Multi-bit Decentralized Detection of a Weak Signal in Wireless Sensor Networks with a Rao test

Xu Cheng
Armed Police College of PAP
Chengdu, China
chengxu@nudt.edu.cn

Domenico Ciuonzo
Network Measurement and Monitoring (NM2) s.r.l.
Naples, Italy
domenico.ciuonzo@ieee.org

Pierluigi Salvo Rossi
Kongsberg Digital AS
Trondheim, Norway
salvorossi@ieee.org

***Abstract*—We consider decentralized detection (DD) of an unknown signal corrupted by zero-mean unimodal noise via wireless sensor networks (WSNs). To cope with energy and/or bandwidth constraints, we assume that sensors adopt multi-level quantization. The data are then transmitted through binary symmetric channels to a fusion center (FC), where a Rao test is proposed as a simpler alternative to the generalized likelihood ratio test (GLRT). The asymptotic performance analysis of the multi-bit Rao test is provided and exploited to propose a (signal-independent) quantizer design. Numerical results show the effectiveness of Rao test in comparison to GLRT and the performance gain obtained by threshold optimization.**

***Index Terms*—Decentralized detection (DD), multilevel quantization, Rao test, wireless sensor networks (WSNs).**

I. Introduction

Decentralized detection (DD) via wireless sensor networks (WSNs) has received significant attention by the scientific community in last decade [1]–[6]. Due to stringent energy and/or bandwidth constraints, sensors are usually required to *quantize* their observations (in one-bit as the simplest and coarsest option), before reporting them to a fusion center (FC) where a global decision is taken [7], [8]. In this case, the optimal per-sensor test is a quantization of the local Likelihood-Ratio (LR) [9], [10]. Sadly, (a) the (crucial) optimized design of sensors' thresholds is a complex task [1], [2] and (b) lack of knowledge of the parameters of the target to be detected precludes sensor LR computation [2]. Thus the bit(s) sent is either the result of a "dumb" quantization [11] or (in one-bit case) embodies the estimated binary event via a sub-optimal rule [5]. Also, often the signal model is only partially-known and the FC is then faced to tackle a composite hypothesis test; in such a case the generalized likelihood ratio test (GLRT) is usually employed as the relevant fusion rule [12]–[14].

Accordingly, in [12] one-bit DD (over error-prone reporting channels) via a GLRT at the FC was tackled to detect an unknown deterministic signal, whereas, as a simpler alternative, an one-bit Rao test was adopted in [11]. In both these works, threshold optimization was performed via their common (weak-signal) asymptotic performance [15] and the optimal value shown to be zero, except for some heavy-tailed distributions. More recently, a generalized form of Rao test has been devised for one-bit DD of uncooperative targets [16].

Apparently, there is a notable performance gap between the one-bit detector and that using unquantized observations, due to the amount of useful information lost [12]. In this respect *multi-level quantization* is sought to fill this gap by trading off performance and complexity. In view of these reasons, multi-bit DD of a signal parameter in Gaussian noise in WSNs has been recently considered in [13], where a *non closed-form* multi-bit GLRT has been devised and a (weak-signal) asymptotically-optimal threshold set choice obtained, resorting to particle swarm optimization algorithm (PSOA) [17].

To this end, herein we focus on DD of a noise-corrupted unknown parameter in WSNs [11]–[13], with sensors adopting multi-bit quantizers, similarly to [13]. However, as opposed to [13] where Gaussian noise was assumed, we only constrain the noise to be *zero-mean unimodal-symmetric*. Also, to model low-powered transmissions, the quantized data is assumed to be transmitted via binary symmetric channels (BSCs) to the FC. To capitalize multi-level measurements, we develop a (computationally-) simpler alternative *fusion rule* to the GLRT in [13], corresponding to a multi-bit Rao test, comprising the one-bit counterpart in [11] as a *special case*. Its appeal lies in *absence of any estimation procedure* and *availability of closed-form* even in the considered general model. We provide the asymptotic (weak-signal) performance of Rao test and then, leveraging its closed-form, we propose a quantizer design for the sensors, via PSOA (following [13]). Simulations show that Rao test, other than asymptotically behaving as the GLRT, it practically achieves the same performance for a finite number of sensors and different resolutions.

