ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) | 978-1-7281-6327-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICASSP49357.2023.10095996

# SPARSE BAYESIAN LEARNING ASSISTED DECISION FUSION IN MILLIMETER WAVE MASSIVE MIMO SENSOR NETWORKS

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## ABSTRACT

This paper investigates decision fusion in millimeter wave (mmWave) massive multiple-input multiple-output (MIMO) wireless sensor network (WSNs), where the sparse Bayesian learning (SBL) algorithm is employed to estimate the channel between the sensors and the fusion center (FC). We present low-complexity fusion rules based on the hybrid combining architecture for the considered framework. Further, a deflection coefficient maximization-based optimization framework is developed to determine the transmit signaling matrix that can improve detection performance. The performance of the proposed fusion rule is presented through simulation results demonstrating the validation of the analytical findings.

***Index Terms*—** Distributed detection, hybrid combining, massive MIMO, mmWave communication, sparse Bayesian learning, wireless sensor networks.

## 1. INTRODUCTION

Wireless sensor networks (WSNs) are conceived to play a pivotal role in next-generation wireless systems due to their applicability in diverse domains related to surveillance, disaster management, health care, and several others [1]. In such systems, the sensors typically transmit their local decisions about an observed phenomenon to a fusion center (FC) for a global decision obtained using a suitably designed fusion rule, which is termed decision fusion [2].

The growing interest in such applications, along with the drastic increase in the number of sensors, results in severe bandwidth scarcity in the sub-6 GHz band. To overcome this challenge, millimeter wave (mmWave) technology, which leverages the spectrum ranging from 30 - 300 GHz, has shown significant potential in realizing bandwidth-intensive and high-speed applications in next-generation wireless networks [3]. However, practical concerns arise in implementing the mmWave technology, such as higher path losses, severe signal blockages, and increased hardware complexity. In this context, massive MIMO technology, where a large antenna array is deployed at the FC to simultaneously communicate with multiple sensors using the same time-frequency resource, serves as a promising solution [4]. Further, the short wavelength of mmWave signals enables the close packing of a large number of antennas within limited physical dimensions, which helps in realizing practical mmWave massive MIMO systems. In such systems, the use of conventional fully digital baseband signal processing (DSP) architectures, which require a dedicated radio frequency (RF) chain per antenna, seems practically infeasible because of its high cost, complexity, and high power consumption. Thus, hybrid combining-based architecture, wherein the signal is processed in both the analog and digital domains, has shown to be well suited for mmWave massive MIMO systems as one can significantly reduce the number of RF chains and hence the power consumption [5].

The advantages offered by hybrid combining architecture may serve beneficial for decision fusion in mmWave massive MIMO WSNs. In this context, distributed detection for massive MIMO WSN has been investigated in [6–8]. Further, fusion rules are designed for the mmWave massive MIMO WSN in [9, 10]. However, the proposed analysis is restricted to the perfect CSI scenario. Considering the imperfect CSI scenario, sparse Bayesian learning (SBL) based fusion rules are determined in [11] for data fusion in mmWave massive MIMO WSN, wherein the sensors transmit their measurements instead of their decisions to the FC. However, *none of the existing works have proposed fusion rules for decision fusion in mmWave massive MIMO WSNs considering imperfect CSI.* The novelty of our work can be summarized as follows: $(i)$ we exploit the joint advantages of mmWave and massive MIMO to design low-complexity fusion rules for decision fusion in a scenario where sensors transmit their binary decision vectors over one or more signaling intervals corresponding to their local decisions [12], which are susceptible to errors, to a massive antenna equipped FC over a mmWave channel; $(ii)$ proposed fusion rules utilize the hybrid combining architecture, i.e. fewer RF chains as compared to a fully-DSP architecture, thus reducing the energy consumption associated with A/D components; $(iii)$ the detection rules account for a realistic scenario with imperfect CSI, where the channel is estimated using the novel SBL framework; $(iv)$ deflection coefficient maximization based transmit signaling matrix is derived to enhance the detection performance. The proposed fusion rules and the corresponding theoretical analysis in terms of closed-form expressions of probabilities of detection and false alarm are crucial to facilitate reliable decision-making by processing massive amount of sensor data related to mission-critical applications. Moreover, the simulation results assessed our analytical findings and examined the impact of the number of receive antennas and the number of signaling intervals on the system performance.

