that although the received energy is a sufficient statistic for such scenarios, the ED test is not always uniformly most powerful (UMP).[1] However, numerical simulations show that ED test undergoes near-optimal performance, also in cases in which it is explicitly shown not being UMP.

The outline of the letter is the following: in Section II we present the system model under investigation, including the signal model; Section III presents the optimal fusion rule at the FC and the optimality analysis of ED for MIMO decision fusion over NLOS fading; numerical results to confirm our claims are provided and discussed in Section IV.

II. SYSTEM MODEL

We consider a scenario with K sensors taking autonomously a local decision on a binary event, with the two hypotheses denoted $\mathcal{H}_0$ and $\mathcal{H}_1$. We assume that the local sensing and decision process at the kth sensor is fully described by the local probabilities of false alarm $(p_{f,k})$ and detection $(p_{d,k})$, being conditionally independent given the specific hypothesis. In the case of identical local performance (namely, *homogeneous scenario*) they will be denoted p_f and p_d, respectively.

Sensors, each with one single transmit antenna, communicate simultaneously their decision to a FC, equipped with N co-located receive antennas, whose aim is to provide a robust decision on the basis of the multiple received information. All the sensors employ the same binary modulation with identical parameters (transmission pulse, carrier frequency, etc.), and for

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[1] A test is said UMP if it maximizes the probability of detection, subject to a given probability of false alarm [10].

energy saving purposes we consider OOK modulation.[2] We assume that the system is fully synchronized: the impact of synchronization errors on system performance falls beyond the scope of this letter.

We denote: $x_k \in \mathcal{X} = \{0,1\}$ the symbol transmitted by the kth sensor encoding its local decision (we assume i for $\mathcal{H}_i$); the local probabilities are $p_{f,k} = \Pr(x_k = 1|\mathcal{H}_0)$ and $p_{d,k} = \Pr(x_k = 1|\mathcal{H}_1)$; $H_{n,k}$ the fading coefficient on the link between the kth sensor and the nth antenna at the FC; y_n and w_n the signal received by the nth antenna at the FC and the corresponding additive white Gaussian noise, respectively. We denote $\boldsymbol{h}_{(k)} = (H_{1,k},\ldots,H_{N,k})^t$ the kth channel vector, collecting the fading coefficient on the links from the kth sensor to all the antennas at the FC. Channel vectors are assumed *iid* N-dimensional complex GM with M zero-mean components, i.e.,

$$\boldsymbol{h}_{(k)} \sim \sum_{m=1}^{M} \rho_m \mathcal{N}_{\mathbb{C}}\left(\boldsymbol{0}_N;\sigma_m^2 \boldsymbol{I}_N\right). \tag{1}$$

It is worth noticing that (i) the case with $M = 1$ component represents the classical Rayleigh fading analyzed in [8] for arbitrary number of antennas (N) at the FC; (ii) the analysis was extended to the case with $M = 2$ components and $N = 1$ antenna at the FC using a scalar GM model with arbitrary mean [9], without focusing on optimality properties.

The discrete-time model for the received signal is

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{w}. \tag{2}$$

where $\boldsymbol{y} = (y_1,\ldots,y_N)^t$ is the received signal vector, $\boldsymbol{w} = (w_1,\ldots,w_N)^t \sim \mathcal{N}_{\mathbb{C}}(\boldsymbol{0}_N;\sigma_w^2\boldsymbol{I}_N)$ the corresponding noise contribution, $\boldsymbol{x} = (x_1,\ldots,x_K)^t$ is the transmitted vector (of local decisions), and $\boldsymbol{H} = (\boldsymbol{h}_{(1)},\ldots,\boldsymbol{h}_{(K)})$ is the channel matrix. Finally we define $\boldsymbol{\rho} = (\rho_1,\ldots,\rho_M)^t$ and (with a slight abuse of notation) $\boldsymbol{\sigma}^2 = (\sigma_1^2,\ldots,\sigma_M^2)^t$.