The rest of the paper is organized as follows. Sec. II introduces the model whereas in Sec. III the multi-bit Rao test is derived; in Sec. IV an asymptotic analysis of the multi-bit Rao test is presented, and the multi-level quantizers designed by using the PSOA. Numerical results are provided in Sec. V. Finally, conclusions and future directions are given in Sec. VI[1].

[1] *Notation* - Lower-case bold letters denote vectors, with a_n being the nth element of $\boldsymbol{a}$; upper-case calligraphic letters, e.g. $\mathcal{A}$, denote finite sets; $\mathbb{E}\{\cdot\}$ and $(\cdot)^T$ denote expectation and transpose, respectively; $P(\cdot)$ and $p(\cdot)$ denote probability mass functions (PMF) and probability density functions (PDF), respectively, while $P(\cdot|\cdot)$ and $p(\cdot|\cdot)$ their corresponding conditional counterparts; $F(\cdot)$ is used to denote the complementary cumulative distribution function (CCDF); $\mathcal{N}(\mu, \sigma^2)$ denotes a Gaussian PDF with mean μ and variance σ^2; χ_k^2 (resp. $\chi_k'^2(\xi)$) denotes a chi-square (resp. a non-central chi-square) PDF with k degrees of freedom (resp. and non-centrality parameter ξ); $\mathcal{L}(\mu, \beta)$ denotes a Laplace PDF with mean μ and scale parameter β; $\mathcal{Q}(\cdot)$ denotes the CCDF of the standardized normal random variable; the symbols $\sim$ and $\overset{a}{\sim}$ mean "distributed as" and "asymptotically distributed as".

II. PROBLEM STATEMENT

We consider a binary hypothesis testing problem in which a collection of K sensors collaborate to detect the presence of an *unknown* deterministic parameter $\theta \in \mathbb{R}$. The problem at each sensor can be summarized as follows

$$\begin{cases} \mathcal{H}_0 & : \quad x_k = w_k, \\ \mathcal{H}_1 & : \quad x_k = h_k\,\theta + w_k, \end{cases} \tag{1}$$

where $x_k \in \mathbb{R}$ denotes the kth sensor measurement, $h_k \in \mathbb{R}$ is a known coefficient and $w_k \in \mathbb{R}$ denotes the noise random variable (RV) with $\mathbb{E}\{w_k\} = 0$ and *unimodal symmetric* PDF[2], denoted with $p_{w_k}(\cdot)$ in what follows. Furthermore, the RVs w_k are assumed mutually independent. It is worth noting that Eq. (1) refers to a *two-sided test* [15], where $\{\mathcal{H}_0, \mathcal{H}_1\}$ corresponds to $\{\theta = \theta_0, \theta \neq \theta_0\}$ (in our case $\theta_0 = 0$).

In this paper we assume that sensors, to meet stringent bandwidth and energy budgets, have to quantize their observations before transmitting them to the FC. Specifically, we assume that kth sensor employs a (multi-level) $q(k)$-bit quantizer where the observation x_k is compared with a set of quantization thresholds $\{\tau_k(i)\}_{i=0}^{2^{q(k)}}$ (being $\tau_k(0) \triangleq -\infty$ and $\tau_k(2^{q(k)}) \triangleq +\infty$), determining $2^{q(k)}$ non-overlapping quantization intervals covering the whole $\mathbb{R}$. Specifically, the corresponding quantizer output is encoded as a binary codeword denoted by $\boldsymbol{b}_k \in \{0,1\}^{q(k)}$, where $k = 1, 2, \ldots, K$. The non-overlapping quantization intervals are associated to $q(k)$-bit binary codewords $\boldsymbol{v}(i) = \begin{bmatrix} v_1(i) & \cdots & v_{q(k)}(i) \end{bmatrix}^T$, where $v_t(i) \in \{0,1\}$. Hence, the output codeword of $q(k)$-bit quantizer at kth sensor can be expressed as:

$$\boldsymbol{b}_k \triangleq \begin{cases} \boldsymbol{v}(1) & -\infty < x_k < \tau_k(1) \\ \boldsymbol{v}(2) & \tau_k(1) \leq x_k < \tau_k(2) \\ \vdots & \vdots \\ \boldsymbol{v}(2^{q(k)}) & \tau_k(2^{q(k)} - 1) \leq x_k < +\infty \end{cases} \tag{2}$$

