Perceptive Mobile Network with Distributed Target Monitoring Terminals: Leaking Communication Energy for Sensing

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Abstract

Integrated sensing and communication enables sensing capability for wireless networks. However, the interference management and resource allocation between sensing and communication have not been fully studied. In this paper, we consider the design of perceptive mobile networks (PMNs) by adding sensing capability to current cellular networks. To avoid the full-duplex operation and reduce interference, we propose the PMN with distributed target monitoring terminals (TMTs) where passive TMTs are deployed over wireless networks to locate the sensing target (ST). We then jointly optimize the transmit and receive beamformers towards the communication user terminals (UEs) and the ST by alternating-optimization (AO) and prove its convergence. To reduce computation complexity and obtain physical insights, we further investigate the use of linear transceivers, including zero forcing and beam synthesis (B-syn), and show that B-syn can achieve comparable sensing performance as AO especially when the communication requirement is high. Some interesting physical insights are also revealed. For example, instead of forming a dedicated sensing signal, it is more efficient to jointly design the communication signals for different UEs such that they “collaboratively leak” energy to the ST. Furthermore, the amount of energy leakage from one UE to the ST depends on their relative locations.

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Index Terms

Integrated sensing and communication, perceptive mobile network, target monitoring terminals, alternative optimization, beam synthesis.

I. INTRODUCTION

Wireless communications systems have evolved for several generations and the recently commercialized 5G systems have partially met the needs for high data rate, reliable, and low latency communication services. However, with the development of innovative applications such as autonomous driving and industrial IoT [1]–[3], future wireless systems are expected to provide new services, e.g., target tracking and environmental monitoring [4], [5]. To this end, the recently proposed integrated sensing and communication (ISAC) framework provides a promising platform to integrate sensing capability in communication systems [6]. The use of millimeter-wave (mmWave) in 5G and beyond further facilitates the integration between radar and communication systems with possible hardware and software sharing between two functionalities. In this case, there have been some interesting developments in three different areas, i.e., dual-functional radar-communication (DFRC) [7]–[10], sensing-aided communication [11], and communication-aided sensing [12]–[18].

Some research efforts have been made for the transmit beamformer and waveform design of ISAC systems. [7] optimized the transmit beamformers for the dual DFRC systems to achieve a target radar beam pattern while satisfying a given communication performance requirement. [8] investigated the transmit waveform design by minimizing the multi-user interference in communication while allowing a tolerable mismatch between the designed and the desired radar beam patterns. The hybrid beamforming technique was considered in [9] to save the energy consumption. To improve the parameter estimation performance, [19] proposed to design the ISAC system by minimizing the Cramér-Rao bound (CRB) for sensing. In [20], [21], the perceptive mobile network (PMN) was studied to enable different types of sensing capabilities for wireless communications. However, the joint transmitter and receiver design for PMN systems is not available in the literature. More importantly, the interplay between sensing and communication, especially the interference management and resource allocation, has not been well understood.

In this paper, we first propose the PMN with distributed target monitoring terminals (PMN-TMT), where TMTs are deployed to add sensing capability to wireless communications systems. In the proposed PMN-TMT, the base stations (BSs) will not only serve communication but also
work as the radar transmitters. In particular, BSs will transmit/receive communication signals and also send sounding signals to the sensing target (ST). However, to avoid the full-duplex operation and reduce interference between sensing and communication, the radar signal estimation task will be taken over by the TMTs, which are passive sensing terminals deployed as IoT devices for sensing and monitoring tasks [3], [22]. They can be deployed on the BSs, but normally will be spread around the BSs to provide additional angles for sensing and monitoring purposes. TMTs are connected to the BSs through high capacity links and form the sensing network.

Next, we will consider the joint design of sensing and communication in the proposed PMN-TMT. Due to the different nature of sensing and communication systems, the PMN-TMT has some unique characteristics: 1) Sensing signal, if not handled properly, will cause interference to the communication receivers; 2) Communication signals can be utilized for sensing purpose, given they are known by the BSs; and 3) Communication signals will be reflected by the environment, creating the clutter (interference) for sensing. As a result, how to manage the interference and allocate resources between sensing and communication are two of the most important questions to be addressed. In this paper, we will jointly design the transmitter and receiver to optimize the sensing and communication performance. This problem is first solved by an alternating optimization (AO) framework, whose convergence proof is also given. However, the complexity of the AO-based design is high. To reduce the complexity and obtain physical insights regarding the interference management and resource allocation between the two subsystems, we further derive linear transceiver structures and compare their performance with that of the AO-based solution.