III. Fusion Rule

A. LLR and ED Tests

The (optimal) LLR test [10] and the ED test are defined as

$$\lambda \underset{\hat{\mathcal{H}}=\mathcal{H}_0}{\overset{\hat{\mathcal{H}}=\mathcal{H}_1}{\gtrless}} \gamma, \qquad \mathcal{E} \underset{\hat{\mathcal{H}}=\mathcal{H}_0}{\overset{\hat{\mathcal{H}}=\mathcal{H}_1}{\gtrless}} \gamma, \tag{3}$$

respectively, where γ is a threshold, $\hat{\mathcal{H}}$ is the estimated hypothesis, $\mathcal{E} = \|\boldsymbol{y}\|^2$ represents the received energy, and

$$\lambda = \log\left(\frac{p(\boldsymbol{y}|\mathcal{H}_1)}{p(\boldsymbol{y}|\mathcal{H}_0)}\right) = \log\left(\frac{\sum_{\ell=0}^{K} p(\boldsymbol{y}|\ell)\Pr(\ell|\mathcal{H}_1)}{\sum_{\ell=0}^{K} p(\boldsymbol{y}|\ell)\Pr(\ell|\mathcal{H}_0)}\right), \tag{4}$$

represents the LLR with $\ell = \boldsymbol{x}^t\boldsymbol{1}_K$ being the number of sensors transmitting 1.

[2]In practical scenarios, e.g., anomaly detection, OOK ensures implicit nearly-optimal censoring policy [6].

Analogously to the scalar case [9], it is straightforward to show that the conditional received signal at the FC $(\boldsymbol{y}|\ell)$ is an N-dimensional complex GM with PDF given by

$$p(\boldsymbol{y}|\ell) = \sum_{\boldsymbol{m}^t\boldsymbol{1}_M=\ell} \frac{\theta_{\boldsymbol{m}}(\ell)}{(\pi\zeta_{\boldsymbol{m}}^2)^N}\exp\left(-\frac{\|\boldsymbol{y}\|^2}{\zeta_{\boldsymbol{m}}^2}\right), \tag{5}$$

where $\boldsymbol{m} = (m_1,\ldots,m_M)^t$ is a vector of integers, with m_u representing the number of sensors undergoing the uth component of the complex GM in Eq. (1), and

$$\theta_{\boldsymbol{m}}(\ell) = \binom{\ell}{\boldsymbol{m}}\exp\left(\boldsymbol{m}^t\log(\boldsymbol{\rho})\right), \zeta_{\boldsymbol{m}}^2 = \boldsymbol{m}^t\boldsymbol{\sigma}^2 + \sigma_w^2. \tag{6}$$

Furthermore, it is worth noticing that in the case of homogeneous scenarios $\ell|\mathcal{H}_i$ is a binomial RV, i.e., $\Pr(\ell|\mathcal{H}_i) = \binom{K}{\ell}p_i^\ell(1-p_i)^{K-\ell}$, where $p_i = p_f$ (resp. $p_i = p_d$) in the case $\mathcal{H}_0$ (resp. $\mathcal{H}_1$), while in case of non-homogeneous scenarios $\ell|\mathcal{H}_i$ is a Poisson-binomial RV, i.e., $\Pr(\ell|\mathcal{H}_i) = \sum_{\boldsymbol{x}:\boldsymbol{x}^t\boldsymbol{1}_K=\ell}(\prod_{k=1}^{K} p_{i,k}^{x_k})(\prod_{k=1}^{K}(1-p_{i,k})^{1-x_k})$, where $p_{i,k} = p_{f,k}$ (resp. $p_{i,k} = p_{d,k}$) for $\mathcal{H}_0$ (resp. $\mathcal{H}_1$).

We investigate the possibility that the ED test is UMP on the basis of the Karlin-Rubin theorem [11], i.e., (i) the received energy $(\mathcal{E})$ represents a sufficient statistic, and (ii) the LLR (λ) is a strictly increasing function of the received energy $(\mathcal{E})$. Apparently, the main reason for such an interest is that, differently than the LLR test, the ED test does not require knowledge of the local performance. Additionally, ED test reduces the computational complexity dramatically.

B. Sufficient Statistic

From Eqs. (4) and (5), it is apparent that the received energy $(\mathcal{E})$ represents a sufficient statistic [10] for the LLR test, with the LLR (λ) being expressed equivalently as

$$\lambda = \log\left(\frac{\sum_{\ell=0}^{K}\Pr(\ell|\mathcal{H}_1)s_\ell(\mathcal{E})}{\sum_{\ell=0}^{K}\Pr(\ell|\mathcal{H}_0)s_\ell(\mathcal{E})}\right), \tag{7}$$

where $s_\ell(\mathcal{E}) = \sum_{\boldsymbol{m}^t\boldsymbol{1}_M=\ell}\frac{\theta_{\boldsymbol{m}}(\ell)}{(\pi\zeta_{\boldsymbol{m}}^2)^N}\exp(-\frac{\mathcal{E}}{\zeta_{\boldsymbol{m}}^2})$.