## 2. SYSTEM MODEL

Consider a distributed binary test of hypotheses, where $K$ single-antenna sensors observe a phenomenon of interest to distinguish between the hypotheses in the set $\mathcal{H} = \{\mathcal{H}_0, \mathcal{H}_1\}$. Based on its measurement, the $k$th sensor, $k \in \mathcal{K} \triangleq \{1, 2, ..., K\}$, makes a local decision about the observed phenomenon and transmits a vector $\mathbf{x}_k = [x_k(1), x_k(2), \dots, x_k(L)]^T$ over $L$ signaling intervals about the presence/absence of the phenomenon of interest. Under an an-

[0]This work was partially supported by the Research Council of Norway under the Project 311902 (SIGNIFY) within the framework IKTPLUSS.

**Algorithm 1:** SBL-assisted CSI estimation in mmWave massive MIMO sensor networks

**Input :** Sensing matrix $\mathbf{Q}$, pilot output $\mathbf{y}$, pilot power $p_p$ and stopping parameter $\epsilon$

**Initialization:** $\widehat{\mathbf{\Gamma}}^{(0)} = \mathbf{I}_{MK}$

Set $s = 0$ and $\widehat{\mathbf{\Gamma}}^{(-1)} = \mathbf{0}_{MK \times MK}$

**while** $\|\hat{\mathbf{\Gamma}}^{(s)} - \hat{\mathbf{\Gamma}}^{(s-1)}\|_F > \epsilon$ **do**

  **E-step:** Evaluate *a posteriori* covariance and mean

  $\mathbf{\Sigma}^{(s)} = \left(p_p \mathbf{Q}^H \mathbf{C}_w^{-1} \mathbf{Q} + \left(\widehat{\mathbf{\Gamma}}^{(s)}\right)^{-1}\right)^{-1}$

  $\boldsymbol{\mu}^{(s)} = \sqrt{p_p} \mathbf{\Sigma}^{(s)} \mathbf{Q}^H \mathbf{C}_w^{-1} \mathbf{y}$

  **M-step:** Evaluate hyperparameter estimates

  **for** $j = 1, 2, \ldots, MK$ **do**

   $\left[\widehat{\mathbf{\Gamma}}^{(s+1)}\right]_{j,j} = \left[\mathbf{\Sigma}^{(s)}\right]_{j,j} + \left|\left[\boldsymbol{\mu}^{(s)}\right]_j\right|^2$

  **end for**

  $s \leftarrow s + 1$

**end while**

**Output:** $\hat{\mathbf{h}}_b = \boldsymbol{\mu}^{(s)}$

tipodal signaling scheme, the $k$th sensor transmits $\mathbf{x}_k \in \{-\mathbf{u}_k, \mathbf{u}_k\}$ indicating the absence ($\mathcal{H}_0$) or the presence ($\mathcal{H}_1$) of the phenomenon of interest. Further, the local probabilities of false alarm and detection of the $k$th sensor are defined as $P_{F,k} = P(\mathbf{x}_k = \mathbf{u}_k | \mathcal{H}_0)$ and $P_{D,k} = P(\mathbf{x}_k = \mathbf{u}_k | \mathcal{H}_1)$, respectively.

The sensors communicate with a fusion center (FC) equipped with $M$ antennas and $N$ radio frequency (RF) chains over a wireless flat-fading multiple access channel (MAC), where $M \gg K$ and $N = K$, which implies that each sensor can communicate with the FC via a single data stream. Let $\mathbf{G} = \mathbf{A}_R \mathbf{H}_b \in \mathbb{C}^{M \times K}$ be the mmWave channel matrix from the $K$ sensors to the FC, $\mathbf{A}_R \triangleq [\mathbf{a}_R(\psi_1), \mathbf{a}_R(\psi_2), \ldots, \mathbf{a}_R(\psi_M)] \in \mathbb{C}^{M \times M}$ be the quantized receive array response dictionary matrix, where the set of quantized angle of arrival (AoA) $\Psi_R = \{\psi_v, \forall 1 \leq v \leq M\}$ spans the angular range $[0, \pi]$ such that $\sin(\psi_v) = \frac{2}{M}(v-1) - 1, \forall v$ [13] and $\mathbf{H}_b \in \mathbb{C}^{M \times K}$ be the equivalent beamspace channel matrix. Further, the receive array response vector $\mathbf{a}_R(\psi_v)$ is defined as $\mathbf{a}_R(\psi_v) = \frac{1}{\sqrt{M}}[1, e^{j\frac{2\pi d}{\lambda}\sin(\psi_v)}, \ldots, e^{j\frac{2\pi d}{\lambda}\sin(\psi_v)(M-1)}]^T$, where $d$ is the receive antenna spacing and $\lambda$ is the operating wavelength. When the angle grids $\psi_v$ satisfy the condition $\sin(\psi_v) = \frac{2}{M}(v-1) - 1, \forall v$ and $d = \lambda/2$, then $\mathbf{A}_R \mathbf{A}_R^H = \mathbf{A}_R^H \mathbf{A}_R = \mathbf{I}_M$ [13]. Therefore, the received signal $\mathbf{Y} \in \mathbb{C}^{M \times L}$ at the FC corresponding to $L$ signaling intervals is given by

$$\mathbf{Y} = \sqrt{p_u} \mathbf{G} \mathbf{X} + \mathbf{N}, \tag{1}$$

where $p_u$ is the average transmit power of each sensor, $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_K]^T \in \mathbb{C}^{K \times L}$ is the transmitted signal matrix and the noise matrix $\mathbf{N}$ has i.i.d entries, distributed as $n_{i,j} \sim \mathcal{CN}(0, \sigma_n^2)$.

