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Wireless Inference Gets Smarter: RIS-assisted Channel-Aware MIMO Decision Fusion

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***Abstract*—We study channel-aware binary-decision fusion over a shared flat-fading channel with multiple antennas at the Fusion Center (FC). This paper considers the aid of a Reconfigurable Intelligent Surface (RIS) to effectively convey the information of the phenomenon of interest to the FC and foster energy-efficient data analytics supporting the Internet of Things (IoT) paradigm. We present the optimal rule and derive a (sub-optimal) joint fusion rule & RIS design, representing an alternative with reduced complexity and lower system knowledge required. Simulation results for performance are presented showing the benefit of RIS adoption even in a suboptimal case.**

***Index Terms*—Decision Fusion, Internet of Things, Reconfigurable Intelligent Surface, Wireless Sensor Networks.**

I. Introduction

The Internet of Things (IoT) envisages the pervasive deployment of tiny devices with sensing, processing, and communication capabilities to be used in everyday life and currently represents a game-changing technology for the wireless communications and sensing sector [1]. Wireless Sensor Networks (WSNs) constitute the "sensing arm" of the IoT, with Distributed Detection (DD) representing a mature research topic having multifold applications, ranging from cognitive radio systems [2] to industrial contexts [3].

From a chronological standpoint, we can categorize DD literature into three "waves". The **first wave** of DD (coinciding with its inception) dates back to the seminal work of Tenney and Sandell [4], and was nurtured by the milestone contributions from [5]–[7]. In "earlier days", single- or multi-bit quantization of measurements/likelihoods was assumed, and the design of local detectors and/or fusion rules investigated. In these works, however, decoupled (or noise-free) reporting channels was the implicit assumption. Then, the **second wave** of DD ignited in the early 2000s along with the widespread diffusion of WSNs. This wave of research effort centered around the use of channel-aware techniques for design of fusion rules [8] and the investigation of diverse reporting protocols, e.g. type/time/frequency/code-based [9], [10] or interfering [11]. Further efforts toward performance improvement implied power-allocation [12], censoring schemes [13] and sensor subset selection [14]. In recent years, the **third wave** of DD has attempted to capitalize novel concepts, such as green (near-zero-energy) sensors (e.g. exploiting backscattering [15] and energy-harvesting [16]) and the use of mmWave sensors [17] and massive MIMO [18], [19] to reduce the energy expenditure of the WSN by achieving desired performance. Still, the appealing use of flexible **Reconfigurable Intelligent Surfaces (RISs) [20], [21] appears unexplored in DD**.

Hence, the **main contributions** of this work are the following. We study DD with sensors transmitting their decisions to a Fusion Center (FC) over a multiple-access channel. The FC is equipped with a receive array (hence we consider a distributed MIMO setup [12], [22]) and information alignment of sensors' contributions is achieved via the assistance of suitably-designed RIS [20], [21]. To overcome the infeasibility of the Log-likelihood Ratio (LLR) and the consequent difficulty in obtaining a RIS design (due to unavailability of LLR theoretical performance) in such context, **we devise a joint fusion rule & RIS design based on the "Ideal Sensors" (IS) assumption** [8], [18], [22]. The proposed design, albeit relying on a simplistic rationale, provides an effective (while sensor-performance-agnostic) joint fusion rule & RIS design. The resulting optimization is elegantly solved via Alternating Optimization (AO) and Majorization-Minimization (MM) [23].

Focusing on the use of smart surfaces for aiding decentralized inference, the closest works to ours are [24], [25]. Still, while the former tackles over-the-air-computation of generic nomographic functions [24] (i.e. not suited for dependent and non-zero-mean decisions), the latter tackles distributed estimation with a single-antenna FC with secrecy objectives [25].

The rest of the paper is organized as follows. Sec. II describes the system model considered, whereas Sec. III introduces the proposed joint fusion & RIS design. Our approach

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is then evaluated via simulations in Sec. IV. Sec. V ends the paper with some pointers to research prospects.[1]