The contributions of this paper can be summarized as follows:

1) We propose a novel ISAC framework, i.e., PMN-TMT, where passive TMTs are deployed over traditional wireless networks to locate the ST. Then, we jointly design the transmitter and receiver by maximizing the weighted average of sensing and communication performance, where the performance metrics for sensing and communication are chosen to be the signal-to-clutter-and-noise-ratio (SCNR) for the ST and the minimum signal-to-interference-plus-noise-ratio (SINR) for the UEs, respectively.

2) To address the non-convex optimization problem, we transfer the fractional programming to a parametric square-root subtractive-form problem by exploiting the quadratic transform technique [23]. Then, we propose an AO-based framework to iteratively optimize the transmit and receive beamformers and prove the convergence of the proposed algorithm.
3) We derive linear transceiver structures, including the zero-forcing (ZF) and beam synthesis (B-syn) transmitter, and the minimum variance distortionless response (MVDR) receiver. These linear transceivers not only reduce the computation complexity but also provide interesting physical insights: (1) “Leaking” energy from communication signals to the ST is more efficient than forming a dedicated sensing signal; and (2) the amount of energy leaked from one UE to the ST depends on their channel correlation, which is determined by their locations.

The remainder of this paper is organized as follows. Section II introduces the system model of the proposed PMN-TMT. Section III formulates the problem and provides the AO-based joint transceiver design algorithm, together with its convergence proof. The sub-optimal linear transceiver structures are derived in Section IV, where several interesting physical insights regarding the interference management and resource allocation between sensing and communication are also revealed. Section V provides simulation results to illustrate the performance of the proposed methods and Section VI concludes the paper.

II. System Model

A. Perceptive Mobile Network with Distributed Target Monitoring Terminals

PMN represents a promising framework to integrate radar sensing in wireless communications networks. However, due to the different nature of communication and sensing functionalities, a fully integrated system with dual-functionality will face many challenging issues such as full-duplex operation. In this paper, to release such demanding requirements, we propose the PMN-TMT, as illustrated in Fig. 1. The PMN-TMT can be implemented by adding another layer of passive TMTs over the current cellular networks. In particular, TMTs are passive nodes with only perception functionalities, including radar, vision, and other sensing capabilities [3], [22]. They are distributed in a target area and connected with the base stations (BSs) through low latency links.

In the proposed PMN-TMT, the communication between the BSs and the UEs is achieved in the same way as traditional cellular networks. To perform radar sensing, the sounding signal is generated by the BSs during the downlink communication period. To avoid transmitting and receiving at the same time (full-duplex), the sensing estimation is performed by the TMTs. The distributed TMTs not only reduce the implementation difficulty but also provide multiple angles
to monitor the environment. Such design also facilitates the integration of other IoT applications in the PMN-TMT.

In this paper, we consider a simplified network with one base station (BS) and one TMT equipped with $N_t$ and $N_r$ antennas\(^1\) respectively. This network serves $K$ single-antenna UEs and detects a ST simultaneously. Denote $h_{c,k} \in \mathbb{C}^{N_r \times 1}$ and $h_R \in \mathbb{C}^{N_r \times 1}$ as the channels from the BS to the $k$th UE and the ST, respectively. To serve both communication and sensing, the BS transmits $N_s$ data streams by $N_t$ transmit antennas. The transmit signal $s \in \mathbb{C}^{N_s \times 1}$ consists of $K$ data streams for the UEs and $N_s - K$\(^2\) data streams for sensing. Without loss of generality, the transmitted symbol vector is given by

$$s = \begin{bmatrix} s_c \\ s_R \end{bmatrix} \in \mathbb{C}^{N_s \times 1},$$

which is assumed to be Gaussian distributed with zero means and covariance matrix $\mathbf{I}$. Each entry of $s$ corresponds to a single-carrier waveform, where $s_c$ and $s_R$ denote the symbols for communication and sensing, respectively. Specially, $s_{k}$, i.e., the $k$th entry of $s_c$, denotes the symbol transmitted to the $k$-th UE.

In this paper, we consider the widely used Saleh-Valenzuela (SV) model to characterize the sparse nature of mmWave channels \cite{24-26}. Suppose uniform linear arrays (ULAs) are

\(^1\)Collaborative sensing by several TMTs will provide better sensing performance, which is left for the future work.

\(^2\)Here we assume that the number of UEs $K$ is no more than $N_s$.  

