Non-cooperative Distributed Detection via Federated Sensor Networks

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***Abstract*—In this study, we address the challenge of non-cooperative target detection by federating two wireless sensor networks. The objective is to capitalize on the diversity achievable from both sensing and reporting phases. The target's presence results in an unknown signal that is influenced by unknown distances between the sensors and target, as well as by symmetrical and single-peaked noise. The fusion center, responsible for making more accurate decisions, receives quantized sensor observations through error-prone binary symmetric channels. This leads to a two-sided testing problem with nuisance parameters (the target position) only present under the alternative hypothesis. To tackle this challenge, we present a generalized likelihood ratio test and design a fusion rule based on a generalized Rao test to reduce the computational complexity. Our results demonstrate the efficacy of the Rao test in terms of detection/false-alarm rate and computational simplicity, highlighting the advantage of designing the system using federation.**

***Index Terms*—Data Fusion, Distributed Detection, Energy-efficiency, Federated Sensor Networks, Internet of Things, Score Tests, Target Detection, Wireless Sensor Networks.**

I. Introduction

The concept of Internet of Things (IoT) involves the widespread implementation of small devices equipped with sensing, computational, and communication abilities, in various domains including e-health, smart city/building, and digital twins [1], [2]. The IoT is revolutionizing the wireless communications and sensing fields [3], with Wireless Sensor Networks (WSNs) playing a crucial role as the "sensing arm". In this context, Distributed Detection (DD) is a highly researched and in-demand topic [4] with a wide range of applications, from industry [5] to surveillance/reconnaissance [6]. Still, *two main challenges* for accomplishing effective (while efficient) DD via WSNs are (i) gathering collective intelligence from heterogeneous and inexpensive IoT sensors/devices by coping with modeling uncertainties and (ii) minimizing device cost and energy consumption. Both these challenges *are essential* to ensure perpetual and pervasive monitoring/sensing.

Accordingly, in recent years several studies [7], [8], [9], [10] have provided methodological contributions toward DD of an uncooperative target (i.e. *an unknown source located at an unknown position*) via the use of bandwidth- and energy-efficient WSNs (usually limited to sending one bit to the Fusion Center, FC, regarding the inferred hypothesis), ranging from the design of nearly-optimal fusion rules to WSN optimization.

It has been shown that the optimal fusion rule, given the assumption of conditional independence, involves comparing a weighted sum of sensor bits received to a threshold, with the weights being dependent on unknown target parameters [11]. When the model is parametrically-specified (with some unknown parameters, as in the uncooperative case), the FC faces a composite hypothesis test, for which the Generalized LRT (GLRT) is the typical choice [12]. This is why GLRT-based fusion of quantized data has been widely studied in the WSN literature focused on DD [13], [14], including the challenging case of an uncooperative target. Recent works have addressed this problem [7], [8], [9], [10], including a GLRT for detecting a target with unknown position and emitted power in [7]. In an effort to simplify the computations (i.e. avoiding the need for a grid search of both target location and emitted power/signal domains), researchers have proposed using *generalized* forms of *score tests* in detecting non-cooperative targets that emit signals that are *deterministic* [8], *stochastic [9] or subject to multiplicative-fading* [10]. *Unfortunately, all the aforementioned contributions are limited to the case of a single-operated WSN with a single associated FC.*

On the contrary, large-scale surveillance in the IoT era requires *federating* multiple WSNs possibly owned to different organizations. It is worth noticing that the concept of federation in WSNs is not new [15], [16]. However, this concept has been mostly investigated at an abstract level in the context of high-level data management [15] or connectivity establishment between distinct WSNs [16] without a task-oriented capitalization. In other terms, federation-aware (viz. federation-exploiting) inference approaches in resource-constrained WSNs *are still lacking despite their urgent need*. Indeed, DD literature has seldom investigated the case of multiple WSNs and, in affirmative case, efforts have been mostly put towards DD with a *WSN-myopic* philosophy: the contributions from other existing WSNs were considered as *additional interference* to be managed [17]. Conversely, in this work, the presence of multiple WSNs which can *cooperate/be federated is leveraged* to improve the detection performance (rather than minimizing performance degradation) by *exploiting diversity at both sensing and communication levels*.

We underline the some works on DD have investigated the concept of cooperation *within* WSNs to achieve diversity at the communication level. Still, the aforementioned studies deal with cooperation *at the transmit side* (i.e. cooperation is operated between two or multiple sensors) to improve the final performance at a single WSN [18], [19]. This is however

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achieved at the expenses of an increased intelligence (viz. complexity) at the sensor side. Conversely, in this work diversity at the communication level *is investigated at the receive (FC) side* without implying higher complexity at sensor nodes.

The *main focus of this work* is to address the challenge of DD of a non-cooperative target by federating two WSNs. The goal is to take advantage of the diversity that can be achieved from *both* the sensing (i.e. leveraging sensors from both WSNs) and reporting (i.e. leveraging collection from both FCs) phases. In this setting, when the target is present, the sensors observe an unknown signal, with the strength of the signal being affected by an unknown distance between the target and sensor, as well as symmetrical and unimodal noise. The FC, which is responsible for making a more accurate decision, receives quantized sensor observations through error-prone binary channels. This leads to a two-sided parameter test with nuisance parameters (the target position) only present under the alternative hypothesis. In this work, we introduce a novel, low-complexity fusion rule, the Generalized Rao test, and compare it with the Generalized Likelihood Ratio Test (GLRT) in terms of accuracy and computational costs. The results show the advantage of the Generalized Rao test and the benefits of federating decisions instead of processing them separately (i.e. a per-WSN inference).