## 3. CHANNEL ESTIMATION

For channel estimation, consider the transmission of a block of $N_f = M/K$ training frames such that the channel is assumed to be constant over $N_f$ frames. Therefore, the received signal $\mathbf{Y}^{(n)} \in \mathbb{C}^{K \times K}$ at the FC during the $n$th training frame can be expressed as $\mathbf{Y}^{(n)} = \sqrt{p_p}(\mathbf{F}^{(n)})^H \mathbf{G} \mathbf{X}_p + (\mathbf{F}^{(n)})^H \mathbf{N}$, where the training RF combiner $\mathbf{F}^{(n)} \in \mathbb{C}^{M \times K}$ during the $n$th frame is chosen as the submatrix of the normalized DFT matrix $\mathbf{F} \in \mathbb{C}^{M \times M}$, the orthogonal training matrix $\mathbf{X}_p$ is chosen as $\mathbf{I}_K$ and $p_p$ is the training power. After stacking $N_f$ RF combiner outputs, the equivalent system model can be expressed as

$$\mathbf{Y} = \sqrt{p_p} \mathbf{F}^H \mathbf{G} \mathbf{X}_p + \mathbf{F}^H \mathbf{N}, \tag{2}$$

where $\mathbf{F} = \left[\mathbf{F}^{(1)}, \mathbf{F}^{(2)}, \ldots, \mathbf{F}^{(N_f)}\right] \in \mathbb{C}^{M \times M}$ is the equivalent training RF combiner. On stacking the columns of the matrix $\mathbf{Y}$ one below another, one obtains

$$\mathbf{y} = \sqrt{p_p} \mathbf{Q} \mathbf{h}_b + \mathbf{w}, \tag{3}$$

where $\mathbf{Q} = (\mathbf{X}_p^T \otimes \mathbf{F}^H)(\mathbf{I}_K \otimes \mathbf{A}_R) \in \mathbb{C}^{MK \times MK}$ is the equivalent sensing matrix such that $\mathbf{Q}^H \mathbf{Q} = \mathbf{I}_{MK}$, $\mathbf{h}_b = \text{vec}(\mathbf{H}_b)$ is the vectorized version of the matrix $\mathbf{H}_b$ and $\mathbf{w} = \text{vec}(\mathbf{F}^H \mathbf{N}) \sim \mathcal{CN}(\mathbf{0}, \mathbf{C}_w)$ is the equivalent noise vector with $\mathbf{C}_w = \sigma_n^2 \mathbf{I}_{MK}$. Using the received observation vector $\mathbf{y}$ in (3), the SBL estimate of the beamspace channel vector $\mathbf{h}_b$ can be determined as discussed in Algorithm 1. By virtue of EM algorithm properties, the convergence of SBL algorithm is guaranteed to a fixed point of the log-likelihood function, irrespective of initialization, which renders its performance robust and ideally suited for mmWave channel estimation. Further, it yields the maximally-sparse solution and guaranteed convergence at a low number of iterations.

Upon convergence, the estimated beamspace channel vector can be expressed as $\hat{\mathbf{h}}_b = \boldsymbol{\mu}^{(s)}$, where $\boldsymbol{\mu}^{(s)}$ is the *a posteriori* mean, and the *a posteriori* covariance matrix is given by $\mathbf{\Sigma} = \mathbf{\Sigma}^{(s)} \in \mathbb{C}^{MK \times MK}$, which is diagonal. Using the above quantities, the SBL estimate of $\mathbf{G}$ can be given as $\hat{\mathbf{G}} = \mathbf{A}_R \hat{\mathbf{H}}_b$ [14], where $\hat{\mathbf{H}}_b = \text{vec}^{-1}(\hat{\mathbf{h}}_b)$. Let $\boldsymbol{\mathcal{E}}_b = \hat{\mathbf{H}}_b - \mathbf{H}_b$ be the beamspace estimation error matrix, $\boldsymbol{\mathcal{E}} = [\mathbf{e}_1, \ldots, \mathbf{e}_K] = \hat{\mathbf{G}} - \mathbf{G} = \mathbf{A}_R \boldsymbol{\mathcal{E}}_b$ be the estimation error matrix and $\mathbf{e}_k \sim \mathcal{CN}(\mathbf{0}, \mathbf{C}_{e_k})$ is the $k$th sensor estimation error with $\mathbf{C}_{e_k} = \mathbf{A}_R \mathbf{\Sigma}_k \mathbf{A}_R^H$ and $\mathbf{\Sigma}_k = \mathbf{\Sigma}[(k-1)M + 1 : kM, (k-1)M + 1 : kM]$.