The codeword of kth sensor is then transmitted to the FC over an error-prone link, modeled as an independent BSC with (known) BEP $P_{e,k}$. The FC then receives a distorted codeword $\boldsymbol{y}_k$ from kth sensor, whose conditional probability is:

$$P(\boldsymbol{y}_k = \boldsymbol{v}_k(i) | \boldsymbol{b}_k = \boldsymbol{v}_k(j)) = \underbrace{P_{e,k}^{d_{i,j}}\,(1 - P_{e,k})^{(q(k) - d_{i,j})}}_{\triangleq G_{q(k)}(P_{e,k}, d_{i,j})} \tag{3}$$

where $d_{i,j} \triangleq d(\boldsymbol{v}_k(i), \boldsymbol{v}_k(j))$ denotes the Hamming distance between codewords $\boldsymbol{v}_k(i)$ and $\boldsymbol{v}_k(j)$. For the sake of notational convenience, we collect the noisy codewords (viz. soft-quantized measurements) received from the sensors in the set $\boldsymbol{Y} \triangleq \{\, \boldsymbol{y}_1 \;\; \cdots \;\; \boldsymbol{y}_K \}$ (recall that $\boldsymbol{y}_k \in \{0,1\}^{q(k)}$ and thus codewords from sensors may differ in length).

The problem here is the derivation of a (computationally) simple test on the basis of $\boldsymbol{Y}$ and the corresponding quantizer design for each sensor. The PMF of the observations $\boldsymbol{Y}$ as a function of θ is given by $p(\boldsymbol{Y};\theta) = \prod_{k=1}^{K} P(\boldsymbol{y}_k;\theta)$. The corresponding PMF of the quantized and (channel-)distorted measurement from kth sensor can be further expanded as

$$P(\boldsymbol{y}_k;\theta) = \sum_{\boldsymbol{v}(i) \in \{0,1\}^{q(k)}} P(\boldsymbol{y}_k | \boldsymbol{b}_k = \boldsymbol{v}(i))\, P(\boldsymbol{b}_k = \boldsymbol{v}(i);\theta). \tag{4}$$

Based on the quantizer law reported in Eq. (2), the PMF $P(\boldsymbol{b}_k = \boldsymbol{v}(i);\theta)$ is given by

$$\begin{aligned} P(\boldsymbol{b}_k = \boldsymbol{v}(i);\theta) &= \Pr\{\tau_k(i-1) \leq x_k < \tau_k(i)\} \\ &= F_{w_k}(\tau_k(i-1) - h_k\theta) - F_{w_k}(\tau_k(i) - h_k\theta), \end{aligned} \tag{5}$$

where $F_{w_k}(\cdot)$ denotes the CCDF of w_k.

III. FUSION RULES DESIGN

A common approach to handle the detection task in the presence of unknown parameters (viz. composite hypothesis testing) relies on the use of the GLRT [15]. For the specific detection problem at hand, the corresponding decision statistic is obtained by replacing the unknown parameter θ with its maximum likelihood (ML) estimate $\hat{\theta}$ (under $\mathcal{H}_1$) in the likelihood ratio, i.e. [13]

$$\left\{ \Lambda_{\mathrm{G}} \triangleq \frac{P(\boldsymbol{Y};\hat{\theta})}{P(\boldsymbol{Y};\theta_0)} \right\} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma\,, \tag{6}$$

where $\theta_0 = 0$, γ is the system threshold, usually employed to ensure a desired false-alarm rate, and the ML estimate $\hat{\theta}$ is evaluated via $\hat{\theta} \triangleq \arg\max_{\theta} P(\boldsymbol{Y};\theta)$. It is clear from Eq. (6) that Λ_{G} requires the solution to an optimization problem, which increases the computational burden of its implementation. Specifically, in the case $w_k \sim \mathcal{N}(0, \sigma^2_{w,k})$, it has been proved in [13] that ML estimation is a convex problem and thus can be efficiently solved with local optimizers. Sadly, a closed form of $\hat{\theta}$ is not available even in this peculiar case.

