Channel-Aware Decision Fusion with Rao Test for Multisensor Fusion

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Abstract. This paper tackles unknown signal detection in a distributed fashion via a Wireless Sensor Network (WSN) made of tiny and low-cost sensor devices. The sensors are assumed to measure an unknown deterministic parameter within unimodal and symmetric noise. Since usual Internet of Things (IoT) scenarios require energy-constrained operations, one-bit quantization of the raw measurement is locally performed at each sensor. A Fusion Center (FC) receives noisy quantized sensor observations through reporting parallel-access Rayleigh channels and makes a global decision. We propose the Rao test as a simpler alternative to the Generalized Likelihood Ratio Test (GLRT) for multisensor fusion. The intent of our work is performing fusion directly from the received signals, following a decode-and-fuse approach. Then, we study the design of the (channel-aware) quantizer of each sensor with the intent of maximizing the asymptotic detection probability. Finally, we compare the performance of the Rao test with that of the GLRT by simulations (related to a practical WSN scenario).

Keywords: Distributed detection · GLRT · Information fusion · IoT · Rao test · Threshold design · Wireless Sensor Networks

1 Introduction

The deployment of billions of tiny devices with sensing, computation, and communicating functionalities is envisaged by the Internet of Things (IoT) paradigm. IoT paradigm is expected to be used in numerous peculiar areas of everyday life [1]. These vertical applications include smart cities and farming, e-health, cyber-surveillance and security [2], digital industry. The pervasive presence of such devices allows to (a) sense the whole environment, (b) interact with it and (c) use the Internet to provide the basis for information transfer, data analytics, and applications usage [3].

The federation of such wireless sensing nodes into Wireless Sensor Networks (WSNs) constitutes the stepping stone of IoT capitalization toward situation awareness by means of collective data analytics. For this reason, WSNs have been steadily attracting interest by the research community. Their main advantages consist of their flexibility and affordable costs [4,5]. Distributed detection

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constitutes a main important task, among the different collective inference tasks which can be accomplished by WSNs, which has been deeply investigated in the last years [6].

Unfortunately, full-precision transmission of measurements by sensors is precluded due to harsh bandwidth and energy constraints in WSNs. As a consequence, only one bit is usually communicated to the Fusion Center (FC) by each node, concerning the inferred hypothesis. In this context the optimal test at each sensor consists of quantizing the local likelihood-ratio test (LRT) into one-bit. This result holds under both Bayesian and Neyman-Pearson frameworks. Still, the complexity in the design of the quantizer thresholds grows exponentially with the WSN size [7,8]. Equally important, the evaluation of sensor LRT is precluded by the incomplete knowledge of all parameters concurring to define the sensing model [8]. Hence, the bit transmitted is either obtained as raw measurement quantization [9,10] or corresponds to the inferred binary-valued event. In the latter case, the bit is usually obtained via a sub-optimal detection statistic [11]. In both situations, FC receives sensors bits sent over the wireless medium and combines them via a wisely-designed fusion rule, with the intent of overcoming the detection limitations of the single sensor. The optimum strategy to fuse the sensors' noisy bits at the FC, under conditional independence assumption, is a sum of sensor-individual log-likelihood terms, each depending on unknown sensing parameters, as well as the communication channel parameters [12].

Some simple approaches have been thus proposed which neglect the dependence with respect to the unknown sensing parameters [12–14]. Still, the parametric specification of a sensing model (via some unknown parameters) allows the FC to define a composite test of hypotheses. In this case, the Generalized LRT (GLRT) is usually considered as the most common design solution [15]. Indeed, WSN literature has extensively addressed distributed detection of quantized data via the GLRT [9,16,17]. Specific applications include revealing a cooperative target with unknown location, an uncooperative target modelled by known observation coefficients, or an unknown source at unknown position.

Conversely, the Rao test [15] does not require maximum likelihood estimates under the alternative hypothesis ($\mathcal{H}_1$). Hence, it represents a simpler detection method for tackling composite hypothesis testing, while asymptotically yielding the same performance as the GLRT. Accordingly, several works have appeared leveraging Rao test in WSN-based detection in recent years. For example, Ciuonzo et al. [18] have proposed a Rao fusion rule based on one-bit quantization of scalar measurements, whereas a corresponding generalization to multi-bit case has been devised in [19]. Recently, its simplicity has been exploited to detect an uncooperative target (e.g. with also unknown location) at the FC, by developing a generalized version of the test for the one-bit [10] and multi-bit cases [20]. The uncooperative-target case has been recently analyzed also in an online setup with a sequential version of the above fusion (one-bit) rule [21]. Furthermore, [22] has applied the Rao test to collision-aware reporting for fusion design. Still, *none of the above works have directly attempted to design fusion rules directly from the received signals at the FC.*

To fill this gap, we focus on distributed detection of an unknown signal buried in zero-mean sensing noise (with symmetric and unimodal pdf), via *channel-aware techniques*. In detail, we study the problem of decision fusion over parallel-access fading channels. In the aforementioned scenario, to cope with the computational complexity of the GLRT, we propose the Rao test as a simpler alternative not requiring any estimation procedure and we obtain its explicit form.