The structure of the paper is presented as follows. Sec. II explains the system model. In Sec. III, the Generalized Rao test for federated fusion is introduced and compared with the GLR test in a similar scenario, as well as with non-federated alternatives. The validity of the results is established in Sec. IV. Finally, the paper concludes with future perspectives in Sec. V.

Notation - Vectors are denoted by lower-case bold letters (e.g. a_n is the nth entry of $\boldsymbol{a}$); sets are denoted by uppercase calligraphic letters (e.g. $\mathcal{A}$). The symbols $\mathbb{E}\{\cdot\}$, $\mathrm{var}\{\cdot\}$ and $(\cdot)^T$, $\oplus$ represent expectation, variance, transpose and XOR, respectively. The function $u(\cdot)$ is the unit step function. $P(\cdot)$ and $p(\cdot)$ denote probability mass functions (pmf) and probability density functions (pdf), respectively, with $P(\cdot|\cdot)$ and $p(\cdot|\cdot)$ being their conditional forms. $\mathcal{N}(\mu, \sigma^2)$ represents a Gaussian pdf with mean μ and variance σ^2. χ_k^2 (resp. $\chi_k^{\prime 2}(\xi)$) denotes a chi-square (resp. a non-central chi-square) pdf with k degrees of freedom (resp. and non-centrality parameter ξ). The notations $\sim$ and $\overset{a}{\sim}$ indicate "distributed as" and "asymptotically distributed as", respectively.

II. System Model

We consider a binary hypothesis test to be tackled by two WSNs (referred to as WSN_1 and WSN_2), whose sensors are indexed as $\mathcal{K}_1 \triangleq \{1, \ldots, K_1\}$ and $\mathcal{K}_2 \triangleq \{K_1+1, \ldots, K_1+K_2\}$, respectively. Also, for compactness, we define the set $\mathcal{K} = \mathcal{K}_1 \cup \mathcal{K}_2 = \{1, \ldots, K_1+K_2\}$ and $K \triangleq (K_1+K_2)$. The deployment (in *possibly-overlapping fashion*) goal of both WSNs within the surveillance area $\mathcal{A}$ is to detect the presence ($\mathcal{H}_1$) or absence ($\mathcal{H}_0$) of a target with a partially known spatial signature. Specifically, each sensor k faces the following testing problem:

$$\begin{cases} \mathcal{H}_0 & : \quad y_k = w_k, \\ \mathcal{H}_1 & : \quad y_k = \theta\, g(\boldsymbol{x}_T, \boldsymbol{x}_k) + w_k; \end{cases} \tag{1}$$

The radiated signal θ of the target ($\mathcal{H}_1$), modeled as an *unknown* deterministic signal, is considered isotropic and undergoes distance-dependent pathloss and additive noise before being received by individual sensors. In Equation (1), $y_k \in \mathbb{R}$ represents the measurement taken by the kth sensor , and $w_k \in \mathbb{R}$ represents the noise Random Variable (RV) with *mean of zero* and a *symmetric unimodal* pdf, denoted as $p_{w_k}(\cdot)$. These RVs are assumed to be mutually independent. $\boldsymbol{x}_T$ is the *unknown* position of the target, and $\boldsymbol{x}_k$ is the known position of the kth sensor, both in $\mathbb{R}^d$. In this work, the position pair $(\boldsymbol{x}_T, \boldsymbol{x}_k)$ determines the Amplitude Attenuation Function (AAF), denoted by $g(\boldsymbol{x}_T, \boldsymbol{x}_k)$, which is expressed as g_k for simplicity.

To ensure efficient bandwidth & energy usage in WSNs, sensor k quantizes y_k into a 1-bit signal b_k using a deterministic quantizer (analysis of random quantizers is left for future work). This implies $b_k \triangleq u(y_k - \tau_k)$, where τ_k is quantizer threshold. Accordingly, the bit detection probability under $\mathcal{H}_1$ (i.e. $P(b_k = 1; \mathcal{H}_1)$) equals $\beta_k(\theta, \boldsymbol{x}_T) \triangleq F_{w_k}(\tau_k - \theta g(\boldsymbol{x}_T, \boldsymbol{x}_k))$. Similarly, for $\mathcal{H}_0$ the bit probability equals $\beta_{0,k} \triangleq \beta_k(\theta = 0, \boldsymbol{x}_T) = F_{w_k}(\tau_k)$. Both expressions are based on the complementary cumulative distribution function of w_k, namely $F_{w_k}(\cdot)$.