Therefore, we resort to the Rao test a simpler and closed-form alternative to GLRT, available in closed-form for the broad class of unimodal noise PDFs. In this context, the Rao test is expressed in implicit form as [15]

$$\left\{ \Lambda_{\mathrm{R}} \triangleq \frac{\left(\left.\frac{\partial \ln P(\boldsymbol{Y};\theta)}{\partial \theta}\right|_{\theta=\theta_0} \right)^2}{\mathrm{I}(\theta_0)} \right\} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma, \tag{7}$$

where $\mathrm{I}(\theta_0)$ is the *Fisher information* (FI), i.e., $\mathrm{I}(\theta) \triangleq \mathbb{E}\{(\partial \ln[P(\boldsymbol{Y};\theta)]/\partial\theta)^2\}$ evaluated at θ_0. The rationale of the proposed choice is the simplicity of the test implementation (since $\hat{\theta}$ is not required, cf. Eq. (7)) and the same weak-signal asymptotic performance as the GLRT [15].

So as to obtain Λ_{R} explictly, we first obtain the numerator term in Eq. (7) (before evaluation at $\theta = \theta_0$) as:

$$\left(\frac{\partial \ln[P(\boldsymbol{Y};\theta)]}{\partial\theta} \right)^2 = \tag{8}$$

$$\left(\sum_{k=1}^{K} \frac{h_k \sum_{i=1}^{2^{q(k)}} P(\boldsymbol{y}_k | \boldsymbol{b}_k = \boldsymbol{v}(i))\, \rho(\boldsymbol{b}_k = \boldsymbol{v}(i);\theta)}{\sum_{i=1}^{2^{q(k)}} P(\boldsymbol{y}_k | \boldsymbol{b}_k = \boldsymbol{v}(i))\, P(\boldsymbol{b}_k = \boldsymbol{v}(i);\theta)} \right)^2$$

[2]This class of PDFs comprises many noteworthy examples, such as the Gaussian, Laplace, Cauchy and generalized Gaussian distributions [15].

Secondly, it can be shown that the total FI has the form

$$\mathrm{I}(\theta) = \sum_{k=1}^{K} \mathrm{i}_k(\theta) = \tag{9}$$

$$\sum_{k=1}^{K} h_k^2 \sum_{i=1}^{2^{q(k)}} \frac{\left\{ \sum_{j=1}^{2^{q(k)}} G_{q(k)}\left(P_{e,k}, d_{i,j}\right) \rho\left(\boldsymbol{b}_k = \boldsymbol{v}\left(j\right); \theta\right) \right\}^2}{\sum_{j=1}^{2^{q(k)}} G_{q(k)}\left(P_{e,k}, d_{i,j}\right) P\left(\boldsymbol{b}_k = \boldsymbol{v}\left(j\right); \theta\right)}$$

where the auxiliary definition $\rho(\boldsymbol{b}_k = \boldsymbol{v}(i); \theta) \triangleq p_{w_k}\left(\tau_k(i-1) - h_k\theta\right) - p_{w_k}\left(\tau_k(i) - h_k\theta\right)$ has been employed.