The reporting channel is herein taken explicitly into account and the fusion rule is designed directly from the received signals, following a *decode-and-fuse* rationale [14], as opposed to previous literature (e.g. [18]). Then, the (weak-signal) asymptotic performance of both GLR and Rao tests is obtained and the optimal choice of the quantizer threshold (in the channel-aware context) is investigated according to the resulting objective. Remarkably the quantizer design can be decoupled among sensors and, while the objective explicitly considers the *fading* channel condition between each sensor and the FC, the optimized thresholds seem to be independent on the above term. Furthermore, the Rao test is compared to the GLRT through simulations. Results highlight that our proposal performs at least as well as the GLRT for a finite number of sensors, in addition to sharing the same asymptotic distribution.

Paper Organization: Section 2 details the system model; Sect. 3 develops GLR and Rao tests in the channel-aware setup; then, in Sect. 4, we design asymptotically-optimal quantizers; in Sect. 5 we report numerical results and discuss them; finally, in Sect. 6 we summarize take-home messages and point to future directions of research.

Summary of Math Notations: Vectors are represented with lower-case bold letters , with a_n being the nth entry of $\boldsymbol{a}$; $\mathbb{E}\{\cdot\}$, $(\cdot)^T$, $(\cdot)^*$ and $\Re(\cdot)$ are the expectation, transpose, conjugate and real part operators, respectively; the unit (Heaviside) step function is denoted with $u(\cdot)$; $P(\cdot)$ denotes a probability mass function (pmf), whereas $p(\cdot)$ a probability density functions (pdf); we denote a real-valued (resp. complex-valued) Gaussian pdf having mean μ and variance σ^2 with $\mathcal{N}(\mu,\sigma^2)$ (resp. $\mathcal{N}_{\mathbb{C}}(\mu,\sigma^2)$); $p_{\mathcal{N}}(\cdot)$ (resp.$\mathcal{Q}(\cdot)$) denotes the pdf (resp. the complement of the cumulative distribution function) of the standard normal random variable $\mathcal{N}(0,1)$; last, the symbol $\sim$ (resp. $\overset{a}{\sim}$) corresponds to "distributed as" (resp. to "asymptotically distributed as").

2 System Model

We consider a collection of sensors $k \in \mathcal{K} \triangleq \{1,\ldots,K\}$ collaborating to test an unknown deterministic parameter $\theta \in \mathbb{R}$, i.e. to perform a *composite* binary hypothesis testing. In summary, the problem is formulated as follows:

$$\begin{cases} \mathcal{H}_0 & : \quad z_k = w_k, \\ \mathcal{H}_1 & : \quad z_k = g_k\,\theta + n_k, \qquad k \in \mathcal{K}; \end{cases} \tag{1}$$

where $z_k \in \mathbb{R}$ denotes the kth sensor measurement, $g_k \in \mathbb{R}$ is a known observation coefficient and $n_k \in \mathbb{R}$ denotes the noise random variable (RV) with $\mathbb{E}\{n_k\} = 0$

and *unimodal symmetric* pdf[1], denoted with $p_{n_k}(\cdot)$. Furthermore, the RVs n_k are assumed mutually independent. It is worth noticing that Eq. (1) determines a *two-sided test* [15], where $\{\mathcal{H}_0, \mathcal{H}_1\}$ corresponds to $\{\theta = \theta_0, \theta \neq \theta_0\}$ (in our case $\theta_0 = 0$).

Then, the kth sensor quantizes z_k within one bit of information, i.e. $d_k \triangleq u\,(z_k - \tau_k)$, $k \in \mathcal{K}$, where τ_k represents the quantizer threshold (to be designed). This operation is performed in realistic IoT scenarios to meet stringent bandwidth and energy budgets. Due to the distributed nature and design limitations of WSNs, the bits encoding the quantized information are usually directly transmitted from local sensors to the FC through parallel channels that undergo independent fading. Each decision d_k is then mapped into a BPSK modulation, corresponding to a symbol $x_k \in \mathcal{X} = \{-1, +1\}$. Without loss of generality, we assume that $d_k = \mathcal{H}_0$ maps into $x_k = -1$, whereas $d_k = \mathcal{H}_1$ is encoded into $x_k = +1$.