## 4. FUSION RULE DESIGN

Using the estimated channel, the signal received at the FC can be remodeled as

$$\mathbf{Y} = \sqrt{p_u} \hat{\mathbf{G}} \mathbf{X} - \sqrt{p_u} \boldsymbol{\mathcal{E}} \mathbf{X} + \mathbf{N}. \tag{4}$$

For the above system model, the optimal fusion rule, i.e. the log-likelihood ratio (LLR) test is formulated as

$$T(\mathbf{Y}) = \ln\left[\frac{p(\mathbf{Y}|\hat{\mathbf{G}}, \mathcal{H}_1)}{p(\mathbf{Y}|\hat{\mathbf{G}}, \mathcal{H}_0)}\right], \tag{5}$$

where $\gamma$ is the detection threshold and can be obtained using the Neyman-Pearson criterion or Bayesian approach [15]. Exploiting the independence of $\mathbf{Y}$ from $\mathcal{H}_i$, given $\mathbf{X}$, an explicit expression of the LLR in (5) is determined as

$$T(\mathbf{Y}) = \ln\left[\frac{\sum_{\mathbf{X}} p(\mathbf{Y}|\hat{\mathbf{G}}, \mathbf{X}) P(\mathbf{X}|\mathcal{H}_1)}{\sum_{\mathbf{X}} p(\mathbf{Y}|\hat{\mathbf{G}}, \mathbf{X}) P(\mathbf{X}|\mathcal{H}_0)}\right]. \tag{6}$$

Unfortunately, the above test has exponential computational complexity with the number of sensors $K$ and requires the knowledge of $P(\mathbf{X}|\mathcal{H}_i)$ and $\hat{\mathbf{G}}$. Hence, the test becomes numerically intractable. To overcome this challenge, a two-step architecture is employed to design sub-optimal decision fusion rules with a simpler implementation. The first step utilizes a hybrid combining architecture at the FC denoted by $\mathbf{W} = \mathbf{W}_{\text{RF}}\mathbf{W}_{\text{BB}} \in \mathbb{C}^{M\times K}$, where $\mathbf{W}_{\text{RF}}$ and $\mathbf{W}_{\text{BB}}$ represent the analog and digital combiners, respectively. The processed signals are further combined in the second step to form a final decision. The RF combiner $\mathbf{W}_{\text{RF}} = [\mathbf{a}_R(\psi_{j_1}), \mathbf{a}_R(\psi_{j_2}), \ldots, \mathbf{a}_R(\psi_{j_K})] \in \mathbb{C}^{M\times K}$ is designed by selecting the receive array response vectors for each sensor corresponding to the indices of the maximum estimated path gains in $\hat{\mathbf{H}}_b$ such that $j_k$ denotes the index in the $k$th column of $\hat{\mathbf{H}}_b$ linked with the maximum estimated path gain. Further, the baseband combiner is determined as $\mathbf{W}_{\text{BB}} = \mathbf{W}_{\text{RF}}^H\hat{\mathbf{G}} \in \mathbb{C}^{K\times K}$. Under the assumption that different AoAs are assigned to different sensors and exploiting the asymptotic orthogonality property of the mmWave massive MIMO channel [16], the baseband combiner $\mathbf{W}_{\text{BB}}$ can be approximated as a diagonal matrix with its $k$th diagonal entry as $[\mathbf{W}_{\text{BB}}]_{k,k} = \hat{h}_{j_k,k} = [\hat{\mathbf{H}}_b]_{j_k,k}$. Consequently, the hybrid combiner output of the $k$th sensor can be approximated as

$$\mathbf{z}_k \approx \sqrt{p_u}\breve{g}_k\mathbf{x}_k + \boldsymbol{\eta}_k, \tag{7}$$