It is worth noticing that the analysis can be further generalized by replacing $\sigma_m^2\boldsymbol{I}_N$ with a general covariance matrix $\boldsymbol{\Upsilon}_m$ in Eq. (1). In such a general case, $\boldsymbol{y}|\ell$ would be a complex GM with $\boldsymbol{\Omega}_{\boldsymbol{m}} = \sum_{u=1}^{M} m_u\boldsymbol{\Upsilon}_u + \sigma_w^2\boldsymbol{I}_N$ replacing $\zeta_{\boldsymbol{m}}^2\boldsymbol{I}_N$. Denoting $\check{\zeta}_{\boldsymbol{m}}^2$ and $\hat{\zeta}_{\boldsymbol{m}}^2$ the minimum and maximum eigenvalues of $\boldsymbol{\Omega}_{\boldsymbol{m}}$, respectively, then each exponential term in the conditional PDF would be bounded as $\frac{\|\boldsymbol{y}\|^2}{\hat{\zeta}_{\boldsymbol{m}}^2} \leq \boldsymbol{y}^\dagger\boldsymbol{\Omega}_{\boldsymbol{m}}^{-1}\boldsymbol{y} \leq \frac{\|\boldsymbol{y}\|^2}{\check{\zeta}_{\boldsymbol{m}}^2}$. If the condition number of each covariance matrix $\boldsymbol{\Omega}_{\boldsymbol{m}}$ is (exactly or approximately) 1, i.e., $\check{\zeta}_{\boldsymbol{m}}^2 \approx \hat{\zeta}_{\boldsymbol{m}}^2$, the analysis still applies.

C. Strictly Increasing Behavior

From Eq. (7), the first derivative of the LLR is given by Eq. (8), shown at the bottom of the page. The denominator is apparently positive, while the numerator can be rearranged as

$$\frac{\partial\lambda(\mathcal{E})}{\partial\mathcal{E}} = \frac{\sum_{\ell_0=0}^{K}\sum_{\ell_1=0}^{K}\Pr(\ell_0|\mathcal{H}_0)\Pr(\ell_1|\mathcal{H}_1)s_{\ell_0}(\mathcal{E})\frac{\partial s_{\ell_1}(\mathcal{E})}{\partial\mathcal{E}} - \sum_{\ell_0=0}^{K}\sum_{\ell_1=0}^{K}\Pr(\ell_0|\mathcal{H}_0)\Pr(\ell_1|\mathcal{H}_1)\frac{\partial s_{\ell_0}(\mathcal{E})}{\partial\mathcal{E}}s_{\ell_1}(\mathcal{E})}{\sum_{\ell_0=0}^{K}\sum_{\ell_1=0}^{K}\Pr(\ell_0|\mathcal{H}_0)\Pr(\ell_1|\mathcal{H}_1)s_{\ell_0}(\mathcal{E})s_{\ell_1}(\mathcal{E})} \tag{8}$$

$\sum_{\ell_1=0}^{K}\sum_{\ell_0=0}^{\ell_1-1} u(\ell_0,\ell_1)v(\ell_0,\ell_1)$, where $u(\ell_0,\ell_1) = \Pr(\ell_0|\mathcal{H}_0)\Pr(\ell_1|\mathcal{H}_1) - \Pr(\ell_1|\mathcal{H}_0)\Pr(\ell_0|\mathcal{H}_1)$, and $v(\ell_0,\ell_1)$ is shown in Eq. (9), shown at the bottom of the page, with the sums meant over $\boldsymbol{m}_0^t\mathbf{1}_M = \ell_0$ and $\boldsymbol{m}_1^t\mathbf{1}_M = \ell_1$.

Assuming $p_{d,k} > p_{f,k}$, which is realistic for practical sensors, it was shown in [8] that $\Pr(\ell|\mathcal{H}_1)/\Pr(\ell|\mathcal{H}_0)$ is increasing with ℓ, then $u(\ell_0,\ell_1) > 0$ (being $\ell_1 > \ell_0$). However, differently from the Rayleigh case, $v(\ell_0,\ell_1)$ is not always positive: the ED test cannot always be claimed as UMP.