In practice, sensor communication ranges are usually small and the data rates are relatively low. Transmission links can be assumed experiencing flat fading. Herein, we adopt the Rayleigh fading channel model as a consequence of a homogeneous scattering environment. In other terms:

$$y_k = h_k\, x_k + w_k \qquad k \in \mathcal{K}; \tag{2}$$

where $y_k \in \mathbb{C}$, $h_k \in \mathbb{C}^N$, $w_k \sim \mathcal{N}_{\mathbb{C}}(0, \sigma^2_{w,k})$ are the received signal, the fading channel, and the (channel) noise term, respectively. For notational compactness, the received signals from different sensors are collected as $\boldsymbol{y} \triangleq \begin{bmatrix} y_1 \cdots y_K \end{bmatrix}^T$.

The objective of our study consists of the derivation of a simple statistical test (from the perspective of computational complexity) having the following form

$$\Lambda(\boldsymbol{y}) \underset{\hat{\mathcal{H}}=\mathcal{H}_0}{\overset{\hat{\mathcal{H}}=\mathcal{H}_1}{\gtrless}} \gamma_{\mathrm{fc}} \tag{3}$$

i.e. deciding for $\mathcal{H}_0$ (resp. $\mathcal{H}_1$) when the statistic $\Lambda(\boldsymbol{y})$ is below (resp. above) the threshold γ_{fc}, and the design of the quantizer (i.e. an optimized τ_k, $k \in \mathcal{K}$) for each sensor. In the previous definition, Λ denotes the generic decision statistic implemented at the FC.

Accordingly, FC system performance will be measured in terms of the detection ($P_{\mathrm{D}} \triangleq \Pr\{\Lambda > \gamma_{\mathrm{fc}} | \mathcal{H}_1\}$) and false alarm ($P_{\mathrm{F}} \triangleq \Pr\{\Lambda > \gamma_{\mathrm{fc}} | \mathcal{H}_0\}$) probabilities, respectively.

3 Fusion Rules

A common tool for a detector in composite hypothesis testing problems is given by the GLRT [15], which for the model under investigation is expressed in implicit form as:

[1] Such class of pdfs includes the well-known Gaussian, Laplace, generalized Gaussian and Cauchy distributions with zero mean [15].

$$\varLambda_{\mathrm{G}} \triangleq 2 \cdot \ln\left[\frac{p(\boldsymbol{y};\hat{\theta}_1)}{p(\boldsymbol{y};\theta_0)}\right]\;; \tag{4}$$

where $p(\boldsymbol{y};\theta)$ represents the likelihood as a function of θ. Furthermore, the term $\hat{\theta}_1$ denotes the maximum likelihood (ML) estimate under $\mathcal{H}_1$, defined as:

$$\hat{\theta}_1 \triangleq \arg\max_{\theta} p(\boldsymbol{y};\theta) \tag{5}$$

The observation of Eq. (4) highlights that $\varLambda_{\mathrm{G}}$ requires the solution to an optimization problem. Accordingly, this increases the computational complexity of its implementation (e.g.. by grid search or local-optimization methods).

Due to the above technical difficulties, in this work we propose the adoption of the Rao test as a simpler solution. Its corresponding decision statistic, for the scalar case ($\theta \in \mathbb{R}$), is given in the implicit form as:

$$\varLambda_{\mathrm{R}} \triangleq \frac{\left(\left.\frac{\partial \ln p(\boldsymbol{y};\theta)}{\partial \theta}\right|_{\theta=\theta_0}\right)^2}{\mathrm{I}(\theta_0)} \tag{6}$$

where $\mathrm{I}(\theta_0)$ is the *Fisher information* (FI), i.e. $\mathrm{I}(\theta) \triangleq \mathbb{E}\{\left(\frac{\partial \ln[p(\boldsymbol{y};\theta)]}{\partial \theta}\right)^2\}$ evaluated at θ_0. The motivation of our choice is given by the extreme simplicity of the test implementation (since $\hat{\theta}_1$ is not required, cf. Eq. (6)), but with the same weak-signal asymptotic performance as the GLRT, as supported from the theory [15].

In order to obtain $\varLambda_{\mathrm{R}}$ explicitly, we expand $\ln[p(\boldsymbol{y};\theta)]$ as:

$$\ln[p(\boldsymbol{y};\theta)] = \sum_{k=1}^{K} \ln[p(y_k;\theta)]$$

$$= \sum_{k=1}^{K} \ln\left[\mathcal{N}_{\mathbb{C}}(y_k; h_k, \sigma^2_{w,k})\,\alpha_k(\theta) + \mathcal{N}_{\mathbb{C}}(y_k; -h_k, \sigma^2_{w,k})(1-\alpha_k(\theta))\right] \tag{7}$$

where $\alpha_k(\theta) \triangleq F_{n_k}(\tau_k - g_k\theta)$, with $F_{n_k}(\cdot)$ denoting the complementary cumulative distribution function of n_k.