II. System Model

We consider a distributed binary test of hypotheses, where K sensors are used to discern between the hypotheses in the set $\mathcal{H} \triangleq \{\mathcal{H}_0, \mathcal{H}_1\}$ (e.g. $\mathcal{H}_0/\mathcal{H}_1$ may represent the absence/presence of a phenomenon of interest). The kth sensor, $k \in \mathcal{K} \triangleq \{1, 2, \ldots, K\}$, takes a binary local decision $\xi_k \in \mathcal{H}$ about the observed phenomenon on the basis of its own measurements. Here we do not make any conditional (given $\mathcal{H}_i \in \mathcal{H}$) mutual independence assumption on ξ_k. Each decision ξ_k is mapped into $x_k \in \mathcal{X} = \{-1, +1\}$, namely a Binary Phase-Shift Keying (BPSK) modulation: without loss of generality we assume that $b_k = \mathcal{H}_i$ maps into $x_k = (2i-1)$, $i \in \{0,1\}$. The quality of the WSN is characterized by the conditional joint pmfs $P(\boldsymbol{x}|\mathcal{H}_i)$. Also, we denote $P_{D,k} \triangleq P(x_k = 1|\mathcal{H}_1)$ and $P_{F,k} \triangleq P(x_k = 1|\mathcal{H}_0)$ the probability of detection and false alarm of the kth sensor, respectively (we reasonably assume $P_{D,k} \geq P_{F,k}$).

Sensors communicate with a FC equipped with N antennas over a wireless flat-fading multiple access channel [22] and are assisted by a RIS with M elements. Let $\boldsymbol{H}^d \in \mathbb{C}^{N\times K}$ ($\boldsymbol{h}_k^d \in \mathbb{C}^N$ being the kth sensor contribution), $\boldsymbol{H}^r \in \mathbb{C}^{M\times K}$ ($\boldsymbol{h}_k^r \in \mathbb{C}^M$ being the kth sensor contribution) and $\boldsymbol{G} \in \mathbb{C}^{N\times M}$ be the equivalent channels from the WSN to the FC, from the WSN to the RIS, and from the RIS to the FC, respectively. The received signal vector $\boldsymbol{y} \in \mathbb{C}^N$ at the FC is:

$$\boldsymbol{y} = \left(\boldsymbol{G}\boldsymbol{\Theta}\boldsymbol{H}^r + \boldsymbol{H}^d\right)\boldsymbol{D}_\alpha\,\boldsymbol{x} + \boldsymbol{w} = \boldsymbol{H}^e(\boldsymbol{\Theta})\,\boldsymbol{D}_\alpha\,\boldsymbol{x} + \boldsymbol{w} \quad (1)$$

where $\boldsymbol{x} \in \mathcal{X}^K$ and $\boldsymbol{w} \sim \mathcal{N}_{\mathbb{C}}(\boldsymbol{0}_N, \sigma_w^2 \boldsymbol{I}_N)$ are the transmitted signal and noise vectors, respectively. In Eq. (1), the diagonal matrix $\boldsymbol{\Theta} = \mathrm{diag}(e^{j\varphi_1}, \ldots, e^{j\varphi_M})$, $0 \leq \varphi_m < 2\pi$, $\forall m = 1, \ldots M$, collects the RIS phase-shifts. Conversely, the matrix $\boldsymbol{D}_\alpha = \mathrm{diag}(\alpha_1, \ldots, \alpha_K)$, with $\alpha_k \in \mathbb{R}^+$, $\forall k \in \mathcal{K}$, accounts for unequal transmit energy. Last, we have defined $\boldsymbol{H}^e(\boldsymbol{\Theta}) \triangleq \left(\boldsymbol{G}\boldsymbol{\Theta}\boldsymbol{H}^r + \boldsymbol{H}^d\right)$ for compactness. It can be shown that $\boldsymbol{y}|\mathcal{H}_i$ has the following statistical 2nd-order characterization: $\mathbb{E}\{\boldsymbol{y}|\mathcal{H}_i\} = \boldsymbol{H}^e(\boldsymbol{\Theta})\,\boldsymbol{D}_\alpha\,\boldsymbol{\rho}_i$, $\mathrm{Cov}(\boldsymbol{y}|\mathcal{H}_i) = \boldsymbol{H}^e(\boldsymbol{\Theta})\,\boldsymbol{D}_\alpha\,\mathrm{Cov}(\boldsymbol{x}|\mathcal{H}_i)\,\boldsymbol{D}_\alpha\,\boldsymbol{H}^e(\boldsymbol{\Theta})^\dagger + \sigma_w^2\,\boldsymbol{I}_N$ and $\mathrm{PCov}(\boldsymbol{y}|\mathcal{H}_i) = \boldsymbol{H}^e(\boldsymbol{\Theta})\,\boldsymbol{D}_\alpha\,\mathrm{Cov}(\boldsymbol{x}|\mathcal{H}_i)\,\boldsymbol{D}_\alpha\,\boldsymbol{H}^e(\boldsymbol{\Theta})^T$, where $\boldsymbol{\rho}_1 \triangleq [P_{D,1} \cdots P_{D,K}]^T$ and $\boldsymbol{\rho}_0 \triangleq [P_{F,1} \cdots P_{F,K}]^T$, respectively.