where $\breve{g}_k = |\hat{h}_{j_k,k}|^2$ and $\boldsymbol{\eta}_k \sim \mathcal{CN}(\mathbf{0}, \sigma^2_{\eta_k}\mathbf{I}_L)$ with $\sigma^2_{\eta_k} = p_u\breve{g}_k\mathbf{a}_R^H(\psi_{j_k})\mathbf{A}_R(\sum_{i=1}^K \mathbf{C}_{e_i})\mathbf{A}_R^H\mathbf{a}_R(\psi_{j_k}) + \breve{g}_k\sigma_w^2$ is the equivalent noise vector. Using the hybrid combiner outputs of $K$ sensors, the LLR test for decision fusion in mmWave massive MIMO WSN considering CSI uncertainty can be formulated as

$$T(\mathbf{Z}) = \ln\left[\frac{p(\mathbf{Z}|\mathcal{H}_1)}{p(\mathbf{Z}|\mathcal{H}_0)}\right] = \ln\left[\prod_{k=1}^{K}\frac{p(\mathbf{z}_k|\mathcal{H}_1)}{p(\mathbf{z}_k|\mathcal{H}_0)}\right] \tag{8}$$

$$= \sum_{k=0}^{K-1}\ln\left[\frac{P_{D,k}+(1-P_{D,k})\exp\left(-4\sqrt{p_u}\breve{g}_k\Re\left(\frac{\mathbf{z}_k^H\mathbf{u}_k}{\sigma^2_{\eta_k}}\right)\right)}{P_{F,k}+(1-P_{F,k})\exp\left(-4\sqrt{p_u}\breve{g}_k\Re\left(\frac{\mathbf{z}_k^H\mathbf{u}_k}{\sigma^2_{\eta_k}}\right)\right)}\right], \tag{9}$$

where the expression in (8) is obtained by exploiting the independence of $\mathbf{z}_k$ across different sensors. Further, the above test can be simplified for the low SNR regime by leveraging the approximations $e^{-x} \approx 1 - x$ and $\ln(1 + x) \approx x$, as

$$T(\mathbf{Z}) = \sum_{k=0}^{K-1} a_k\breve{g}_k\Re\left(\frac{\mathbf{z}_k^H\mathbf{u}_k}{\sigma^2_{\eta_k}}\right) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma', \tag{10}$$

where $a_k \triangleq P_{D,k} - P_{F,k}$. Observe that the test $T(\mathbf{Z})$ in (10) has a linear structure and hence, low computational complexity. Moreover, the proposed detector for the low SNR regime is appropriate for practical implementation as WSNs are usually resource-constrained, especially in terms of transmit power. The detection performance of the above test is discussed in the theorem below.

**Theorem 1.** *For mmWave massive MIMO WSN, the probabilities of detection* ($P_D$) *and false alarm* ($P_{FA}$) *for the fusion rule in* (10) *can be determined as*

$$P_D = Q\left(\frac{\gamma' - \mu_{T|\mathcal{H}_1}}{\sigma_{T|\mathcal{H}_1}}\right), P_{FA} = Q\left(\frac{\gamma' - \mu_{T|\mathcal{H}_0}}{\sigma_{T|\mathcal{H}_0}}\right),$$

*where the mean* $\mu_{T|\mathcal{H}_i}$ *and the variance* $\sigma^2_{T|\mathcal{H}_i}$ *are defined as*

$$\mu_{T|\mathcal{H}_i} = \sum_{k=0}^{K-1}\frac{\sqrt{p_u}}{\sigma^2_{\eta_k}}a_k b_k^i\breve{g}_k^2\|\mathbf{u}_k\|^2, \tag{11}$$

$$\sigma^2_{T|\mathcal{H}_i} = \sum_{k=0}^{K-1}a_k^2\frac{\breve{g}_k^2}{\sigma^2_{\eta_k}}\|\mathbf{u}_k\|^2\left(\frac{p_u}{\sigma^2_{\eta_k}}\breve{g}_k^2\|\mathbf{u}_k\|^2\left(1-(b_k^i)^2\right)+\frac{1}{2}\right), \tag{12}$$

*where* $b_k^0 = 2P_{F,k} - 1$ *and* $b_k^1 = 2P_{D,k} - 1$.

The fusion rule in (9) can be further simplified for the high SNR regime by exploiting the max-log approximation [17], as $T_{\text{max-log}}(\mathbf{Z}) = \sum_{k=0}^{K-1} T_{\text{max-log}}(\mathbf{z}_k)$. Further, the sensor $T_{\text{max-log}}(\mathbf{z}_k)$ can be expressed as

$$T_{\text{max-log}}(\mathbf{z}_k) = \begin{cases}\gamma_{1,k}, & s_k < \alpha_{1,k}\\ 2s_k + \gamma_{2,k}, & \alpha_{1,k} \le s_k < \alpha_{2,k}\\ \gamma_{3,k}, & s_k \ge \alpha_{2,k}\end{cases}, \tag{13}$$

where $s_k = \exp(2\sqrt{p_u}\breve{g}_k\Re\{(\mathbf{z}_k^H\mathbf{u}_k)/\sigma^2_{\eta_k}\})$, $\gamma_{1,k} = \ln((1 - P_{D,k})/(1 - P_{F,k}))$, $\gamma_{2,k} = \ln(P_{D,k}/(1 - P_{F,k}))$, $\gamma_{2,k} = \ln(P_{D,k}/P_{F,k})$, $\alpha_{1,k} = \ln((1 - P_{D,k})/P_{D,k})/2$ and $\alpha_{2,k} = \ln((1 - P_{F,k})/P_{F,k})/2$.