The closed-form expression of $\varLambda_{\mathrm{R}}$ is drawn by means of the explicit forms of the score function (i.e. $\partial \ln[p(\boldsymbol{y}\,;\theta)\,/\partial\theta]$) and the FI (i.e. $\mathrm{I}(\theta)$), *both evaluated* at $\theta = \theta_0$. In the former case, the final expression of the score function at $\theta = \theta_0$ is given by:

$$\left.\frac{\partial \log p(\boldsymbol{y};\theta)}{\partial \theta}\right|_{\theta=\theta_0} = \sum_{k=1}^{K} g_k\, p_{n_k}(\tau_k)\left[\frac{\exp\left(4\Re(h_k^* y_k)/\sigma^2_{w,k}\right) - 1}{\exp\left(4\Re(h_k^* y_k)/\sigma^2_{w,k}\right) F_{n_k}(\tau_k) + (1 - F_{n_k}(\tau_k))}\right] \tag{8}$$

In the latter case, $\mathrm{I}(\theta_0)$ is given in closed form as:

$$\mathrm{I}(\theta_0) = \sum_{k=1}^{K} g_k^2\, p_{n_k}^2(\tau_k) \left\{ F_{n_k}(\tau_k) \int_{-\infty}^{+\infty} \left(\frac{\exp(2\,\xi_k) - 1}{\exp(2\,\xi_k)\, F_{n_k}(\tau_k) + \left(1 - F_{n_k}(\tau_k)\right)} \right)^2 \mathcal{N}\left(\xi_k; \Xi_k, \Xi_k\right)\, d\xi_k \right.$$
$$\left. + \left(1 - F_{n_k}(\tau_k)\right) \int_{-\infty}^{+\infty} \left(\frac{\exp(2\,\xi_k) - 1}{\exp(2\,\xi_k)\, F_{n_k}(\tau_k) + \left(1 - F_{n_k}(\tau_k)\right)} \right)^2 \mathcal{N}\left(\xi_k; -\Xi_k, \Xi_k\right)\, d\xi_k \right\} \tag{9}$$

where we have employed the definition $\Xi_k \triangleq 2\,|h_k|^2 / \sigma_{w,k}^2$. Both derivations are not reported for the sake of brevity. Combining Eqs. (8) and (9) we obtain Λ_{R} in closed form, as shown in Eq. (10):

$$\Lambda_{\mathrm{R}} = \frac{\left(\sum_{k=1}^{K} g_k\, p_{n_k}(\tau_k) \left[\frac{\exp\left(4\Re(h_k^* y_k)/\sigma_{w,k}^2\right) - 1}{\exp\left(4\Re(h_k^* y_k)/\sigma_{w,k}^2\right) F_{n_k}(\tau_k) + \left(1 - F_{n_k}(\tau_k)\right)} \right] \right)^2}{\mathrm{I}(\theta_0)} \tag{10}$$

It is apparent that Λ_{R} (as well as Λ_{G}) depends on τ_k's. Hence the threshold set, gathered within $\boldsymbol{\tau} \triangleq \left[\tau_1 \cdots \tau_K\right]^T$, can be designed to optimize performance. The aim of Sect. 4 will be then the derivation of a corresponding objective required to accomplish this task.

4 Asymptotically-Optimal Quantizer Design

Previous literature has shown that Λ_{R} (as well as Λ_{G}) is asymptotically distributed as follows [15]:

$$\Lambda_{\mathrm{R}} \stackrel{a}{\sim} \begin{cases} \chi_1^2 & \text{under} \quad \mathcal{H}_0 \\ \chi_1^{\prime 2}(\lambda_Q) & \text{under} \quad \mathcal{H}_1 \end{cases} \tag{11}$$

where the non-centrality parameter λ_Q is given by

$$\lambda_Q \triangleq (\theta_1 - \theta_0)^2 \mathrm{I}(\theta_0)\,, \tag{12}$$

in which $\theta_1 = \theta$ denotes the true value under $\mathcal{H}_1$. The above asymptotic result holds when the signal is weak, namely $|\theta_1 - \theta_0| = c/\sqrt{K}$ for a suitably-defined constant $c > 0$ [15]. Clearly a larger λ_Q leads to improved performance of both GLR and Rao tests. Also, as shown in [9], $\mathrm{I}(\theta_0)$ is a function of τ_k, $k \in \mathcal{K}$. Thus, we choose $\tau_1, \ldots \tau_K$ in order to maximize λ_Q, which is equivalent to the following optimization:

$$\arg \max_{\{\tau_1, \ldots, \tau_K\}} \mathrm{I}(\theta_0, \boldsymbol{\tau})\,. \tag{13}$$