[1]**Notation** – vectors (resp. matrices) are denoted with lower-case (resp. upper-case) bold letters; $\mathbb{E}\{\cdot\}$, $\mathrm{var}\{\cdot\}$, $\mathrm{Cov}(\cdot)$, $\mathrm{PCov}(\cdot)$ $(\cdot)^T$, $(\cdot)^\dagger$, $\Re(\cdot)$, $\angle(\cdot)$ and $\|\cdot\|$ denote expectation, variance, covariance, pseudocovariance, transpose, conjugate transpose, real part, phase, and Euclidean norm operators, respectively; $\boldsymbol{O}_{N\times K}$ (resp. $\boldsymbol{I}_N$) denotes the $N \times K$ (resp. $N \times N$) null (resp. identity) matrix; $\boldsymbol{0}_N$ (resp. $\boldsymbol{1}_N$) denotes the null (resp. ones) vector of length N; $\mathrm{diag}(\boldsymbol{a})$ denotes the diagonal matrix with $\boldsymbol{a}$ on the main diagonal; $\underline{\boldsymbol{a}}$ (resp. $\underline{\boldsymbol{A}}$) denotes the augmented vector (resp. matrix) of $\boldsymbol{a}$ (resp. $\boldsymbol{A}$), that is $\underline{\boldsymbol{a}} \triangleq \begin{bmatrix} \boldsymbol{a}^T & \boldsymbol{a}^\dagger \end{bmatrix}^T$ (resp. $\underline{\boldsymbol{A}} \triangleq \begin{bmatrix} \boldsymbol{A}^T & \boldsymbol{A}^\dagger \end{bmatrix}^T$); $\Pr(\cdot)$ and $p(\cdot)$ denote probability mass functions (pmfs) and probability density functions (pdfs), while $\Pr(\cdot|\cdot)$ and $p(\cdot|\cdot)$ their corresponding conditional counterparts; $\mathcal{N}_{\mathbb{C}}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ denotes a proper complex normal distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$; the symbol $\sim$ means "distributed as".

III. Joint Fusion Rule and RIS design

Optimal fusion rule: the optimal test [26] for this problem is

$$\left\{\Lambda_{\mathrm{opt}} \triangleq \ln\left[\frac{p(\boldsymbol{y}|\mathcal{H}_1)}{p(\boldsymbol{y}|\mathcal{H}_0)}\right]\right\} \underset{\hat{\mathcal{H}}=\mathcal{H}_0}{\overset{\hat{\mathcal{H}}=\mathcal{H}_1}{\gtrless}} \gamma \quad (2)$$

where $\hat{\mathcal{H}}$, Λ_{opt} and γ denote the estimated hypothesis, the LLR and the threshold which the LLR is compared to. The latter (γ) is usually determined to assure a fixed system false-alarm rate or to minimize the probability of error [26]. Exploiting the independence[2] of $\boldsymbol{y}$ from $\mathcal{H}_i$, given $\boldsymbol{x}$, an explicit expression of the LLR in Eq. (2) is obtained as

$$\Lambda_{\mathrm{opt}} = \ln\left[\frac{\sum_{\boldsymbol{x}\in\mathcal{X}^K} p(\boldsymbol{y}|\boldsymbol{x})P(\boldsymbol{x}|\mathcal{H}_1)}{\sum_{\boldsymbol{x}\in\mathcal{X}^K} p(\boldsymbol{y}|\boldsymbol{x})P(\boldsymbol{x}|\mathcal{H}_0)}\right] \quad (3)$$

$$= \ln\left[\frac{\sum_{\boldsymbol{x}\in\mathcal{X}^K} \exp\left(-\frac{\|\boldsymbol{y}-\boldsymbol{H}^e(\boldsymbol{\Theta})\boldsymbol{D}_\alpha\boldsymbol{x}\|^2}{\sigma_w^2}\right)P(\boldsymbol{x}|\mathcal{H}_1)}{\sum_{\boldsymbol{x}\in\mathcal{X}^K} \exp\left(-\frac{\|\boldsymbol{y}-\boldsymbol{H}^e(\boldsymbol{\Theta})\boldsymbol{D}_\alpha\boldsymbol{x}\|^2}{\sigma_w^2}\right)P(\boldsymbol{x}|\mathcal{H}_0)}\right]$$

Unfortunately, the LLR requires a computational complexity which scales as $\mathcal{O}(2^K)$ and also does not lend itself to a tractable analysis of its closed-form performance. The latter observation still applies even in the case a deflection measure is taken as the relevant evaluation metric:

$$D_i(\Lambda) \triangleq \left(\mathbb{E}\{\Lambda|\mathcal{H}_1\} - \mathbb{E}\{\Lambda|\mathcal{H}_0\}\right)^2 / \mathrm{var}\{\Lambda|\mathcal{H}_i\} \quad (4)$$

where $D_0(\cdot)$ and $D_1(\cdot)$ correspond to the normal [27] and modified [28] deflections, respectively. Accordingly, we pursue a simplified approach described in what follows.