Thus, combining Eqs. (8) and (9), we obtain Λ_{R} in closed form as

$$\Lambda_{\mathrm{R}} = \frac{1}{\mathrm{I}(\theta_0)} \left(\sum_{k=1}^{K} \frac{h_k \sum_{i=1}^{2^{q(k)}} P(\boldsymbol{y}_k | \boldsymbol{b}_k = \boldsymbol{v}(i))\, \rho(\boldsymbol{b}_k = \boldsymbol{v}(i); \theta_0)}{\sum_{i=1}^{2^{q(k)}} P(\boldsymbol{y}_k | \boldsymbol{b}_k = \boldsymbol{v}(i))\, P(\boldsymbol{b}_k = \boldsymbol{v}(i); \theta_0)} \right)^2 \tag{10}$$

It is apparent from Eq. (10) that Λ_{R} (as well as Λ_{G}) is a function of $\{\tau_k\,(i)\}_{i=0}^{2^{q(k)}}$, $k = 1, 2, \ldots, K$, through the terms $P(\boldsymbol{b}_k = \boldsymbol{v}(i); \theta_0)$ and $\rho(\boldsymbol{b}_k = \boldsymbol{v}(i); \theta_0)$. Therefore, the thresholds of sensors' (multi-bit) quantizers can be optimized to achieve improved performance.

IV. Quantizer design

According to [15], the asymptotic (i.e. in a large WSN and weak-signal condition) PDF of Λ_{R} (as well as $2 \ln \Lambda_{\mathrm{G}}$) is

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

where the non-centrality parameter λ_q is given by

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

with θ_1 being the true value under $\mathcal{H}_1$ (in our case $\theta_0 = 0$). Clearly, larger value of λ_q imply higher performance for both the GLRT and the Rao test.

From Eq. (12) we can see that the non-centrality parameter λ_q is a *monotonically increasing* function of the FI evaluated at $\theta = 0$. The latter is a function of the $\left(2^{q(k)} - 1\right)$-dimensional quantization threshold vector $\boldsymbol{\tau}_k \triangleq \left[\tau_k(1), \ldots, \tau_k(2^{q(k)} - 1)\right]$, where the two extreme thresholds for each sensor are obviously fixed as $\tau_k(0) = -\infty$ and $\tau_k(2^{q(k)}) = +\infty$, respectively. In other words, by optimally choosing the quantizer thresholds $\boldsymbol{\tau}_k$'s for sensors, we can *optimize* the detection performance of the Rao test.

As a consequence, the asymptotic detection performance of the Rao detector (as well as GLRT) can be optimized by solving the following optimization problem

$$\max_{\{\boldsymbol{\tau}_k\}_{k=1}^{K}} \mathrm{I}\left(\theta_0, \{\boldsymbol{\tau}_k\}_{k=1}^{K}\right) \tag{13}$$

where, with a slight abuse of notation, we have highlighted the dependence of the FI on the $\boldsymbol{\tau}_k$'s. Finally, exploiting the mutual independence of the distortion channels, the optimization can be further decoupled into the following K independent threshold vector problems

$$\boldsymbol{\tau}_k^\star \triangleq \arg\max_{\boldsymbol{\tau}_k} g_k(\boldsymbol{\tau}_k), \quad k = 1, \ldots, K, \tag{14}$$

where $g_k(\boldsymbol{\tau}_k)$ is explicitly defined as $g_k(\boldsymbol{\tau}_k) \triangleq \mathrm{i}_k(\theta_0, \boldsymbol{\tau}_k)$ (cf. Eq. (9)). We highlight that each problem is subject to the ordered constraints $\tau_k(i) < \tau_k(i+1)$, for $i = 1, \ldots 2^{q(k)} - 1$.

Clearly, given the same asymptotic performance achieved by both GLRT and Rao test, the optimization problem (14) has the same form as [13, Eq. (22)], used to optimize the performance of the more complex GLRT. Consequently, we can utilize the same method proposed therein, i.e. the PSOA, to search the optimal quantization thresholds in (14), due to its appeal with high-dimensional, non-convex optimization problems.