In this work, bits b_k's are assumed to be sent over error-prone reporting channels modelled as Binary Symmetric Channels (BSCs). In this paper, we consider **two types** of strategies between the WSNs:

- **No federation**: *each WSN capitalizes the knowledge of (a) its sensors only and (b) of the corresponding FC*. In detail, all the sensors $k \in \mathcal{K}_1$ (from WSN_1) report *only* to the FC_1 and the same applies for WSN_2 and FC_2. The (noisy) decisions from WSN_1 and WSN_2 collected at FC_1 and FC_2, respectively, are gathered within $\hat{\boldsymbol{b}}^{1\to 1} \triangleq \begin{bmatrix} \hat{b}_1^{1\to 1} & \cdots & \hat{b}_{K_1}^{1\to 1} \end{bmatrix}^T$ and $\hat{\boldsymbol{b}}^{2\to 2} \triangleq \begin{bmatrix} \hat{b}_{K_1+1}^{2\to 2} & \cdots & \hat{b}_{K_1+K_2}^{2\to 2} \end{bmatrix}^T$. Accordingly, at each FC a *separate* inference is taken only based on the decisions from the corresponding WSN, i.e. $\Lambda_1(\hat{\boldsymbol{b}}^{1\to 1})$ and $\Lambda_2(\hat{\boldsymbol{b}}^{2\to 2})$.
- **Full-Federation**: *both WSNs cooperate to capitalize on both (a) sensing and (b) reporting diversity*. In detail, all the sensors $k \in \mathcal{K}_1$ (from WSN_1) report bits to *both* FC_1 and FC_2, leveraging the wireless channel as a shared medium. The same is done by each sensor $k \in \mathcal{K}_2$ (i.e. belonging to WSN_2). In such a case, the cross-sensing bits from WSN_1 (resp. WSN_2) received at FC_2 (resp. FC_1) are denoted with $\hat{\boldsymbol{b}}^{1\to 2} \triangleq \begin{bmatrix} \hat{b}_1^{1\to 2} & \cdots & \hat{b}_{K_1}^{1\to 2} \end{bmatrix}^T$ (resp. $\hat{\boldsymbol{b}}^{2\to 1} \triangleq \begin{bmatrix} \hat{b}_{K_1+1}^{2\to 1} & \cdots & \hat{b}_{K_1+K_2}^{2\to 1} \end{bmatrix}^T$). Accordingly, both FCs take a *shared* inference based on the decisions from both WSNs, reported to both FCs (exploit-

ing high-speed backhaul links between them), namely $\Lambda(\hat{\boldsymbol{b}}^{1\to 1}, \hat{\boldsymbol{b}}^{1\to 2}, \hat{\boldsymbol{b}}^{2\to 1}, \hat{\boldsymbol{b}}^{2\to 2})$.

In both cases, the test decides in favor of $\mathcal{H}_0$ (resp. $\mathcal{H}_1$) when the generic statistic Λ is below (resp. above) the threshold γ_{fc}.

As previously anticipated, because of low-energy reporting, *received sensing bits are assumed to be error-prone at the FCs*. Specifically, it holds $\hat{b}_k^{i\to i} = b_k$ (resp. $\hat{b}_k^{i\to i} = (1-b_k)$) with probability $(1-P_{e,k}^{i\to i})$ (resp. $P_{e,k}^{i\to i}$) for WSN_i. Here, $P_{e,k}^{i\to i}$ denotes the (known) Bit Error Probability (BEP) associated to links between WSN_i and FC_i. Similarly, for cross-sensing bits from WSN_i received at FC_j ($i \neq j$) we assume $\hat{b}_k^{i\to j} = b_k$ (resp. $\hat{b}_k^{i\to j} = (1-b_k)$) with probability $(1-P_{e,k}^{i\to j})$ (resp. $P_{e,k}^{i\to j}$). All the BEPs are assumed to be known and the BSCs are mutually independent.

For the sake of a compact notation, we define $\boldsymbol{r}_1 \triangleq \left[\, (\hat{\boldsymbol{b}}^{1\to 1})^T \quad (\hat{\boldsymbol{b}}^{2\to 1})^T \,\right]^T \in \{0,1\}^{K\times 1}$ and $\boldsymbol{r}_2 \triangleq \left[\, (\hat{\boldsymbol{b}}^{1\to 2})^T \quad (\hat{\boldsymbol{b}}^{2\to 2})^T \,\right]^T \in \{0,1\}^{K\times 1}$, i.e. the vectors collecting the bits from WSN_{1+2} received at FC_1 and FC_2, respectively. Additionally, we denote the overall bit matrix as $\boldsymbol{D} \triangleq \left[\, \boldsymbol{r}_1 \quad \boldsymbol{r}_2 \,\right]^T \in \{0,1\}^{2\times K}$. Accordingly, the kth column of $\boldsymbol{D}$ (i.e. $\boldsymbol{d}_k$) contains the two bits received by FC_1 and FC_2 from kth sensor regarding the same bit b_k. Similarly, $\boldsymbol{\rho}_{e,k} \in \mathbb{R}^{2\times 1}$ is the BEP (column) vector associated to kth sensor, with first (resp. second) entry representing the BEP between the kth sensor and FC_1 (resp. FC_2).

It is important to note that the *unknown* target position $\boldsymbol{x}_T$ can *only* be estimated at the FC when the signal is present, meaning $\theta \neq \theta_0$ (where $\theta_0 = 0$). The problem defined in Eq. (1) therefore involves a *two-sided parameter test,* with $\mathcal{H}_0$ and $\mathcal{H}_1$ corresponding to $\theta = \theta_0$ and $\theta \neq \theta_0$, respectively. Nuisance parameters (i.e. $\boldsymbol{x}_T$) are present only under the *alternative hypothesis* $\mathcal{H}_1$ [20].