The optimization of the FI $\mathrm{I}(\theta_0, \boldsymbol{\tau})$ with respect to $\{\tau_1, \ldots, \tau_K\}$ can be decoupled in this particular case. Indeed, by separating the optimization variables τ_K's, we obtain K independent threshold design problems, formulated as follows:

$$\arg\max_{\tau_k} \left\{ p_{n_k}^2(\tau_k) \left\{ F_{n_k}(\tau_k) \int_{-\infty}^{+\infty} \left(\frac{\exp(2\,\xi_k) - 1}{\exp(2\,\xi_k)\, F_{n_k}(\tau_k) + \left(1 - F_{n_k}(\tau_k)\right)} \right)^2 \mathcal{N}\left(\xi_k; \Xi_k, \Xi_k\right)\, d\xi_k \right\} \right. \tag{14}$$

$$\left. (1 - F_{n_k}(\tau_k)) \int_{-\infty}^{+\infty} \left(\frac{\exp(2\,\xi_k) - 1}{\exp(2\,\xi_k)\, F_{n_k}(\tau_k) + \left(1 - F_{n_k}(\tau_k)\right)} \right)^2 \mathcal{N}\left(\xi_k; -\Xi_k, \Xi_k\right)\, d\xi_k \right\}$$

In the case of ideal reporting channels, it is known that many unimodal and symmetric $p_{n_k}(\cdot)$ with $\mathbb{E}\{n_k\} = 0$ lead to $\tau_k^* \triangleq \arg\max_{\tau_k} g_k(\tau_k) = 0$ [23,24]. These include the Gaussian, Laplace, Cauchy and the widely used generalized normal distribution (with the further constraint $0 \leq \epsilon \leq 2$). For the mentioned reasons, and due to the particular symmetry of BPSK modulation employed in the non-ideal channel case considered, we choose $\tau_k^* = 0$ in what follows.

Accordingly, we obtain the following expression for Rao test with optimized thresholds (referred to as Λ_{R}^*) by setting $\tau_k^* = 0$, $k \in \mathcal{K}$, in Eq. (10):

$$\Lambda_{\mathrm{R}}^* = \frac{\left[\sum_{k=1}^K g_k\, p_{n_k}(0) \frac{\exp\left(4\Re(h_k^* y_k)/\sigma_{w,k}^2\right) - 1}{\exp\left(4\Re(h_k^* y_k)/\sigma_{w,k}^2\right) + 1} \right]^2}{\sum_{k=1}^K g_k^2\, p_{n_k}^2(0) \int_{-\infty}^{+\infty} \left(\frac{\exp(2\,\xi_k) - 1}{\exp(2\,\xi_k) + 1} \right)^2 \left[\frac{1}{2}\mathcal{N}\left(\xi_k; \Xi_k, \Xi_k\right) + \frac{1}{2}\mathcal{N}\left(\xi_k; -\Xi_k, \Xi_k\right) \right] d\xi_k} \tag{15}$$

which is extremely simpler than the GLRT, as it avoids to solve an optimization problem (which depends on $p_{n_k}(\cdot)$).

Additionally, the non-centrality parameter corresponding to the above threshold choice (denoted with λ_Q^*), is given by:

$$\lambda_Q^* = 4\theta_1^2 \sum_{k=1}^K g_k^2\, p_{n_k}^2(0) \tag{16}$$

$$\times \left\{ \int_{-\infty}^{+\infty} \left(\frac{\exp(2\,\xi_k) - 1}{\exp(2\,\xi_k) + 1} \right)^2 \left[\frac{1}{2}\mathcal{N}\left(\xi_k; \Xi_k, \Xi_k\right) + \frac{1}{2}\mathcal{N}\left(\xi_k; -\Xi_k, \Xi_k\right) \right] d\xi_k \right\}$$

Comparison with Previous Literature: Recall that in the binary-symmetric channel case, the corresponding threshold-optimized non-centrality equals [9] $\lambda_Q^* \triangleq 4\,\theta_1^2 \cdot \sum_{k=1}^K \left[g_k^2\, p_{n_k}^2(0) \right] (1 - 2\,P_{e,k})^2$, while in the ideal case it reduces to $\lambda_Q^* \triangleq 4\,\theta_1^2 \cdot \sum_{k=1}^K \left[g_k^2\, p_{n_k}^2(0) \right]$. Hence, the effect due to fading channels is entirely represented via the term within the curly brackets of Eq. (16).