## 5. TRANSMIT SIGNALING MATRIX DESIGN

This section presents a deflection coefficient maximization-based optimization framework to design the signaling matrix $\mathbf{X}$ to improve the detection performance of the proposed fusion rule. Consider a vector $\mathbf{u} \in \mathbb{C}^{KL\times 1}$, obtained by the column-wise stacking of the matrix $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_K] \in \mathbb{C}^{L\times K}$, i.e., $\mathbf{u} = \text{vec}(\mathbf{U})$. For the signaling vector $\mathbf{u}$, the deflection metric can be expressed as [15]

$$d^2(\mathbf{u}) = \frac{(\mu_{T|\mathcal{H}_1} - \mu_{T|\mathcal{H}_0})^2}{\sigma^2_{T|\mathcal{H}_0}}. \tag{14}$$

On substituting the quantities $\mu_{T|\mathcal{H}_1}$, $\mu_{T|\mathcal{H}_0}$ and $\sigma^2_{T|\mathcal{H}_0}$ from Theorem 1, the above expression reduces to

$$d^2(\mathbf{u}) = \frac{\left(\sum\limits_{k=0}^{K-1}\frac{\sqrt{p_u}}{\sigma^2_{\eta_k}}a_k\breve{g}_k^2(b_k^1 - b_k^0)\|\mathbf{u}_k\|^2\right)^2}{\sum\limits_{k=0}^{K-1}\frac{a_k^2}{\sigma^2_{\eta_k}}\breve{g}_k^2\|\mathbf{u}_k\|^2\left(\frac{p_u}{\sigma^2_{\eta_k}}\breve{g}_k^2\|\mathbf{u}_k\|^2\left(1-(b_k^0)^2\right)+\frac{1}{2}\right)}. \tag{15}$$

Let the diagonal elements of the matrices $\boldsymbol{\Theta} \in \mathbb{C}^{K\times K}$, $\boldsymbol{\Gamma} \in \mathbb{C}^{K\times K}$ and $\boldsymbol{\Psi} \in \mathbb{C}^{K\times K}$ be defined as

$$[\boldsymbol{\Theta}]_{k,k} = \frac{\sqrt{p_u}}{\sigma^2_{\eta_k}}a_k\breve{g}_k^2(b_k^1 - b_k^0), [\boldsymbol{\Gamma}]_{k,k} = \frac{\sqrt{p_u}}{\sigma^2_{\eta_k}}a_k\breve{g}_k^2\sqrt{1 - (b_k^0)^2},$$

$$[\boldsymbol{\Psi}]_{k,k} = \frac{a_k^2}{2\sigma^2_{\eta_k}}\breve{g}_k^2.$$

Using the above quantities, the deflection measure in (15) can be approximated as $d^2(\mathbf{u}) \approx \frac{(\mathbf{u}^H\boldsymbol{\Theta}\mathbf{u})^2}{(\mathbf{u}^H\boldsymbol{\Gamma}\mathbf{u})^2+\mathbf{u}^H\boldsymbol{\Psi}\mathbf{u}}$. However, the above expression is non-convex, hence, its direct maximization is difficult. To obtain a tractable solution, $d^2(\mathbf{u})$ can be modified as

$$d^2(\mathbf{u}) \approx \frac{\mathbf{u}^H\boldsymbol{\Lambda}\mathbf{u}}{\mathbf{u}^H\boldsymbol{\Omega}\mathbf{u}}, \tag{16}$$

where the matrices $\boldsymbol{\Lambda}$ and $\boldsymbol{\Omega}$ are defined as $\boldsymbol{\Lambda} = \boldsymbol{\Theta}\mathbf{u}\mathbf{u}^H\boldsymbol{\Theta}^H$ and $\boldsymbol{\Omega} = \boldsymbol{\Gamma}\mathbf{u}\mathbf{u}^H\boldsymbol{\Gamma}^H + \boldsymbol{\Psi}$, which are dependent on $\mathbf{u}$. Similar to the standard form of the Rayleigh quotient, the objective function can be further simplified as