A sufficient condition for $v(\ell_0,\ell_1) > 0$, and then the ED test being UMP, is $\min_{\boldsymbol{m}_1^t\mathbf{1}_M=\ell_1}\zeta_{\boldsymbol{m}_1} > \max_{\boldsymbol{m}_0^t\mathbf{1}_M=\ell_0}\zeta_{\boldsymbol{m}_0}$, which is equivalent to

$$\xi_H \triangleq \frac{\max_{m=1,\ldots,M}\sigma_m^2}{\min_{m=1,\ldots,M}\sigma_m^2} < \frac{K}{K-1}. \tag{10}$$

Although such a condition is too restrictive, the following considerations hold: (i) $v(\ell_0,\ell_1) > 0$ for a large number of cases such that (10) does not hold, then the ED test is optimal for these cases too; (ii) numerical simulations showed that the ED test exhibits near-optimal performance even for cases in which $v(\ell_0,\ell_1) < 0$, i.e., when the received energy ($\mathcal{E}$) is a sufficient statistic, but the LLR (λ) is not a strictly increasing function of the received energy itself.

D. System Performance

Performance are evaluated through the *receiver operating characteristic* (ROC) [10], i.e., in terms of global probabilities of false alarm and detection. In the case of LLR test, they are defined as $q_f = \Pr(\lambda > \gamma|\mathcal{H}_0)$ and $q_d = \Pr(\lambda > \gamma|\mathcal{H}_1)$, respectively. In the case of ED test, $\Pr(\lambda > \gamma|\mathcal{H}_i)$ is replaced with $\Pr(\mathcal{E} > \gamma|\mathcal{H}_i) = P_{\mathcal{E}}(\gamma|\mathcal{H}_i)$ and performance may be characterized analytically as follows. The conditional received energy is a scaled central chi-square mixture with $2N$ degrees of freedom, i.e., $\mathcal{E}|\ell \sim \sum_{\boldsymbol{m}^t\mathbf{1}_M=\ell}\theta_{\boldsymbol{m}}(\ell)\chi_{2N}^2(0;\frac{\zeta_{\boldsymbol{m}}^2}{2})$, with conditional (given the number of active sensors) CCDF of the received energy ($\mathcal{E}$) and CCDF of the received energy ($\mathcal{E}$) under the generic hypothesis ($\mathcal{H}_i$) being respectively

$$P_{\mathcal{E}}(\gamma|\ell) = \sum_{\boldsymbol{m}^t\mathbf{1}_M=\ell}\frac{\theta_{\boldsymbol{m}}(\ell)}{\Gamma(N)}\Gamma\left(N;\frac{\gamma}{\zeta_{\boldsymbol{m}}^2}\right), \tag{11}$$

$$P_{\mathcal{E}}(\gamma|\mathcal{H}_i) = \sum_{\ell=0}^{K}\Pr(\ell|\mathcal{H}_i)P_{\mathcal{E}}(\gamma|\ell). \tag{12}$$

IV. Simulation Results and Discussion

Numerical results refer to Monte Carlo simulations with up to 10^5 runs using MATLAB. We considered WSNs with $K \in \{5,10\}$ sensors, whose local performance are $(p_f,p_d) = (0.05,0.5)$, and FCs with $N \in \{2,4,8\}$ antennas. ROC curves are labeled with respect to the SNR defined as H_{rms}^2/σ_w^2. We considered SNR $\in \{0,10\}$ dB. Channels with $M = 2$ equally-probable components (i.e., $\rho_1 = \rho_2 = 1/2$) are assumed (named 2ZM in [9]), characterized through the ratio between the average power of the two components ($\xi_H = \sigma_1^2/\sigma_2^2$). We considered 2ZM channels with $\xi_H \in \{5,50\}$.

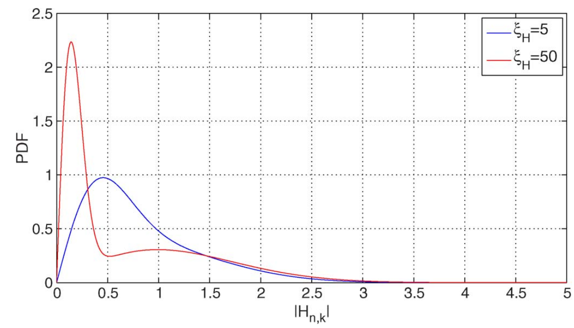

Fig. 1. Impact of ξ_H the PDF of $|H_{n,k}|$.