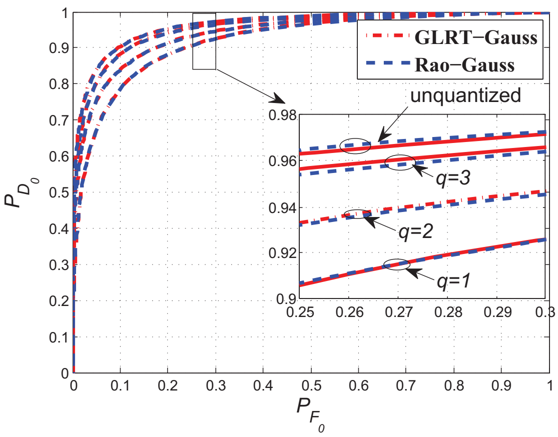
In brief, the PSOA is an iterative stochastic optimization method [17] resorting to a swarm of $m = 1, 2, \ldots, M$ particles, here used[3] to explore the $(2^q - 1)$-dimensional space (constrained in each dimension as $\tau(i) \in \{-\tau_{max}, \tau_{max}\}$) in search of a (hopefully) globally-optimal solution for each problem in Eq. (14). At ℓth iteration, the mth particle is described by two characteristics: the position $\boldsymbol{\tau}_m^\ell$ (i.e. the objective argument) and velocity vectors $\boldsymbol{\nu}_m^\ell$ (i.e. the direction of improvement). The PSOA evolution is characterized by the best personal position achieved by mth particle so far ($\boldsymbol{pbest}_m^\ell$) and the swarm best position ($\boldsymbol{sbest}^\ell$). At $(\ell+1)$th step, both of them are employed to update the velocity of each particle $\boldsymbol{\nu}_m^{\ell+1}$ and, consequently, its position (via $\boldsymbol{\tau}_m^{\ell+1} = \boldsymbol{\tau}_m^\ell + \boldsymbol{\nu}_m^{\ell+1}$). The algorithm terminates when all the norms of particles' velocities are below a certain value v_{tol}.

V. Numerical Results

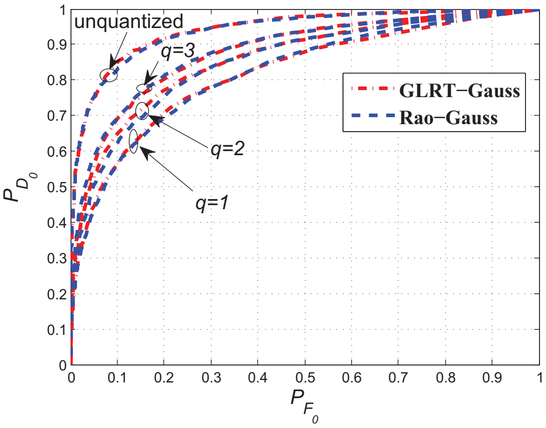
In this section we compare the Rao test to the GLRT and also assess their performance vs. quantization resolution. We evaluate the performance in terms of system false alarm and detection probabilities, defined as $P_{F_0} \triangleq \Pr\{\Lambda > \gamma | \mathcal{H}_0\}$ and $P_{D_0} \triangleq \Pr\{\Lambda > \gamma | \mathcal{H}_1\}$, respectively, where Λ is the statistic employed at the DFC. Also, the kth sensor observation signal-to-noise ratio (SNR) is defined as $\Gamma_k \triangleq \left(h_k^2 \theta^2 / \mathbb{E}\{w_k^2\}\right)$.

In Figs. 1 and 2 we illustrate P_{D_0} vs. P_{F_0} in a WSN made of $K = 10$ sensors with (i) $w_k \sim \mathcal{N}\left(0, \sigma^2\right)$ and (ii) $w_k \sim \mathcal{L}\left(0, \beta\right)$, respectively, where $\mathbb{E}\{w_k^2\} = 1$, $h_k = 1$, $\theta = 1$ (thus $\Gamma_k = 0\,\mathrm{dB}$) and two BEP values, i.e. $P_{e,k} = P_e \in \{0, 0.2\}$. These parameters determine a (simplified) homogeneous scenario. Also, the figures are based on 10^5 Monte Carlo runs. For each detector, we report the performance with $q_k = q \in \{1, 2, 3\}$ quantization bits, with thresholds optimized according to the criterion defined in Sec. IV (via PSOA). Referring to PSOA parameters, we set $M = 100$, $\tau_{max} = 5$ and $\nu_{tol} = 10^{-6}$. Furthermore, aiming at a complete comparison, a WSN with $K = 10$ unquantized sensors is assumed as a reference providing an upper-bound on the performance.