$$\max.\frac{\mathbf{u}^H\boldsymbol{\Lambda}\mathbf{u}}{\mathbf{u}^H\boldsymbol{\Omega}^{\frac{1}{2}}\boldsymbol{\Omega}^{\frac{1}{2}}\mathbf{u}} = \max.\frac{\mathbf{v}^H\boldsymbol{\Omega}^{-\frac{1}{2}}\boldsymbol{\Lambda}\boldsymbol{\Omega}^{-\frac{1}{2}}\mathbf{v}}{\mathbf{v}^H\mathbf{v}} = \max.\frac{\mathbf{v}^H\boldsymbol{\Xi}\mathbf{v}}{\mathbf{v}^H\mathbf{v}}, \tag{17}$$

where the matrix $\boldsymbol{\Xi}$ and the vector $\mathbf{v}$ are given by $\boldsymbol{\Xi} = \boldsymbol{\Omega}^{-\frac{1}{2}}\boldsymbol{\Lambda}\boldsymbol{\Omega}^{-\frac{1}{2}}$ and $\mathbf{v} = \boldsymbol{\Omega}^{\frac{1}{2}}\mathbf{u}$. Now, the optimization problem can be solved iteratively and its solution during the $i$th iteration is discussed below.

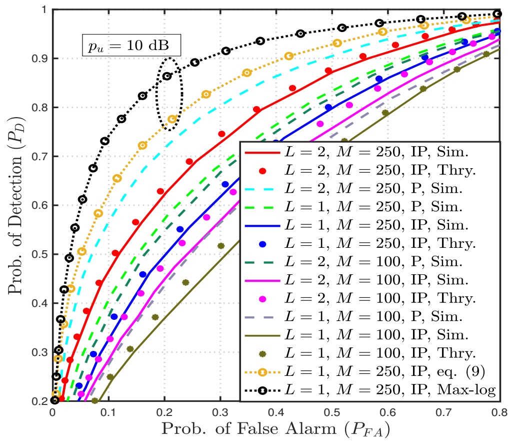


**Fig. 1**: Theoretical and simulated performance comparison of $T(\mathbf{Z})$ for varying $L \in \{1, 2\}$ and $M = \{100, 250\}$ in a WSN with $p_p = 5$ dB and SNR $p_u = \{-18, 10\}$ dB.

**Theorem 2.** *The ith iteration signaling vector* $\mathbf{u}^{(i)}$ *that aims to enhance the detection performance of the proposed fusion rule in* (10) *for mmWave massive MIMO WSN can be expressed as* $\mathbf{u}^{(i)} = \left(\boldsymbol{\Omega}\left(\mathbf{u}^{(i-1)}\right)\right)^{-\frac{1}{2}} \mathbf{v}^{(i)}$*, where the ith iteration vector* $\mathbf{v}^{(i)}$ *can be obtained by solving the objective function*

$$\max_{\mathbf{v}^{(i)}} . \ \frac{\mathbf{v}^{(i)H} \boldsymbol{\Xi}(\mathbf{u}^{(i-1)}) \mathbf{v}^{(i)}}{\mathbf{v}^{(i)H} \mathbf{v}^{(i)}}, \tag{18}$$

*where the vector* $\mathbf{v}^{(i)} = \left(\boldsymbol{\Omega}\left(\mathbf{u}^{(i-1)}\right)\right)^{\frac{1}{2}} \mathbf{u}^{(i)}$ *and the matrix* $\boldsymbol{\Xi}\left(\mathbf{u}^{(i-1)}\right) = \left(\boldsymbol{\Omega}\left(\mathbf{u}^{(i-1)}\right)\right)^{-\frac{1}{2}} \boldsymbol{\Lambda}\left(\mathbf{u}^{(i-1)}\right) \left(\boldsymbol{\Omega}\left(\mathbf{u}^{(i-1)}\right)\right)^{-\frac{1}{2}}$*. The matrices* $\boldsymbol{\Omega}\left(\mathbf{u}^{(i-1)}\right)$ *and* $\boldsymbol{\Lambda}\left(\mathbf{u}^{(i-1)}\right)$ *are evaluated by replacing* $\mathbf{u}$ *with* $\mathbf{u}^{(i)}$ *in* (16) *with the matrix* $\mathbf{U}^{(0)}$ *during the 0th iteration initialized to a semi-orthogonal matrix.*

The solution to the problem in (18) during the $i$th iteration is given as $\mathbf{v}^{(i)} = \kappa \boldsymbol{\nu}^{(i-1)}$, where $\kappa$ is the power scaling factor and $\boldsymbol{\nu}^{(i-1)}$ is the eigenvector associated with the maximum eigenvalue of $\boldsymbol{\Xi}^{(i-1)}$. Hence, the transmit signaling vector for the $i$th iteration can be given as $\mathbf{u}^{(i)} = \kappa \left(\boldsymbol{\Omega}\left(\mathbf{u}^{(i-1)}\right)\right)^{-\frac{1}{2}} \boldsymbol{\nu}^{(i-1)}$.