5 Results and Discussion

In what follows, we consider a WSN with $K = 10$ sensors and compare the Rao test to the GLRT. For simplicity, we consider Gaussian-distributed sensing

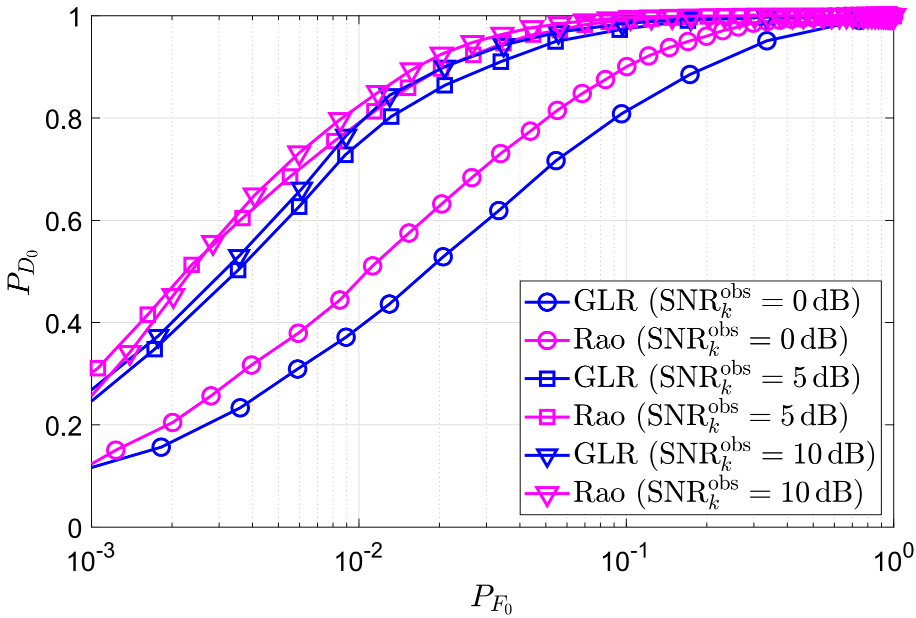

Fig. 1. P_{D_0} vs. P_{F_0} for GLR and Rao tests; WSN with $K = 10$ sensors, $g_k = 1$, and sensor thresholds set as $\tau_k^\star = 0$. The channel SNR is $\mathrm{SNR}_k^{\mathrm{chan}} = 5\,\mathrm{dB}$, while three different cases of sensing SNR are considered, namely $\mathrm{SNR}_k^{\mathrm{obs}} \in \{0, 5, 10\}\,\mathrm{dB}$.

noise, i.e. $n_k \sim \mathcal{N}(0, \sigma_{n,k}^2)$ and $g_k = 1$. We set the sensor thresholds to $\tau_k^\star = 0$. We define the kth sensor observation signal-to-noise ratio (SNR) as $\mathrm{SNR}_k^{\mathrm{obs}} \triangleq \left(g_k^2 \theta^2 / \mathbb{E}\{n_k^2\}\right)$. Conversely, we define the corresponding reporting channel SNR as $\mathrm{SNR}_k^{\mathrm{chan}} \triangleq \left(\mathbb{E}\{|h_k|^2\}/\sigma_{w,k}^2\right)$. For simplicity, the numerical results refer to a *homogeneous scenario,* namely we assume the sensors experience the same sensing and channel SNRs, namely $\mathrm{SNR}_k^{\mathrm{obs}} = \mathrm{SNR}^{\mathrm{obs}}$ and $\mathrm{SNR}_k^{\mathrm{chan}} = \mathrm{SNR}^{\mathrm{obs}}$, for $k \in \mathcal{K}$. The figures are generated by running 10^5 Monte Carlo trials.

First, in Fig. 1 we compare the GLR and Rao tests in the case of a fixed channel $\mathrm{SNR}_k^{\mathrm{chan}} = 5\,\mathrm{dB}$, while three different cases of sensing SNR are considered, namely $\mathrm{SNR}_k^{\mathrm{obs}} \in \{0, 5, 10\}\,\mathrm{dB}$. The two tests are compared in terms of their Receiver Operating Characteristics (ROCs), i.e. P_{D_0} vs. P_{F_0}. Such analysis is performed to appreciate the effect of the unknown signal power on the capabilities of the two channel-aware fusion rules. Results highlight comparable performance among the two fusion rules, with a slight gain achieved by the Rao test. Interestingly, when moving from $\mathrm{SNR}_k^{\mathrm{obs}} = 5\,\mathrm{dB}$ to $\mathrm{SNR}_k^{\mathrm{obs}} = 10\,\mathrm{dB}$, performance do not improve appreciably for both the rules. This saturating effect can be attributed to the fact that fusion performance are limited by the uncertainty given by the communication channel.