Next section is then aimed at the derivation of a (computationally) simple statistic $\Lambda(\boldsymbol{D})$ capitalizing full federation. At the end of the section, the derived rule is qualitatively compared with those available for the separated (non-federated) case.

III. Federation-enabled fusion rules

The log-likelihood of the received matrix $\boldsymbol{D}$ with respect to the parameters $(\theta, \boldsymbol{x}_T)$ can be expressed as the sum of the log-likelihoods of the individual $\boldsymbol{d}_k$'s (due to their independence)

$$\sum_{k=1}^{K_1+K_2} \ln P(\boldsymbol{d}_k; \theta, \boldsymbol{x}_T) \tag{2}$$

where $P(\boldsymbol{d}_k;\theta,\boldsymbol{x}_T) = P(\boldsymbol{d}_k|b_k=1)\beta_k(\theta,\boldsymbol{x}_T) + P(\boldsymbol{d}_k|b_k=0)(1-\beta_k(\theta,\boldsymbol{x}_T))$. A usual approach for tests with composite hypotheses is the GLR (e.g. [7]), with its implicit expression for the decision statistic is given by

$$\Lambda_{\text{GLR}}(\boldsymbol{D}) \triangleq 2\,\ln\left[\frac{P(\boldsymbol{D};\hat{\theta}_1,\widehat{\boldsymbol{x}}_T)}{P(\boldsymbol{D};\theta_0)}\right]. \tag{3}$$

In the above equation, the pair $(\hat{\theta}_1, \widehat{\boldsymbol{x}}_T)$ represents the *Maximum Likelihood* (ML) *estimates* under $\mathcal{H}_1$, i.e.

$$(\hat{\theta}_1, \widehat{\boldsymbol{x}}_T) \triangleq \arg\max_{(\theta,\boldsymbol{x}_T)} P(\boldsymbol{D};\theta,\boldsymbol{x}_T). \tag{4}$$

The GLR decision statistic (Λ_{GLR}) requires solving an optimization problem, see Eq. (3). However, the ML estimate pair $(\hat{\theta}_1, \widehat{\boldsymbol{x}}_T)$ cannot be calculated in a closed form and this makes GLR implementation challenging. Therefore, a (joint) grid approach is commonly used for $(\theta, \boldsymbol{x}_T)$ [13], [8], [7].

Alternatively, Davies' work provides a method to leverage the two-sided nature of the hypothesis test being considered [20]. This approach generalizes score tests to the more complex scenario where nuisance parameters are only observed under $\mathcal{H}_1$. Conventional score tests depend on ML estimates of the nuisance parameters under $\mathcal{H}_0$ [12], but this is not possible in this case because the nuisance parameters are *unobservable*.

If the target position, $\boldsymbol{x}_T$, were known, the Rao statistic would be a suitable decision statistic for the two-sided test on θ [12]. However, since $\boldsymbol{x}_T$ is not known in this case, we instead obtain a functional score statistic *dependent* on$\boldsymbol{x}_T$. To address this challenge, Davies proposed using the *functional supremum* as the relevant statistic, i.e.

$$\Lambda_{\text{GRao}}(\boldsymbol{D}) \triangleq \max_{\boldsymbol{x}_T} \frac{\left(\partial \ln\left[P\left(\boldsymbol{D};\theta,\boldsymbol{x}_T\right)\right] / \partial\theta\right)^2\Big|_{\theta=\theta_0}}{\mathrm{I}(\theta_0,\boldsymbol{x}_T)} \tag{5}$$

The Fisher Information (FI) of $\boldsymbol{D}$ with respect to θ, assuming $\boldsymbol{x}_T$ as known, is represented by $I(\theta,\boldsymbol{x}_T) \triangleq \mathbb{E}\left\{(\partial \ln[P(\boldsymbol{D};\theta,\boldsymbol{x}_T)]/\partial\theta)^2\right\}$. Davies' approach involves selecting a test that accepts the hypothesis $\mathcal{H}_1$ when the functional statistic evaluated at the most-likely target position (i.e. $\arg\max_{\boldsymbol{x}_T} \Lambda(\cdot;\boldsymbol{x}_T)$) exceeds a threshold γ_{fc}. This is similar to a GLRT approach which is restricted to these specific nuisance parameters. Hence, the statistic in Eq. (5) only estimates the target location $\boldsymbol{x}_T$. This decision statistic will be referred to as *Generalized Rao* (G-Rao) to indicate its use of Rao as the inner statistic within the Davies framework [8].