Joint Ideal Sensors (IS) Rule & RIS design: first of all, deflection metrics represent a flexible design tool in case the fusion rule is constrained to be a Widely-Linear (WL) fusion statistic $\Lambda_{\mathrm{wl}} = \underline{\boldsymbol{a}}^\dagger \underline{\boldsymbol{y}}$, namely:

$$D_i(\Lambda_{\mathrm{wl}}) \triangleq \frac{\left(\underline{\boldsymbol{a}}^\dagger\left(\mathbb{E}\{\underline{\boldsymbol{y}}|\mathcal{H}_1\} - \mathbb{E}\{\underline{\boldsymbol{y}}|\mathcal{H}_0\}\right)\right)^2}{\underline{\boldsymbol{a}}^\dagger \mathrm{Cov}(\underline{\boldsymbol{y}}|\mathcal{H}_1)\,\underline{\boldsymbol{a}}} \quad (5)$$

Indeed, WL fusion rules have been reported to provide appealing performance in similar WSN contexts (e.g. [18]). Secondly, we observe that the fusion rule design in Eq. (3) can be further simplified under the **IS assumption** [18], [29], i.e. $P(\boldsymbol{x} = \boldsymbol{1}_K|\mathcal{H}_1) = P(\boldsymbol{x} = -\boldsymbol{1}_K|\mathcal{H}_0) = 1$. Indeed, 2nd-order characterization of $\boldsymbol{y}|\mathcal{H}_i$ simplifies as: $\mathbb{E}\{\boldsymbol{y}|\mathcal{H}_i\} = \boldsymbol{H}^e(\boldsymbol{\Theta})\,\boldsymbol{D}_\alpha\,(2i-1)\boldsymbol{1}_K$, $\mathrm{Cov}(\boldsymbol{y}|\mathcal{H}_i) = \sigma_w^2\,\boldsymbol{I}_N$ and $\mathrm{PCov}(\boldsymbol{y}|\mathcal{H}_i) = \boldsymbol{O}_{N\times N}$. Accordingly, the proposed design requires lower system knowledge, as **WSN (local) decision performance is not needed**. Also, we remark that the IS assumption is only leveraged at the design stage.

Based on IS assumption, both the deflection measures simplify into the **unique** metric [18]:

$$D\left(\underline{\boldsymbol{a}}, \boldsymbol{\Theta}\right) = \left(4\,/\,\sigma_w^2\right)\,\left(\underline{\boldsymbol{a}}^\dagger\left[\underline{\boldsymbol{H}}^e(\boldsymbol{\Theta})\,\boldsymbol{D}_\alpha\,\boldsymbol{1}_k\right]\right)^2\,/\,\left(\underline{\boldsymbol{a}}^\dagger\underline{\boldsymbol{a}}\right) \quad (6)$$

The goal of this work is to maximize the deflection in Eq. (6) (i.e. under the IS assumption) by **jointly** optimizing the WL

[2]Indeed the directed triple formed by hypothesis, the transmitted-signal vector and the received-signal vector satisfies the Markov property.

vector determining the fusion rule $\underline{\boldsymbol{a}}$ and the phase shift matrix $\boldsymbol{\Theta}$. Hence, the resulting optimization is formulated as:

$$\mathcal{P}_1 : \begin{array}{ll} \underset{\underline{\boldsymbol{a}},\boldsymbol{\Theta}}{\text{maximize}} & \frac{\left(\underline{\boldsymbol{a}}^\dagger [\underline{\boldsymbol{H}}^e(\boldsymbol{\Theta})\, \boldsymbol{D}_\alpha\, \boldsymbol{1}_k]\right)^2}{\underline{\boldsymbol{a}}^\dagger \underline{\boldsymbol{a}}} \\ \text{subject to} & \|\underline{\boldsymbol{a}}\| = 1 \\ & \boldsymbol{\Theta} = \text{diag}(e^{j\varphi_1}, \ldots, e^{j\varphi_M}) \end{array} \quad (7)$$

Note that, different from channel-aware DD without RISs, in the second constraint of optimization problem $\mathcal{P}_1$, each diagonal element in the phase shift matrix has unit modulus. This non-convex constraint together with the non-convex objective function makes $\mathcal{P}_1$ a non-convex problem.