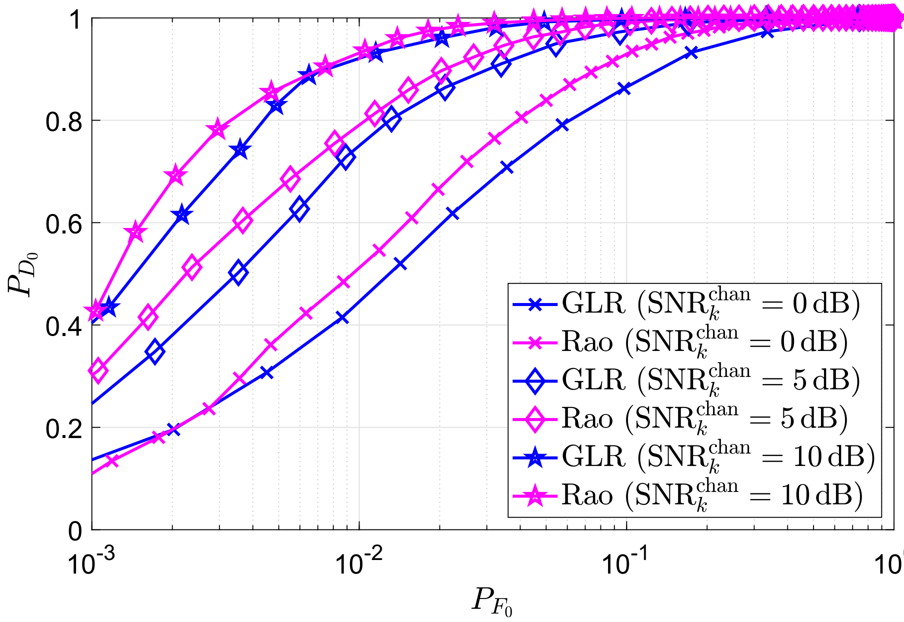

Fig. 2. P_{D_0} vs. P_{F_0} for GLR and Rao tests; WSN with $K = 10$ sensors, $g_k = 1$, and sensor thresholds set as $\tau_k^\star = 0$. The sensing SNR is $\text{SNR}_k^{\text{obs}} = 5\,\text{dB}$, while three different cases of channel SNR are considered, namely $\text{SNR}_k^{\text{chan}} \in \{0, 5, 10\}\,\text{dB}$.

Differently, in Fig. 2 we compare the ROCs of GLR and Rao tests in the case of a fixed channel $\text{SNR}_k^{\text{obs}} = 5\,\text{dB}$, while three different cases of channel SNR are considered, namely $\text{SNR}_k^{\text{chan}} \in \{0, 5, 10\}\,\text{dB}$. This complementary analysis is performed to appreciate the effect of the channel quality on the two channel-aware fusion rules. Results highlight that channel SNR gains directly imply an improvement of the ROC. However, such improvement is upper-limited by the corresponding uncertainty due to the sensing channel. This effect is however not visible due to the particular channel + sensing SNR configuration reported.

6 Conclusion and Future Directions

This work investigated the design and optimization of the Rao test (as an attractive alternative to GLRT) for distributed detection of an unknown deterministic signal θ. The model considered accounts for one-bit quantized measurements, zero-mean, unimodal and symmetric noise (pdf). Additionally, the (parallel-access) reporting channels were explicitly modelled as Rayleigh fading channels and capitalized in the design of the above fusion rules.

Furthermore, we developed an effective criterion (originating from asymptotic theoretical performance expressions) to design sensor thresholds of Rao and GLR tests in an optimized fashion. The sensor thresholds were chosen to be zero based on the asymptotic performance of both rules for some relevant pdfs of interest in some reasonable scenarios. We then leveraged this result to optimize the detection performance of both tests.

Finally, simulations highlighted that the Rao test achieves slightly higher performance than the GLRT when a finite number of sensors is considered. This result complements the asymptotic (large-WSN) case, in which the two tests are known to be asymptotically equivalent [15]. In the future, we will tackle the design of fusion rules (*i*) for detecting non-cooperative targets [25] and (*ii*) with WSNs operating over multiple-access channels [26].