The expression for Λ_{GRao} is derived using the explicit forms of the score function (the derivative of the log-likelihood) and the Fisher Information (FI), both calculated at $\theta = \theta_0$. The details of how the score function and FI were derived are not included in this paper for the sake of conciseness. The explicit expression of the score function (conditional on $\boldsymbol{x}_T$) at $\theta = \theta_0$ is

$$\left.\frac{\partial \ln\left[P\left(\boldsymbol{D};\theta,\boldsymbol{x}_T\right)\right]}{\partial\theta}\right|_{\theta=\theta_0} = \sum_{k=1}^{K_1+K_2} \nu_k(\boldsymbol{d}_k)\, g_k, \tag{6}$$

where the auxiliary definitions

$$\nu_k(\boldsymbol{d}_k) \triangleq \frac{\{G_1(\boldsymbol{\rho}_{e,k},\boldsymbol{d}_k) - G_0(\boldsymbol{\rho}_{e,k},\boldsymbol{d}_k)\}\, p_{w_k}(\tau_k)}{G_1(\boldsymbol{\rho}_{e,k},\boldsymbol{d}_k)\beta_{0,k} + G_0(\boldsymbol{\rho}_{e,k},\boldsymbol{d}_k)(1-\beta_{0,k})} \tag{7}$$

and

$$G_{b_k}(\boldsymbol{\rho}_{e,k},\boldsymbol{d}_k) \triangleq \prod_{i=1}^{2} \rho_{e,k,i}^{d_{i,k}\oplus b_k}\,(1-\rho_{e,k,i})^{(1-d_{i,k}\oplus b_k)} \tag{8}$$

Table I
COMPLEXITY COMPARISON OF DECISION STATISTICS IMPLEMENTED VIA GRID SEARCH.

Fusion Rule	Complexity
GLR: WSN$_i$ only	$\mathcal{O}\left(K_i\, N_{\boldsymbol{x}_T}\, N_\theta\right)$
G-Rao: WSN$_i$ only	$\mathcal{O}\left(K_i\, N_{\boldsymbol{x}_T}\right)$
GLR with Fed.	$\mathcal{O}\left((K_1+K_2)\, N_{\boldsymbol{x}_T}\, N_\theta\right)$
G-Rao with Fed.	$\mathcal{O}\left((K_1+K_2)\, N_{\boldsymbol{x}_T}\right)$

have been employed. Differently, the ($\boldsymbol{x}_T$-conditional) FI at θ_0 is given by

$$I(\theta_0, \boldsymbol{x}_T) = \sum_{k=1}^{K_1+K_2} \psi_{0,k}\, g_k^2 \tag{9}$$

where the following definition has been leveraged:

$$\psi_{0,k} \triangleq p_{w_k}^2(\tau_k) \times \tag{10}$$
$$\sum_{j=1}^{4} \frac{\{G_1(\boldsymbol{\rho}_{e,k}, \boldsymbol{d}_k = \boldsymbol{v}(j)) - G_0(\boldsymbol{\rho}_{e,k}, \boldsymbol{d}_k = \boldsymbol{v}(j))\}^2}{G_1(\boldsymbol{\rho}_{e,k}, \boldsymbol{d}_k = \boldsymbol{v}(j))\beta_{0,k} + G_0(\boldsymbol{\rho}_{e,k}, \boldsymbol{d}_k = \boldsymbol{v}(j))(1-\beta_{0,k})}$$

In the above equation $\boldsymbol{v}(j)$ denotes the two-dimensional binary codeword associated to integer $(j-1)$ (e.g. $\boldsymbol{v}(2) = [\,0 \quad 1\,]^T$). Accordingly, the explicit form of the G-Rao statistic can be thus rewritten as $\Lambda_{\text{GRao}}(\boldsymbol{D}) \triangleq \max_{\boldsymbol{x}_T} \Lambda_{\text{Rao}}(\boldsymbol{D}, \boldsymbol{x}_T)$, where

$$\Lambda_{\text{Rao}}(\boldsymbol{D}, \boldsymbol{x}_T) = \frac{\left\{\sum_{k=1}^{K_1+K_2} \nu_k(\boldsymbol{d}_k)\, g(\boldsymbol{x}_T, \boldsymbol{x}_k)\right\}^2}{\sum_{k=1}^{K_1+K_2} \psi_{0,k}\, g^2(\boldsymbol{x}_T, \boldsymbol{x}_k)} \tag{11}$$

denotes the Rao statistic assuming $\boldsymbol{x}_T$ *as known*. The appeal of G-Rao statistic is motivated by its *simpler implementation* (as $\hat{\theta}_1$ is not needed), requiring solely a grid search with respect to $\boldsymbol{x}_T$, that is

$$\Lambda_{\text{GRao}}(\boldsymbol{D}) \approx \max_{i=1,\dots N_{\boldsymbol{x}_T}} \Lambda_{\text{Rao}}(\boldsymbol{D}, \boldsymbol{x}_T[i]) \tag{12}$$

Thus, its complexity is $\mathcal{O}\left((K_1+K_2)\, N_{\boldsymbol{x}_T}\right)$, implying a *significant reduction* with respect to a GLR exploiting the same federation strategy (see Tab. I). Indeed, the complexity of the latter equals $\mathcal{O}\left((K_1+K_2)\, N_{\boldsymbol{x}_T}\, N_\theta\right)$, where the terms $N_{\boldsymbol{x}_T}$ and N_θ denote the number of position and amplitude bins employed. We remark that both rules have a *linear* complexity with the number of sensors (K_1+K_2).