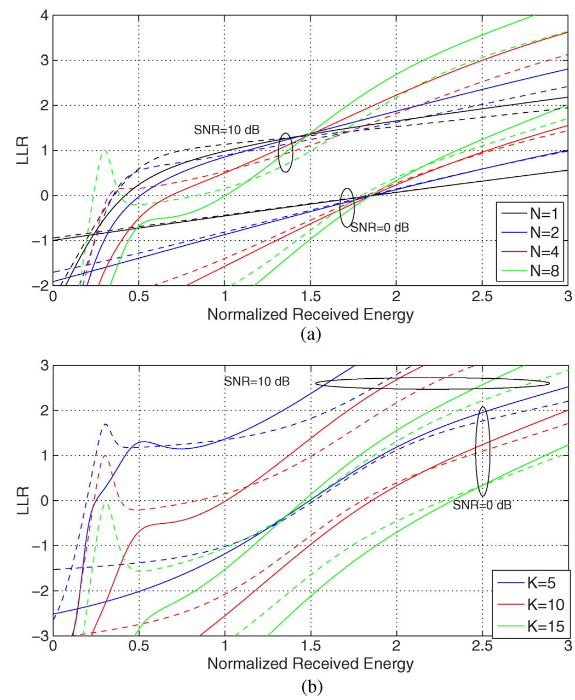

Fig. 2. LLR (λ) vs. normalized received energy ($\mathcal{E}/N$) for 2ZM channels with $\xi_H = 5$ (solid lines) and $\xi_H = 50$ (dashed lines). (a) WSN with $K = 10$ sensors. (b) FC with $N = 8$ antennas.

Fig. 1 shows the statistics of the fading coefficients in the case of 2ZM channels. The channel with $\xi_H = 5$ exhibits a PDF which is extremely similar to the Rayleigh-fading scenario, while the channel with $\xi_H = 50$ exhibits a very different statistical behavior with 2 modes very distinguishable.

Fig. 2 shows the behavior of the LLR (λ) vs. the normalized received energy ($\mathcal{E}/N$) for various system configurations. The cases here shown do not match the sufficient condition in (10), and it is apparent how at low SNR the LLR (λ) is monotonic while high SNR and large number of antennas (N) at the FC make the LLR (λ) non-monotonic. The non-monotonicity is

$$v(\ell_0,\ell_1) = s_{\ell_0}(\mathcal{E})\frac{\partial s_{\ell_1}(\mathcal{E})}{\partial\mathcal{E}} - \frac{\partial s_{\ell_0}(\mathcal{E})}{\partial\mathcal{E}}s_{\ell_1}(\mathcal{E}) = \sum_{\boldsymbol{m}_0}\sum_{\boldsymbol{m}_1}\frac{\zeta_{\boldsymbol{m}_1}-\zeta_{\boldsymbol{m}_0}}{\zeta_{\boldsymbol{m}_0}^2\zeta_{\boldsymbol{m}_1}^2}\frac{\theta_{\boldsymbol{m}_0}(\ell_0)\theta_{\boldsymbol{m}_1}(\ell_1)}{(\pi^2\zeta_{\boldsymbol{m}_0}^2\zeta_{\boldsymbol{m}_1}^2)^N}\exp\left(-\frac{\mathcal{E}}{\zeta_{\boldsymbol{m}_0}^2}\right)\exp\left(-\frac{\mathcal{E}}{\zeta_{\boldsymbol{m}_1}^2}\right) \tag{9}$$