In this paper, we resort to AO approach for solving $\mathcal{P}_1$ efficiently. Specifically, we describe an optimization method based on AO which alternates between maximization of $\underline{\boldsymbol{a}}$ and $\boldsymbol{\Theta}$. AO (being a special case of block-coordinate descent) has been shown to be a widely applicable and empirically successful approach in many applications, and typically leads to a sub-optimal solution for nonconvex problems.

Step (A) - Fusion rule design: we first focus on the optimization of the WL vector $\underline{\boldsymbol{a}}$ for a **fixed** phase-shift matrix $\boldsymbol{\Theta}_{\text{fix}}$. Accordingly, the WL vector design problem is given by:

$$\mathcal{P}_2 : \underset{\|\underline{\boldsymbol{a}}\|=1}{\text{maximize}} \; \left(\underline{\boldsymbol{a}}^\dagger \left[\underline{\boldsymbol{H}}^e(\boldsymbol{\Theta}_{\text{fix}})\, \boldsymbol{D}_\alpha\, \boldsymbol{1}_k\right]\right)^2 / \left(\underline{\boldsymbol{a}}^\dagger \underline{\boldsymbol{a}}\right) \quad (8)$$

The optimal value of $\underline{\boldsymbol{a}}$ in $\mathcal{P}_2$ is the vector attaining the equality in the **Cauchy-Schwarz inequality** [18]:

$$\underline{\boldsymbol{a}}^\star(\boldsymbol{\Theta}_{\text{fix}}) = \underline{\boldsymbol{H}}^{\text{e}}(\boldsymbol{\Theta}_{\text{fix}})\, \boldsymbol{D}_\alpha\, \boldsymbol{1}_k \,/\, \|\underline{\boldsymbol{H}}^{\text{e}}(\boldsymbol{\Theta}_{\text{fix}})\, \boldsymbol{D}_\alpha\, \boldsymbol{1}_k\| \quad (9)$$

Step (B) - RIS design: we then focus on the optimization of the phase-shift matrix $\boldsymbol{\Theta}$ for a **fixed** WL vector $\underline{\boldsymbol{a}}_{\text{fix}}$. The corresponding optimization problem is given by:

$$\mathcal{P}_3 : \begin{array}{ll} \underset{\boldsymbol{\Theta}}{\text{maximize}} & \frac{\left(\underline{\boldsymbol{a}}_{\text{fix}}^\dagger [\underline{\boldsymbol{H}}^e(\boldsymbol{\Theta})\, \boldsymbol{D}_\alpha\, \boldsymbol{1}_k]\right)^2}{\underline{\boldsymbol{a}}_{\text{fix}}^\dagger \underline{\boldsymbol{a}}_{\text{fix}}} \\ \text{subject to} & \boldsymbol{\Theta} = \text{diag}(e^{j\varphi_1}, \ldots, e^{j\varphi_M}) \end{array} \quad (10)$$

After some manipulations, the IS-based deflection in (6) can be recast as follows (isolating dependence on RIS phase-shifts):

$$D\left(\underline{\boldsymbol{a}}_{\text{fix}}, \boldsymbol{\Theta}\right) = (4\,/\,\sigma_w^2)\; \underline{\tilde{\boldsymbol{\theta}}}^\dagger \boldsymbol{\Xi}\left(\underline{\boldsymbol{a}}_{\text{fix}}\right) \underline{\tilde{\boldsymbol{\theta}}} \quad (11)$$

where $\tilde{\boldsymbol{\theta}} \triangleq \begin{bmatrix} e^{j\varphi_1} & \cdots & e^{j\varphi_M} & 1 \end{bmatrix}^T$ and

$$\boldsymbol{\Xi}\left(\underline{\boldsymbol{a}}_{\text{fix}}\right) \triangleq \|\underline{\boldsymbol{a}}_{\text{fix}}\|^{-2} \left(\boldsymbol{N}^\dagger \underline{\boldsymbol{a}}_{\text{fix}}\right) \left(\boldsymbol{N}^\dagger \underline{\boldsymbol{a}}_{\text{fix}}\right)^\dagger \quad (12)$$