[3] In the following, for the sake of a lighter notation, we will drop the subscript "k" referring to the sensor index.

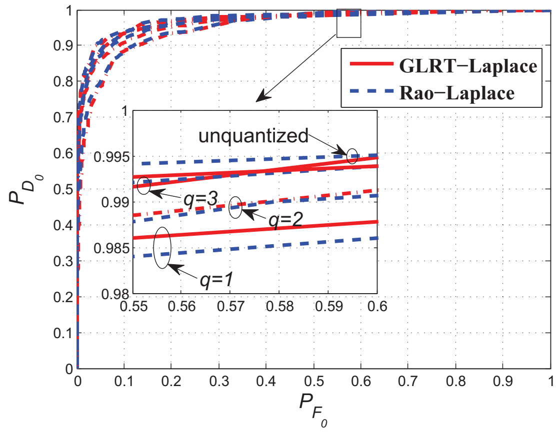


(a)

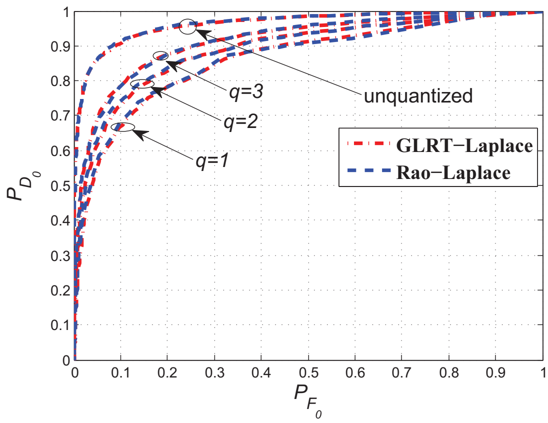


(b)

Fig. 1: P_{D_0} vs P_{F_0}; WSN with $K = 10$ sensors, $w_k \sim \mathcal{N}(0, 1)$, $\Gamma_k = 0\,\text{dB}$, and (a): $P_e = 0$; (b): $P_e = 0.2$.



(a)



(b)

Fig. 2: P_{D_0} vs P_{F_0}; WSN with $K = 10$ sensors, $w_k \sim \mathcal{L}(0, \beta)$, $\Gamma_k = 0\,\text{dB}$, and (a): $P_e = 0$; (b): $P_e = 0.2$.

First, it is shown that the proposed Rao (as well as GLR) test works well in the case of quantized sensors. Secondly, it is apparent that the performances of the GLR and Rao tests are practically the same for all considered scenarios. However, the implementation of the Rao test has the advantage that it is more simpler than the GLRT. Also, the adoption of multi-bit quantization shows a significantly higher detection probability than one-bit quantization. In particular, the detection performance with 3-bit quantized sensors is very close to the considered upper bound, when the channel is perfect. Nevertheless, in the presence of channel errors (e.g., $P_e = 0.2$ in this example), the performance of both detectors is significantly degraded.

Finally, the detection performance under Laplacian noise is observed to be higher than that under Gaussian noise. The reason is that the value of FI information $I(\theta_0)$ under Gaussian noise is smaller than that of Laplacian noise. Indeed, it has been proved that given a certain variance, Gaussian-distributed noise corresponds to the minimum $I(\theta_0)$ [15].

VI. Conclusions and Further Directions

We proposed a Rao test for multi-bit DD of an unknown deterministic signal in WSNs as an attractive (and simpler, *being in closed-form*) alternative to the GLRT for a general model with quantized measurements and zero-mean, unimodal and symmetric noise, over non-ideal and non-identical BSCs. Also, we provided the explicit expression of the asymptotic (weak-signal) performance of Rao fusion rule, and then, to maximize its asymptotic performance, we resorted to PSOA. It was shown through simulations (for Laplacian and Gaussian noises) that the Rao test, in addition to being asymptotically equivalent to the GLRT, achieves practically the same performance for a finite number of sensors. In addition, results also demonstrated the advantage of multi-bit quantization against one-bit quantization. Further directions will include design of Rao test for hybrid combinations of smart/dumb sensors [18], as well as censoring [19].