Non-federated case [8]: when each WSN performs DD in a separate fashion, the following G-Rao rules for WSN$_1$ and WSN$_2$ can be adopted

$$\Lambda_{\text{GRao},1}(\hat{\boldsymbol{b}}^{1\to 1}) = \max_{\boldsymbol{x}_T} \frac{\left\{\sum_{k=1}^{K_1} \bar{\nu}_k(\hat{b}_k^{1\to 1})\, g(\boldsymbol{x}_T, \boldsymbol{x}_k)\right\}^2}{\sum_{k=1}^{K_1} \bar{\psi}_{0,k}\, g^2(\boldsymbol{x}_T, \boldsymbol{x}_k)} \tag{13}$$

$$\Lambda_{\text{GRao},2}(\hat{\boldsymbol{b}}^{2\to 2}) = \max_{\boldsymbol{x}_T} \frac{\left\{\sum_{k=K_1+1}^{K_1+K_2} \tilde{\nu}_k(\hat{b}_k^{2\to 2})\, g(\boldsymbol{x}_T, \boldsymbol{x}_k)\right\}^2}{\sum_{k=K_1+1}^{K_1+K_2} \tilde{\psi}_{0,k}\, g^2(\boldsymbol{x}_T, \boldsymbol{x}_k)} \tag{14}$$

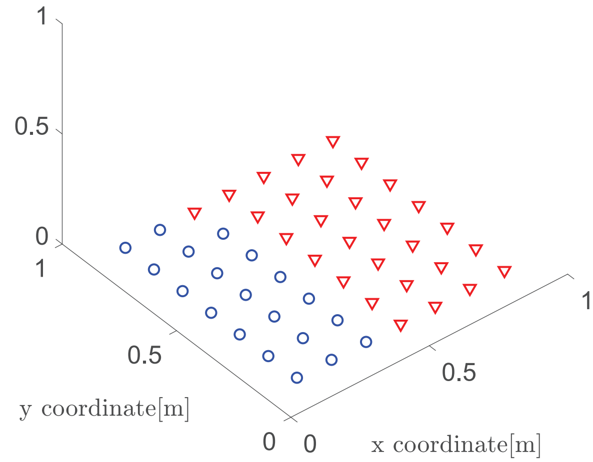

Figure 1. Federated WSN setup considered: WSN$_1$ is made of $K_1 = 20$ sensors ("○" markers) whereas WSN$_2$ is made of $K_2 = 29$ sensors ("△" markers).

$\bar{\nu}_k(\hat{b}_k^{1\to 1}) \triangleq \frac{(1-2\,P_{e,k}^{1\to 1})\, p_{w_k}(\tau_k)\, [\hat{b}_k^{1\to 1} - \bar{\alpha}_{0,k}]}{\bar{\alpha}_{0,k}(1-\bar{\alpha}_{0,k})}$ and $\tilde{\nu}_k(\hat{b}_k^{2\to 2}) \triangleq \frac{(1-2\,P_{e,k}^{2\to 2})\, p_{w_k}(\tau_k)\, [\hat{b}_k^{2\to 2} - \tilde{\alpha}_{0,k}]}{\tilde{\alpha}_{0,k}(1-\tilde{\alpha}_{0,k})}$. Additionally, $\bar{\psi}_{0,k} \triangleq \frac{(1-2\,P_{e,k}^{1\to 1})^2\, p_{w_k}^2(\tau_k)}{\bar{\alpha}_{0,k}\,(1-\bar{\alpha}_{0,k})}$ (resp. $\tilde{\psi}_{0,k} \triangleq \frac{(1-2\,P_{e,k}^{2\to 2})^2\, p_{w_k}^2(\tau_k)}{\tilde{\alpha}_{0,k}\,(1-\tilde{\alpha}_{0,k})}$), where $\bar{\alpha}_{0,k} \triangleq (1-P_{e,k}^{1\to 1})\beta_{0,k} + P_{e,k}^{1\to 1}(1-\beta_{0,k})$ (resp. $\tilde{\alpha}_{0,k} \triangleq (1-P_{e,k}^{2\to 2})\beta_{0,k} + P_{e,k}^{2\to 2}(1-\beta_{0,k})$). Alternatively, at the expenses of higher complexity, the GLR for the non-federated case can be evaluated as [7]:

$$\Lambda_{\text{GLR}}(\hat{\boldsymbol{b}}^{1\to 1}) \triangleq 2\,\ln\left[\frac{P(\hat{\boldsymbol{b}}^{1\to 1}; \hat{\theta}_1, \widehat{\boldsymbol{x}}_T)}{P(\hat{\boldsymbol{b}}^{1\to 1}; \theta_0)}\right] \tag{15}$$

$$\Lambda_{\text{GLR}}(\hat{\boldsymbol{b}}^{2\to 2}) \triangleq 2\,\ln\left[\frac{P(\hat{\boldsymbol{b}}^{2\to 2}; \hat{\theta}_1, \widehat{\boldsymbol{x}}_T)}{P(\hat{\boldsymbol{b}}^{2\to 2}; \theta_0)}\right] \tag{16}$$

Clearly, the complexity comparison between GLR and G-Rao rules in the separated case is the same as the federated case. On the contrary, using a G-Rao (resp. a GLR) on federated data w.r.t. separated data only incurs a *linear* complexity growth due to the enlarged WSN size (i.e. from K_i to $K = K_1+K_2$), see Tab. I.