In the latter term the matrix $\boldsymbol{N} \in \mathbb{C}^{2N \times 2(M+1)}$ has the following explicit expression:

$$\boldsymbol{N} \triangleq \begin{bmatrix} \begin{pmatrix} \boldsymbol{N}_r & \boldsymbol{n}_d \end{pmatrix} & \boldsymbol{O}_{N\times(M+1)} \\ \boldsymbol{O}_{N\times(M+1)} & \begin{pmatrix} \boldsymbol{N}_r & \boldsymbol{n}_d \end{pmatrix}^* \end{bmatrix} \quad (13)$$

where $\boldsymbol{N}_r \triangleq \boldsymbol{G}\,\text{diag}(\boldsymbol{H}^r\, \boldsymbol{D}_\alpha \boldsymbol{1}_K)$ and $\boldsymbol{n}_d \triangleq \left(\boldsymbol{H}^d\, \boldsymbol{D}_\alpha\, \boldsymbol{1}_K\right)$ (hence $\boldsymbol{N}_r \in \mathbb{C}^{N\times M}$ and $\boldsymbol{n}_d \in \mathbb{C}^{N\times 1}$). Therefore, optimization problem $\mathcal{P}_3$ can be recast as:

$$\mathcal{P}_4 : \begin{array}{ll} \underset{\tilde{\boldsymbol{\theta}}}{\text{maximize}} & g(\tilde{\boldsymbol{\theta}}) = \underline{\tilde{\boldsymbol{\theta}}}^\dagger \boldsymbol{\Xi}\left(\underline{\boldsymbol{a}}_{\text{fix}}\right) \underline{\tilde{\boldsymbol{\theta}}} \\ \text{subject to} & \{|\theta_m| = 1\}_{m=1}^M,\; \theta_{M+1} = 1 \end{array} \quad (14)$$

Due to modulus constraint of RIS elements, the problem is non-convex. To avoid cumbersome optimizations at the FC, we propose to solve $\mathcal{P}_4$ via the MM technique[3] [23].

In particular, assuming the value of $\tilde{\boldsymbol{\theta}}$ in the ℓth iteration of the AO is denoted as $\tilde{\boldsymbol{\theta}}^\star_{(\ell)}$, we construct a lower bound on the objective function $g(\tilde{\boldsymbol{\theta}})$ that touches the objective function at point $\tilde{\boldsymbol{\theta}}$, denoted as $f(\tilde{\boldsymbol{\theta}}|\tilde{\boldsymbol{\theta}}^\star_{(\ell)})$. We adopt this lower bound as a surrogate objective function, and the maximizer of this surrogate objective function is then taken as the value of $\tilde{\boldsymbol{\theta}}$ in the next iteration of the AO, i.e., $\tilde{\boldsymbol{\theta}}^\star_{(\ell+1)}$. In this way, the objective value is monotonically increasing from one iteration to the next, i.e., $g(\tilde{\boldsymbol{\theta}}^\star_{(\ell+1)}) \geq g(\tilde{\boldsymbol{\theta}}^\star_{(\ell)})$ and we have first-order optimality. The key to the success of MM lies in constructing a surrogate objective function $f(\tilde{\boldsymbol{\theta}}|\tilde{\boldsymbol{\theta}}^\star_{(\ell)})$ for which the maximizer $\tilde{\boldsymbol{\theta}}^\star_{(\ell+1)}$ is easy to find. For the phase-shift matrix optimization problem $\mathcal{P}_4$, a surrogate objective function is derived in what follows.

Since the objective function $g(\tilde{\boldsymbol{\theta}})$ is convex in $\tilde{\boldsymbol{\theta}}$, it is minorized by its first-order approximation:

$$\begin{aligned} g(\tilde{\boldsymbol{\theta}}) = \underline{\tilde{\boldsymbol{\theta}}}^\dagger \boldsymbol{\Xi}\left(\underline{\boldsymbol{a}}_{\text{fix}}\right) \underline{\tilde{\boldsymbol{\theta}}} \geq \\ f(\tilde{\boldsymbol{\theta}}|\tilde{\boldsymbol{\theta}}^\star_{(\ell)}) = \Re\left\{\left(\underline{\tilde{\boldsymbol{\theta}}}^\star_{(\ell)}\right)^\dagger \boldsymbol{\Xi}\left(\underline{\boldsymbol{a}}_{\text{fix}}\right) \underline{\tilde{\boldsymbol{\theta}}}\right\} + \text{const} \end{aligned} \quad (15)$$

where "const" refers to terms not depending on $\underline{\tilde{\boldsymbol{\theta}}}$. Accordingly, the phase-shift optimization problem in each iteration of the AO can be obtained as:

$$\mathcal{P}_5 : \tilde{\boldsymbol{\theta}}^\star_{(\ell+1)} = \underset{|\theta_m|=1,\, \theta_M=1}{\arg\max} \; \Re\left\{\left(\underline{\tilde{\boldsymbol{\theta}}}^\star_{(\ell)}\right)^\dagger \boldsymbol{\Xi}\left(\underline{\boldsymbol{a}}_{\text{fix}}\right) \underline{\tilde{\boldsymbol{\theta}}}\right\} \quad (16)$$