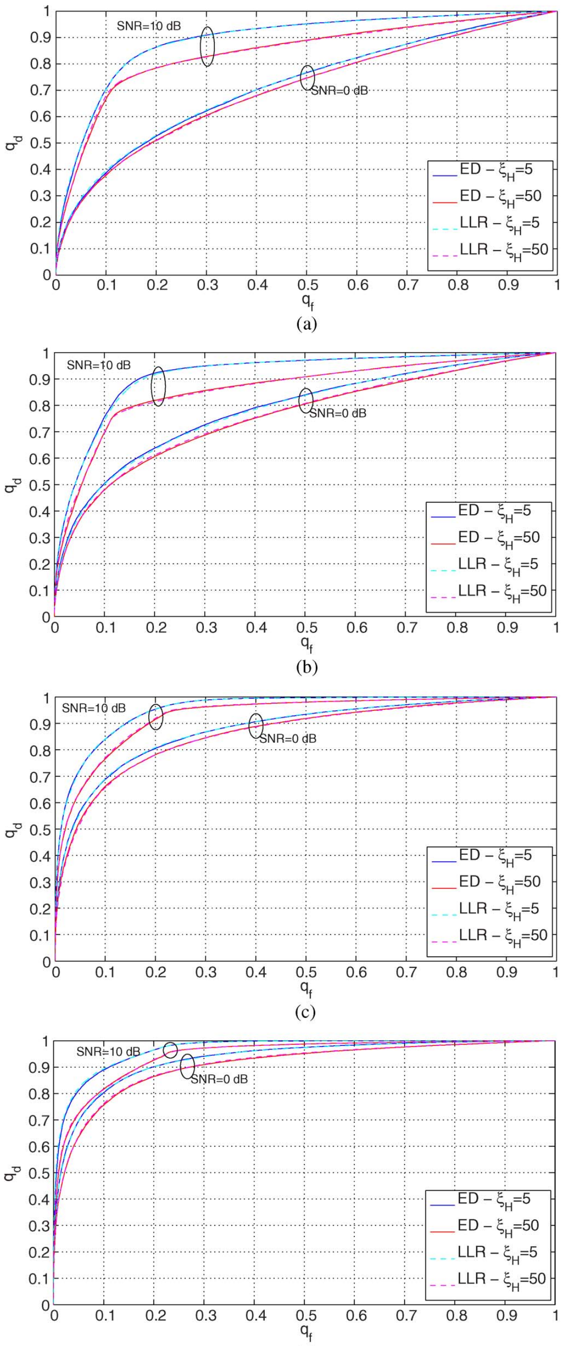

Fig. 3. ROC for 2ZM channels with $\xi_H = 5$ (solid lines) and $\xi_H = 50$ (dashed lines): comparison between ED and LLR tests. (a) WSN with $K = 5$ sensors and FC with $N = 2$ antennas. (b) WSN with $K = 5$ sensors and FC with $N = 4$ antennas. (c) WSN with $K = 10$ sensors and FC with $N = 4$ antennas. (d) WSN with $K = 10$ sensors and FC with $N = 8$ antennas.

further enhanced with increasing ratio ξ_H, while de-enhanced with increasing number of sensors (K) due to effect of the *central-limit theorem* [10] (for large K the test approaches a test between two Gaussian RVs which is monotonic in the received energy).

Fig. 3 shows the ROC performance for various systems configurations, comparing the ED test with the LLR test.[3]

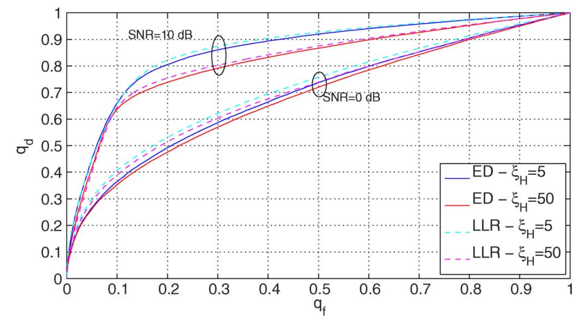

Fig. 4. ROC for rank-deficient 2ZM channels with $\xi_H = 5$ (solid lines) and $\xi_H = 50$ (dashed lines): comparison between ED and LLR tests in WSN with $K = 5$ sensors and FC with $N = 2$ antennas.

Numerical simulations reveals that ED test exhibits near-optimal performance even when it is not UMP. It is apparent how at low SNR and when the ratio N/K is small, performance are not affected significantly by the channel statistics; while at high SNR or when the ratio N/K is not very small, performance decrease significantly with the ratio ξ_H (i.e., the multi-modal behavior degrades performance).

We considered rank-one correlated 2ZM channels in which $\boldsymbol{\Upsilon}_m = \sigma_m^2 \boldsymbol{a}(\theta_m)\boldsymbol{a}(\theta_m)^\dagger$, where $\boldsymbol{a}(\theta) = (1, e^{j\pi\cos(\theta)} \ldots, e^{j\pi(N-1)\cos(\theta)})^t$. Fig. 4 shows the case with $\theta_1 = \pi/6$ and $\theta_2 = \pi/4$: it is apparent a (negligible) performance gap between the ED test and the LLR test.

We conclude emphasizing that ED test in MIMO distributed detection undergoes near-optimal performance for a large class of NLOS scenarios despite not requiring knowledge of the local performance and being computationally inexpensive.

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[3] Due to space limitations, we do not show how the ROC curves for ED test in Eqs. (11) and (12) perfectly match numerical simulations.