IV. SIMULATION RESULTS

In this section, we compare the performance of the G-Rao and GLR tests (based on different federation strategies) by evaluating their system false alarm and detection probabilities. These probabilities are defined as defined as $P_{\text{F}} \triangleq \Pr\{\Lambda > \gamma|\mathcal{H}_0\}$ and $P_{\text{D}} \triangleq \Pr\{\Lambda > \gamma|\mathcal{H}_1\}$, respectively, where Λ is the statistic employed at the FC.

Federation setup considered: in our setup, two WSNs with $K_1 = 20$ and $K_2 = 29$ sensors each ($K_1+K_2 = K = 49$ total) detect the presence of a target in a 2D square region $\mathcal{A} \triangleq [0,1]^2$. Sensors are arranged in a regular grid pattern covering the region, with WSN$_1$ covering the left half and WSN$_2$ covering the right half, as illustrated in Fig. 1. Based on our formulation, irregular displacement WSN structures may be also considered, similarly to [2]. The sensing model

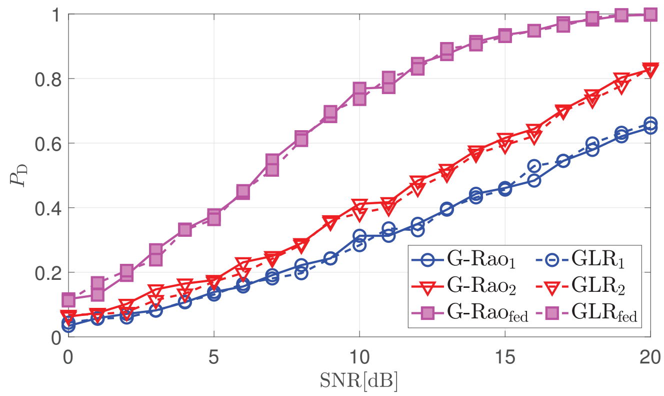

Figure 2. P_{D} vs. SNR (dB); false-alarm probability at FC is set to $P_{\mathrm{F}} = 0.01$. Two WSNs with $K_1 = 20$ and $K_2 = 29$ sensors are considered, as shown in Fig. 1. Sensor thresholds are set to $\tau_k = 0$.

assumes normal noise distribution with unit variance, i.e. $w_k \sim \mathcal{N}(0,1)$. The AAF used is a power-law, namely $g(\boldsymbol{x}_T, \boldsymbol{x}_k) \triangleq 1/\sqrt{1 + (\|\boldsymbol{x}_T - \boldsymbol{x}_k\|/\eta)^{\alpha}}$, with decay exponent $\alpha = 4$ and target extent $\eta = 0.2$. For simplicity, the thresholds are set to $\tau_k = 0$, $\forall k \in \mathcal{K}$, following [8]. In the following results the BEP values are all set to $P_{e,k}^{1\to1} = P_{e,k}^{1\to2} = P_{e,k}^{2\to1} = P_{e,k}^{2\to2} = 0.1$. Target SNR is defined as $\mathrm{SNR} \triangleq 10\,\log_{10}(\theta^2/\sigma_w^2)$.

Implementation of fusion rules: According to Sec. III, the implementation of the decision statistics Λ_{GLR} and Λ_{GRao} relies on grid search. The search space of the target signal θ is set to be between negative and positive values of the parameter $-\bar{\theta}$ to $+\bar{\theta}$, with a SNR of 20 dB. The vector collecting the points on the grid is then $\begin{bmatrix} -\boldsymbol{g}_\theta^T & 0 & \boldsymbol{g}_\theta^T \end{bmatrix}^T$, with $\boldsymbol{g}_\theta$ including the target strengths in dB from -10 to 20 with a step of 2.5. This results in $N_\theta = 25$ amplitude bins. The search support of the target location $\boldsymbol{x}_T$ is the monitored area $\mathcal{A}$, which is sampled uniformly with $N_{\boldsymbol{x}_T} = N_c^2$ points, where $N_c = 100$, leading to $N_c^2 = 10^4$ grid points for evaluating G-Rao and $N_c^2 N_\theta = 2.5 \times 10^5$ points for GLR. The complexity reduction for G-Rao with respect to GLR is +20-fold based on the same federation strategy.

Discussion of results: In Fig. 2 we compare the detection rate (P_{D}) with respect to the signal-to-noise ratio SNR (dB), under the condition that the false alarm probability (P_F) is 0.01. The target position $\boldsymbol{x}_T$ is randomly selected within area $\mathcal{A}$ at each trial (when the hypothesis $\mathcal{H}_1$ is drawn). The performance of *four* different configurations is evaluated: GLR and G-Rao applied on separate or federated data. The results show a close match between GLR and G-Rao when using the same type of data (i.e. separated or federated). Furthermore, *the benefits of federation are clear from the improvement in performance across the entire SNR range*.