Remarkably, the optimal solution of $\mathcal{P}_5$ is in **closed-form**:

$$\angle \underline{\tilde{\boldsymbol{\theta}}}^\star_{(\ell+1)} = \angle \boldsymbol{\Xi}\left(\underline{\boldsymbol{a}}_{\text{fix}}\right) \underline{\tilde{\boldsymbol{\theta}}}^\star_{(\ell)} \quad (17)$$

The resulting design then alternates between the closed-form solutions in Eqs. (9) [**Step (A)**] and (17) [**Step (B)**]. Accordingly, the IS-based deflection in Eq. (6) is guaranteed to monotonically increase (by means of the alternating procedure) and converge to a local optimum. In this work, we select the initial point $\tilde{\boldsymbol{\theta}}^\star_{(0)}$ based on uniformly-generated random phase-shifts. The procedure, summarized in Algo. 1, is provably convergent in the value of the objective, since the objective function monotonically increases with the iteration number.

Algorithm 1 IS-based Joint Fusion Rule & RIS design via AO with MM.

1: Construct an initial $\tilde{\boldsymbol{\theta}}^\star_{(0)}$ and set $\ell = 0$;
2: **repeat**
3: Fix $\tilde{\boldsymbol{\theta}}^\star_{(\ell)}$ and optimize $\underline{\boldsymbol{a}}$ according to Eq. (9);
4: Fix $\underline{\boldsymbol{a}}$ and optimize $\tilde{\boldsymbol{\theta}}^\star_{(\ell+1)}$ via Eqs. (12) and (17);
5: Set $\ell \leftarrow \ell + 1$;
6: **until** convergence

The **computational complexity** of the proposed IS-based joint design is thus $\mathcal{O}(N_{\text{iter}}\,(C_{\text{fus}}+C_{\text{ris}}))$, where N_{iter} denotes

[3] Actually, we exploit the "dual" minorization-maximization formulation.

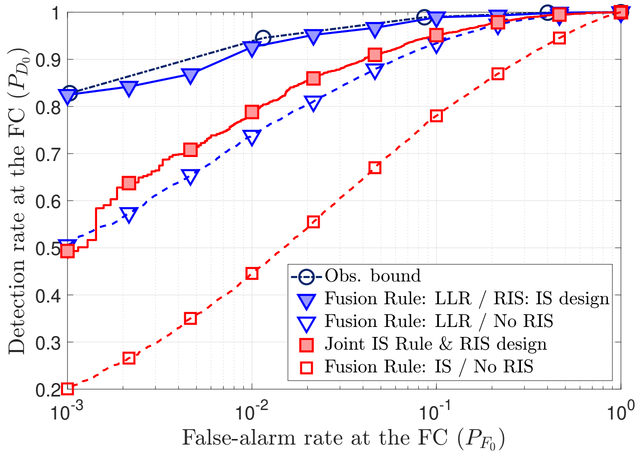

Fig. 1. P_{D_0} vs P_{F_0} of the considered rule/RIS configurations. WSN with $K = 10$ sensors, $(P_{D,k}, P_{F,k}) = (0.5, 0.05)$, $k \in \mathcal{K}$. $N = 4$ antennas at the FC, RIS with $M = 20$ elements; noise variance $\sigma_w^2 = -80$ dBm.

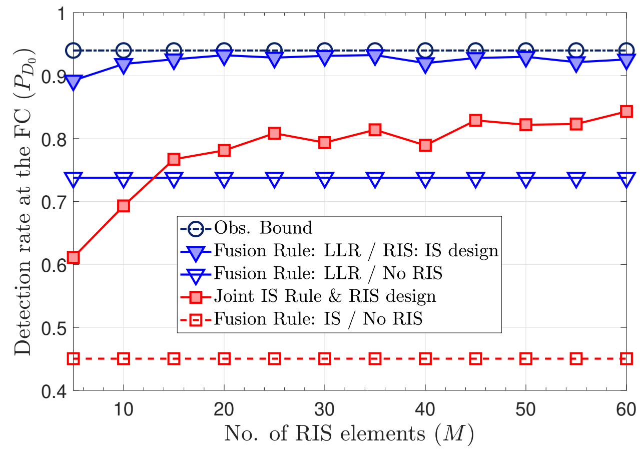

Fig. 2. P_{D_0} vs M (with $P_{F_0} = 0.01$) of the considered rule/RIS configurations. WSN with $K = 10$ sensors, $(P_{D,k}, P_{F,k}) = (0.5, 0.05)$, $k \in \mathcal{K}$. $N = 4$, noise variance $\sigma_w^2 = -80$ dBm.

the number of (complete) iterations of the AO procedure, while C_{fus} (resp. C_{ris}) denotes the cost of the WL vector fusion (RIS phase-shift matrix) design step. It can be shown that the former cost equals $\mathcal{O}(M + MN + N)$ while the latter requires a complexity $\mathcal{O}((M+1)^2 + MN + N)$.