## 6. SIMULATION RESULTS

For simulations, $K = 12$ sensors are assumed to be deployed within an annular region $[r_0, R]$, where $R = 200$ m is the cell radius and $r_0 = 1$ m is the minimum distance between the FC and the sensors. The FC, equipped with a massive antenna array comprising of $M = 250$ antennas [5], is assumed to be located at the cell center. The local performance metrics of the sensors $P_{D,k}$ and $P_{F,k}$ are assumed to be uniformly distributed in the range $[0.95, 0.40]$ and $[0.01, 0.12]$, respectively. The small-scale fading coefficients are generated according to the Rayleigh channels. Further, the path-loss model is considered as $\beta_k = z_k(r_k/r_0)^{-\nu}$, where $z_k$ is the log-normal random variable with mean $\mu = 4$ dB and standard deviation $\sigma = 2$ dB, $r_k$ is the distance of the $k$th sensor from the FC and $\nu = 2$ is the path-loss exponent. The maximum number of propagation paths $L_m$ is chosen as $L_m = 10$, carrier frequency $f_c$ as $f_c = 28$ GHz, training power $p_p$ as $p_p = 5$ dB and noise variance $\sigma_n^2$ as $\sigma_n^2 = 1$ [5].

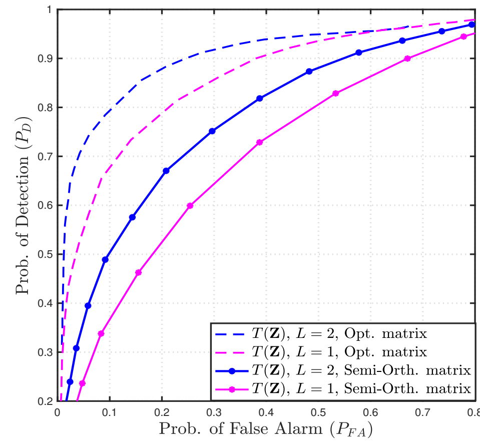


**Fig. 2**: Performance comparison of $T(\mathbf{Z})$ with semi-orthogonal and deflection-coefficient maximization based signaling matrix for $M = 250$, $p_p = 5$ dB, SNR $p_u = -18$ dB and $L = \{1, 2\}$.

In Fig. 1, we demonstrated the receiver operating characteristic ($P_D$ vs. $P_{FA}$) of the proposed fusion rules for different signaling intervals $L = \{1, 2\}$, SNR $p_u = \{-18, 10\}$ dB, and number of antennas $M = \{100, 250\}$ at the FC. From the results, it can be inferred that the performance enhances by allocating more signaling intervals to each sensor. The performance can be further improved by adding more antennas at the FC, thus validating the advantage of exploiting massive MIMO technology. Further, they closely approach the performance of perfect CSI fusion rules. The theoretical results determined in Theorem 1 are in close agreement with simulated plots, hence, confirming our analytical findings. The performance of the max-log fusion rule in (13) approach the performance of the optimum fusion rule in (9) at high SNR.

In Fig. 2, we contrasted the performance of the proposed test for semi-orthogonal and transmit signaling matrix design, derived in Section 5, for $L = \{1, 2\}$. To generate the semi-orthogonal matrix design, a sub-matrix of size $K \times L$ is chosen from a Hadamard matrix of size $K \times K$, which is subsequently multiplied by the local sensor decisions. Since the deflection-coefficient maximization based signaling matrix allocates the sensor transmit power in the direction of the eigenvector corresponding to the maximum eigenvalue. Hence, improved detection performance is observed corresponding to the optimized transmit signaling matrix design.

## 7. CONCLUSIONS AND FUTURE WORKS

This work is the first attempt that employs sparse Bayesian learning for CSI estimation to facilitate decision fusion in mmWave massive MIMO setup. To circumvent the computational complexity and the unavailability of closed-form performance of the LLR test, we have proposed a hybrid combining-based fusion rule design and characterized its closed-form analytical performance. The detection coefficient maximization framework is developed to determine the signaling matrix design to further improve the detection performance of the proposed rule. For the considered framework, the simulated detection performance is in close agreement with the analytical results, thus validating the analytical findings. Further, the impact of employing the transmit signaling matrix design on the system performance is also investigated through simulation results. We are planning to extend the proposed framework for distributed antenna architecture in the future.

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