REFERENCES

[1] J. N. Tsitsiklis, "Decentralized detection," *Advances in Statistical Signal Processing*, vol. 2, no. 2, pp. 297–344, 1993.

[2] R. Viswanathan and P. K. Varshney, "Distributed detection with multiple sensors - Part I: Fundamentals," *Proc. IEEE*, vol. 85, no. 1, pp. 54–63, Jan. 1997.

[3] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102–114, Aug 2002.

[4] T. Wu and Q. Cheng, "Distributed estimation over fading channels using one-bit quantization," *IEEE Trans. Wireless Commun.*, vol. 8, no. 12, pp. 5779–5784, 2009.

[5] D. Ciuonzo and P. Salvo Rossi, "Decision fusion with unknown sensor detection probability," *IEEE Signal Processing Letters*, vol. 21, no. 2, pp. 208–212, 2014.

[6] ——, "Quantizer design for generalized locally optimum detectors in wireless sensor networks," *IEEE Wireless Communications Letters*, vol. 7, no. 2, pp. 162–165, April 2018.

[7] J. Fang and H. Li, "Distributed estimation of Gauss-Markov random fields with one-bit quantized data," *IEEE Signal Process. Lett.*, vol. 17, no. 5, pp. 449–452, May 2010.

[8] D. Ciuonzo, G. Romano, and P. Salvo Rossi, "Optimality of received energy in decision fusion over Rayleigh fading diversity MAC with non-identical sensors," *IEEE Trans. Signal Process.*, vol. 61, no. 1, pp. 22–27, Jan. 2013.

[9] A. R. Reibman and L. L. W. Nolte, "Optimal detection and performance of distributed sensor systems," *IEEE Trans. Aerosp. Electron. Syst.*, no. 1, pp. 24–30, 1987.

[10] I. Y. Hoballah and P. K. Varshney, "Distributed Bayesian signal detection," *IEEE Transactions on Information Theory*, vol. 35, no. 5, pp. 995–1000, 1989.

[11] D. Ciuonzo, G. Papa, G. Romano, P. Salvo Rossi, and P. Willett, "One-bit decentralized detection with a Rao test for multisensor fusion," *IEEE Signal Process. Lett.*, vol. 20, no. 9, pp. 861–864, Sept 2013.

[12] J. Fang, Y. Liu, H. Li, and S. Li, "One-bit quantizer design for multisensor GLRT fusion," *IEEE Signal Process. Lett.*, vol. 20, no. 3, pp. 257–260, Mar. 2013.

[13] F. Gao, L. Guo, H. Li, J. Liu, and J. Fang, "Quantizer design for distributed GLRT detection of weak signal in wireless sensor networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 4, pp. 2032–2042, April 2015.

[14] D. Ciuonzo and P. Salvo Rossi, "Distributed detection of a non-cooperative target via generalized locally-optimum approaches," *Information Fusion*, vol. 36, pp. 261–274, 2017.

[15] S. M. Kay, *Fundamentals of Statistical Signal Processing, Volume 2: Detection Theory*. Prentice Hall PTR, Jan. 1998.

[16] D. Ciuonzo, P. Salvo Rossi, and P. Willett, "Generalized Rao test for decentralized detection of an uncooperative target," *IEEE Signal Process. Lett.*, vol. 24, no. 5, pp. 678–682, 2017.

[17] A. I. F. Vaz and L. N. Vicente, "A particle swarm pattern search method for bound constrained global optimization," *Journal of Global Optimization*, vol. 39, no. 2, pp. 197–219, 2007.

[18] D. Saska, R. S. Blum, and L. Kaplan, "Fusion of quantized and unquantized sensor data for estimation," *IEEE Signal Process. Lett.*, vol. 22, no. 11, pp. 1927–1930, Nov 2015.

[19] P. W. C. Rago and Y. Bar-Shalom, "Censoring sensors: a low-communication-rate scheme for distributed detection," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 32, no. 2, pp. 554–568, April 1996.