Since the very small performance gap between the two rules, we next investigate the detection coverage properties of G-Rao over the surveillance area $\mathcal{A}$. To this end, in Fig. 3, we report P_{D} (under $P_{\mathrm{F}} = 0.01$) versus the target location $\boldsymbol{x}_T$ (for $\mathrm{SNR} = 5\,\mathrm{dB}$). The considered federation (G-Rao$_{\mathrm{fed}}$) is compared with a G-Rao capitalizing either $\boldsymbol{r}_1$ (G-Rao$_{\mathrm{sf1}}$) or $\boldsymbol{r}_2$ (G-Rao$_{\mathrm{sf2}}$), i.e. the bits from *both* WSNs received at a *single* FC. In other terms, each FC is exploiting all the sensing information from both WSNs but they are not cooperating to cope with uncertain communication links originating from usual low-energy reporting. This comparison is aimed at assessing the benefits originating from the *sole diversity at the communication level* (i.e. the multiple reception of the same bit b_k from both FCs assumed in full federation). It is clear from the results that the $P_{\mathrm{D}}(\boldsymbol{x}_T)$ surface has a similar appearance for the three configurations, with lower detection rates observed at the edges of the surveillance area. This pattern is a result of the uniform sensor placement in the area $\mathcal{A}$, as seen in Fig. 1) when considering both WSNs as a whole. From the comparison among the different configurations, it is apparent that G-Rao$_{\mathrm{fed}}$ test achieves a relevant gain also over both G-Rao$_{\mathrm{sf1}}$ and G-Rao$_{\mathrm{sf2}}$. This demonstrates the appeal of full federation between the two WSNs.

V. Conclusions and Future Directions

We investigated the design of computationally-efficient fusion rules capitalizing on federation between two WSNs. Specifically, we described the design of a low-complexity alternative to GLRT called G-Rao, a generalized version of the Rao test, for detecting a non-cooperative target with unknown signal (θ) and location ($\boldsymbol{x}_T$) in a sensing model with quantized measurements, symmetric noise, non-ideal and non-identical BSCs. Unlike GLRT, G-Rao only requires maximization with respect to $\boldsymbol{x}_T$, as $\boldsymbol{x}_T$ is a nuisance parameter present only under $\mathcal{H}_1$. Simulations showed that G-Rao performs similarly to GLRT in the considered federated scenario. Additionally, it was demonstrated in terms of detection performance (a) the significant gain arising from federating WSNs (as opposed to a "per-WSN" inference) and (b) the additional improvement achieved by capitalizing on receive diversity (i.e. using the FCs as redundant receivers for collecting the quantized measurements).

Future directions of research will include (i) quantizer design for GLR/G-Rao fusion rules in the federated case, (ii) investigation of different degrees of federation and their impact on system performance and (iii) more challenging sensing models (e.g. multiplicative fading).

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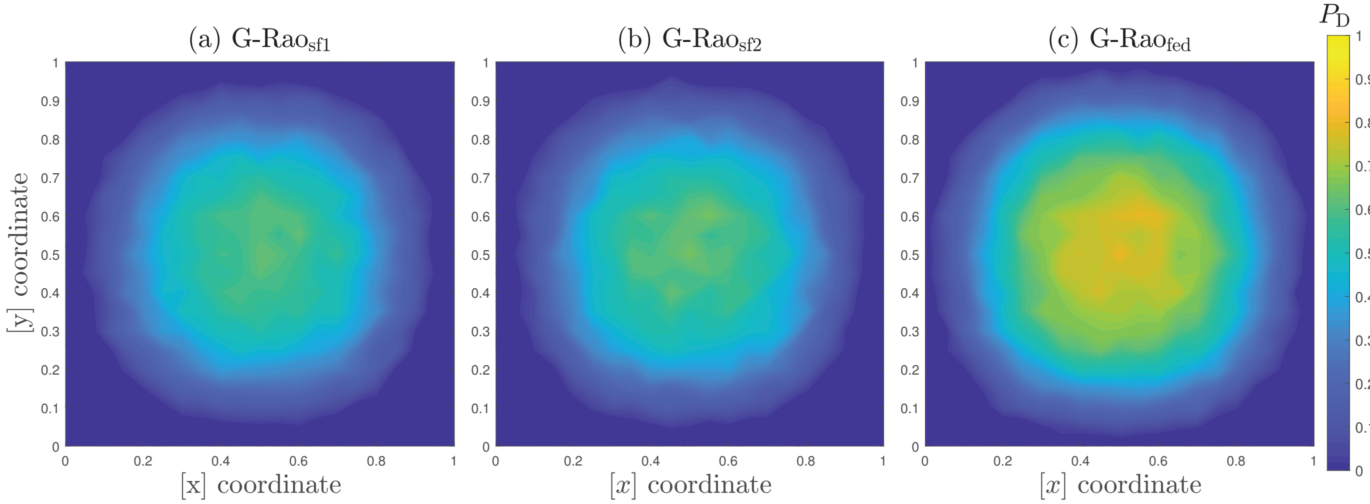

Figure 3. P_{D} heatmaps vs. target position $\boldsymbol{x}_T$ for (a) G-Rao$_{\mathrm{sf1}}$ (exploiting $\boldsymbol{r}_1$), (b) G-Rao$_{\mathrm{sf2}}$ (exploiting $\boldsymbol{r}_2$), and (c) G-Rao$_{\mathrm{fed}}$ (full federation). The FC false-alarm probability is set to $P_{\mathrm{F}} = 0.01$. Two WSNs with $K_1 = 20$ and $K_2 = 29$ sensors are considered, as shown in Fig. 1 and a target with sensing $\mathrm{SNR} = 5\,\mathrm{dB}$ is considered. Corresponding decisions are sent over BSCs with $P_{\mathrm{e},k}^{i\to j} = 0.1$. The sensor thresholds are set to $\tau_k = 0$.

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