IV. Simulation Results

We consider a WSN made of $K = 10$ sensors with equal transmit energy ($\alpha_k = 1$), whose local decisions on the phenomenon of interest are conditionally independent and identically distributed (i.i.d.), i.e., $P(\boldsymbol{x}|\mathcal{H}_i) = \prod_{k=1}^{K} P(x_k|\mathcal{H}_i)$, $(P_{D,k}, P_{F,k}) \triangleq (0.5, 0.05)$, $k \in \mathcal{K}$, as adopted in [8].

In the following simulations, we generate the small-scale fading coefficients according to Rayleigh channels. Differently, the path loss model considered is $\mu\,(d/d_0)^{-\nu}$ where $\mu = -30\,\text{dB}$ is the path loss at the reference distance of 1 m. The path loss exponent ν is set to 2 for both WSN-to-RIS and RIS-to-FC links, and 4 for WSN-FC links. The locations of the WSN, RIS and FC are as follows: the sensors are uniformly distributed at random in the square $[0, 40] \times [0, 40]\,\text{m}^2$, while the RIS and the FC are located at $[60, 20]\,\text{m}$ and $[65, 25]\,\text{m}$, respectively. The noise variance σ_w^2 is set to -80 dBm.

Herein, we analyze the performance of the fusion rules in terms of the probabilities of *false alarm* $P_{F_0} \triangleq \Pr\{\Lambda > \gamma|H_0\}$ and *detection* $P_{D_0} \triangleq \Pr\{\Lambda > \gamma|H_1\}$. As a relevant benchmark to assess detection degradation due to the interfering distributed MIMO channel (and the benefit arising from the RIS aid), we also report the "observation upper bound", i.e. the performance of the optimal decision fusion rule in an **ideal** channel condition, given by $P_{D_0}^{\text{ob}} = \sum_{i=\nu}^{K} \binom{K}{i} (P_D)^i (1 - P_D)^{K-i}$ and $P_{F_0}^{\text{ob}} = \sum_{i=\nu}^{K} \binom{K}{i} (P_F)^i (1 - P_F)^{K-i}$, where $\nu \in \{0, \dots K\}$ is a discrete threshold.

In Fig. 1 we show the receiver operating characteristic (i.e. P_{D_0} vs P_{F_0}), for the presented rules in a WSN with $N = 4$ antennas at the FC, under a channel with $M = 20$ RIS elements. By looking at the performance, the proposed joint design (denoted with "■") is able to **significantly improve** the performance with respect to an IS-based fusion rule not aided by a RIS [18], [22] (denoted with "□"). In the considered scenario, the joint design is also able to outperform the LLR without a RIS (denoted with "▽"). Remarkably, the IS-based RIS design is also **generally beneficial** for the detection capabilities of the WSN, as shown by the improvement of the LLR when the proposed IS-based design is leveraged to set the phase-shifts of the RIS (denoted with "▼").

Then, Fig. 2 we report the P_{D_0} (for a fixed false-alarm rate, set to $P_{F_0} = 0.01$) versus the number of RIS elements (M) to investigate the improvement achievable considering a larger RIS. By looking at the trend with M, the IS design on the RIS improves the detection performance as the number of elements increases. Still, while for joint IS design, there is a settlement of performance achieved at $M \approx 40$, for the LLR the saturation is achieved at $M \approx 20$. This is mainly due to the LLR hitting the maximum achievable performance represented by the observation bound.

V. Conclusions and Future Directions

This work is a first attempt in the use of RIS for aiding channel-aware decision fusion in a distributed MIMO setup. To circumvent the computational complexity and the unavailability of closed-form performance for the LLR, we have devised a sensor-agnostic joint RIS & fusion rule design based on the IS assumption. The resulting non-convex optimization has been tackled via AO and MM frameworks, providing a simple ping-pong closed-form optimization procedure. Simulation results have shown the appeal in the use of a RIS to aid WSNs in performing DD task (even in the case of sub-optimal design), similarly to analogous decentralized inference scenarios (e.g. estimation). Future directions will deal with: more sophisticated joint RIS & fusion rule design; exploitation of multiple RISs; design based on practical RIS constraints (e.g. discrete shift alphabets); imperfect channel state information.

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