Fig. 1: Illustration of PMN-TMT.
employed at the BS. The BS-UE channel \( h_{c,k} \) can then be given by [26]

\[
h_{c,k} = \sqrt{\frac{N_t}{N_p}} \sum_{i=1}^{N_p} \beta_{k,i}^{(t)} a_T(\phi_{k,i}^{(t)}),
\]

(2)

where \( N_p \) denotes the number of paths between the BS and the UE. \( a_T(\phi) \) represents the steering vector of the BS with \( ||a_T(\phi)||^2 = 1 \) and \( \phi_{k,i}^{(t)} \) is the angle-of-departure (AOD) from the BS to the \( k \)th UE in the \( i \)th path. \( \beta_{k,i}^{(t)} \) denotes the path gain in the \( i \)th path of the corresponding channel. The BS-ST and ST-TMT channels can be modeled similarly.

**B. Communication Signal Model**

The signal received at the \( k \)th UE is expressed as [27]

\[
y_{c,k} = h_{c,k}^H F s + n_c,
\]

(3)

where

\[
F = \begin{bmatrix}
    f_{c,1}, \ldots, f_{c,K} \\
    f_{R,1}, \ldots, f_{R,N_s-K}
\end{bmatrix} \in \mathbb{C}^{N_t \times N_s}
\]

(4)

denotes the precoder matrix and \( n_c \) represents the additive white Gaussian noise (AWGN) with zero mean and variance \( \sigma_c^2 \). Note that both communication and sensing signals may impose interference to UEs. Thus, the received SINR at the \( k \)th UE is expressed as

\[
\gamma_k(F) = \frac{|h_{c,k}^H f_{c,k}|^2}{\sum_{i \neq k} |h_{c,i}^H f_{c,i}|^2 + |h_{c,k}^H F_R|^2 + \sigma_c^2}.
\]

(5)

**C. Radar Signal Model**

The sensing signal is regarded as interference by communication systems, but communication signals can be used for sensing because the transmitted communication waveform is known by the TMT. Assuming that the transmit waveform is narrow-band and the propagation path is a line of sight (LoS) path, then the base-band signal at a point-like target can be given by [10]

\[
y_t = a_T^H(\phi_t) F s,
\]

(6)

where \( \phi_t \) denotes the AOD from the BS to the ST. Note that the back-scattered echos from the environment will impose interference to the TMT.
Sensing detection is a binary hypothesis testing problem, where hypotheses \( \mathcal{H}_0 \) and \( \mathcal{H}_1 \) correspond to the absence and presence of the ST, respectively. Besides the echo back-scattered from the ST, the TMT will also receive the echoes from the environment, which is known as the clutter [28]–[30]. The echo signal received by the TMT in the range-Doppler cell under test (CUT) [28]–[30] is expressed as

\[
\begin{align*}
\mathcal{H}_0 : \quad y_{R,0} &= \sum_{l=1}^{L} \epsilon_{c,l} A_{c,l} F_s + n_R, \\
\mathcal{H}_1 : \quad y_R &= \epsilon_s A_R F_s + \sum_{l=1}^{L} \epsilon_{c,l} A_{c,l} F_s + n_R,
\end{align*}
\]

(7)

where \( L \) denotes the number of clutter patches. The response matrices of clutter patches and the target [19] are respectively given as

\[
A_{c,l} = a_R(\phi_{c,l}) a_T^H(\phi_{c,l}), \quad A_R = a_R(\phi_t) a_T^H(\phi_t),
\]

where \( a_R(\phi) \) denotes the steering vector of the TMT with \( ||a_R(\phi)||^2 = 1 \). \( \phi_t^{(r)} \) and \( \phi_{c,l}^{(r)} \) represent the angle-of-arrival (AOA) from the ST and \( l \)th clutter patch to the TMT, respectively. \( \phi_{c,l} \) denotes the AOD of the \( l \)th clutter patch with respect to (w.r.t.) the BS. \( \epsilon_s \) and \( \epsilon_{c,l} \) represent the complex gains of the ST-TMT channel and the channel between the \( l \)th clutter patch and the TMT, which depend on the gain of the matched filtering, the gain of emission patterns, the propagation loss, and the target radar cross section (RCS) [28], [30]. They are assumed to be zero mean Gaussian random variables with variance \( \sigma_t^2 \) and \( \sigma_{c,l}^2 \), respectively [28], [30]. \( n_R \) is modeled as AWGN with zero means and covariance matrix \( \sigma_n^2 I \).