References

1. ITU-T Rec. Y.2060 (06/2012): Overview of the Internet of Things (IoT), June 2012
2. Palmieri, F.A.N., Ciuonzo, D.: Objective priors from maximum entropy in data classification. Inf. Fus. **14**(2), 186–198 (2013)
3. Jin, J., Gubbi, J., Marusic, S., Palaniswami, M.: An information framework for creating a smart city through Internet of Things. IEEE Internet Things J. **1**(2), 112–121 (2014)
4. Chong, C.Y., Kumar, S.P.: Sensor networks: evolution, opportunities, and challenges. Proc. IEEE **91**(8), 1247–1256 (2003)
5. Ciuonzo, D., Salvo Rossi, P. (eds.): Data fusion in wireless sensor networks: a statistical signal processing perspective. Control, Robotics & Sensors, Institution of Engineering and Technology (IET) (2019)
6. Varshney, P.K.: Distributed Detection and Data Fusion, 1st edn. Springer, New York (1996). https://doi.org/10.1007/978-1-4612-1904-0
7. Tsitsiklis, J.N.: Decentralized detection. Adv. Stat. Signal Process. **2**(2), 297–344 (1993)
8. Viswanathan, R., Varshney, P.K.: Distributed detection with multiple sensors - part I: fundamentals. Proc. IEEE **85**(1), 54–63 (1997)
9. Fang, J., Liu, Y., Li, H., Li, S.: One-bit quantizer design for multisensor GLRT fusion. IEEE Signal Process. Lett. **20**(3), 257–260 (2013)
10. Ciuonzo, D., Salvo Rossi, P., Willett, P.: Generalized Rao test for decentralized detection of an uncooperative target. IEEE Signal Process. Lett. (2017)
11. Ciuonzo, D., Salvo Rossi, P.: Decision fusion with unknown sensor detection probability. IEEE Signal Process. Lett. **21**(2), 208–212 (2014)
12. Chen, B., Jiang, R., Kasetkasem, T., Varshney, P.K.: Channel aware decision fusion in wireless sensor networks. IEEE Trans. Signal Process. **52**(12), 3454–3458 (2004)
13. Niu, R., Varshney, P.K.: Performance analysis of distributed detection in a random sensor field. IEEE Trans. Signal Process. **56**(1), 339–349 (2008)
14. Ciuonzo, D., Romano, G., Salvo Rossi, P.: Channel-aware decision fusion in distributed MIMO wireless sensor networks: decode-and-fuse vs. decode-then-fuse. IEEE Trans. Wireless Commun. **11**(8), 2976–2985 (2012)
15. Kay, S.M.: Fundamentals of Statistical Signal Processing, Volume 2: Detection Theory. Prentice Hall PTR (1998)
16. Niu, R., Varshney, P.K.: Joint detection and localization in sensor networks based on local decisions. In: 40th Asilomar Conference on Signals, Systems and Computers, pp. 525–529 (2006)

17. Shoari, A., Seyedi, A.: Detection of a non-cooperative transmitter in Rayleigh fading with binary observations. In: IEEE Military Communications Conference (MILCOM), pp. 1–5 (2012)
18. Ciuonzo, D., Papa, G., Romano, G., Salvo Rossi, P., Willett, P.: One-bit decentralized detection with a Rao test for multisensor fusion. IEEE Signal Process. Lett. **20**(9), 861–864 (2013)
19. Cheng, X., Ciuonzo, D., Salvo Rossi, P.: Multibit decentralized detection through fusing smart and dumb sensors based on Rao test. IEEE Trans. Aerosp. Electron. Syst. **56**(2), 1391–1405 (2019)
20. Cheng, X., Ciuonzo, D., Salvo Rossi, P., Wang, X., Shi, L.: Multi-bit decentralized detection of a non-cooperative moving target through a generalized rao test. In: IEEE 11th Sensor Array and Multichannel Signal Processing Workshop (SAM), pp. 1–5 (2020)
21. Hu, L., Zhang, J., Wang, X., Wang, S., Zhang, E.: Decentralized truncated one-sided sequential detection of a noncooperative moving target. IEEE Signal Process. Lett. **25**(10), 1490–1494 (2018)
22. Laitrakun, S.: Decision fusion for composite hypothesis testing in wireless sensor networks over a shared and noisy collision channel. Int. J. Distributed Sensor Netw. **16**(7), 1550147720940204 (2020)
23. Papadopoulos, H.C., Wornell, G.W., Oppenheim, A.V.: Sequential signal encoding from noisy measurements using quantizers with dynamic bias control **47**(3), 978–1002 (2001)
24. Rousseau, D., Anand, G.V., Chapeau-Blondeau, F.: Nonlinear estimation from quantized signals: quantizer optimization and stochastic resonance. In: Proceedings 3rd International Symposium Physics in Signal and Image Processing. pp. 89–92 (2003)
25. Ciuonzo, D., Salvo Rossi, P.: Distributed detection of a non-cooperative target via generalized locally-optimum approaches. Inf. Fusion **36**, 261–274 (2017)
26. Ciuonzo, D., Salvo Rossi, P., Dey, S.: Massive MIMO channel-aware decision fusion **63**(3), 604–619 (2015)