In practical applications, the TMT is employed on a smart manufacturing or industrial IOT device whose power is limited [3], [22]. To reduce hardware cost and improve the overall energy efficiency (EE) of the TMT, we consider the hybrid beamforming structure. The baseband signal is processed by an analog baseband combiner \( W_{RF} \in \mathbb{C}^{N_r \times N_{RF}} \), a digital baseband combiner \( W_{BB} \in \mathbb{C}^{N_{RF} \times N_s} \), and a detection filter \( w_d \in \mathbb{C}^{N_s \times 1} \) with the output

\[
x_o = w_d^H W_{BB}^H W_{RF}^H y_R.
\]

(8)

Denote \( w = W_{BB} w_d \) as the effective digital baseband processor. Then the signal-to-clutter-and-noise ratio (SCNR) is defined as [30]

\[
\text{SCNR}(w, W_{RF}, F) = \frac{P_s(w, W_{RF}, F)}{P_Q(w, W_{RF}, F)} = \frac{\mathbb{E} \left( ||\epsilon_s w^H W_{RF}^H A_R F_s||^2 \right)}{\mathbb{E} \left( \left|| \sum_{l=1}^{L} \epsilon_{c,l} w^H W_{RF}^H A_{c,l} F_s + w^H W_{RF}^H n_R \right||^2 \right)},
\]

where \( P_s(w, W_{RF}, F) \) is the signal power and \( P_Q(w, W_{RF}, F) \) is the total output signal-to-noise ratio (SNR) power.
where
\[
\mathcal{P}_S(w, W_{RF}, F) \triangleq \sigma_t^2 w^H W_{RF}^H A_R F F^H A_R^H W_{RF} w,
\]
\[
\mathcal{P}_Q(w, W_{RF}, F) \triangleq \sum_{l=1}^{L} \sigma_{c,l}^2 w^H W_{RF}^H A_{c,l} F F^H A_{c,l}^H W_{RF} w + \frac{\sigma_n^2}{\text{Noise}} w^H W_{RF}^H W_{RF} w. \tag{9}
\]

### III. Joint Communication and Sensing Design

The communication performance can be measured by the SINR at the UEs, whereas the sensing performance depends on SCNR. In this paper, we attempt to jointly optimize the receive filter \(w\), the analog combiner \(W_{RF}\), and the precoder \(F\) to maximize the weighted sum of SCNR and the worst case SINR simultaneously. Concretely, the optimization problem is formulated as

\[
\max_{w, W_{RF}, F} \mathcal{L}(w, W_{RF}, F)
\]

\[s.t. \quad \|w\|^2 \leq 1 \quad (10a)
\]
\[\|F\|^2_F \leq P \quad (10b)
\]
\[W_{RF} \in \mathcal{M}_{N_r \times N_{RF}}, \quad (10c)
\]

where

\[
\mathcal{L}(w, W_{RF}, F) = \kappa_r \text{SCNR}(w, W_{RF}, F) + \kappa_c \min_{k \in [1,K]} \gamma_k(F),
\]

with \(\kappa_r \in [0,1]\) and \(\kappa_c = 1 - \kappa_r\) denoting the weighting coefficients for the sensing and communication, respectively. The feasible set of the analog combiner is given by \(\mathcal{M}_{M \times N} = \{X \in \mathbb{C}^{M \times N} \mid \|X(i,j)\| = 1, i = 1, \cdots, M, j = 1, \cdots, N\}\). Note that \((10a)\) forces the receiver to have a unit norm and \((10b)\) limits the power of the transmitter. \((10c)\) represents the unit modulus constraint as the analog precoders are implemented by phase shifters. The knowledge of \(\sigma_t^2, \sigma_n^2\) and \(\sigma_{c,l}^2, l = 1, \cdots, L\) can be obtained by a cognitive paradigm \([31]–[33]\) and is assumed to be known. Moreover, we assume that the channel state information (CSI), i.e., \(h_{c,k}\) and \(h_{c,k}^{(r)}\) are known. However, it can be observed that both the fractional objective function and constraints are non-convex, which causes the optimization problem hard to solve.

Note that the problem in \((10)\) is a multi-ratio fractional programming (FP) problem which is NP-hard. Fortunately, the objective function is continuous and has positive denominator. Thus, the FP problem can be transformed into a parametric subtractive-form problem by exploiting
the Dinkelbach method \cite{34}. However, although the Dinkelbach method can be an efficient solution to those single-ratio problems with a concave numerator and convex denominator, it cannot be easily generalized to the multi-ratio problem, like (10). Also, the numerator of the objective function in (10) has a quadratic form w.r.t. \( W, W_{RF}, \) and \( F, \) and thus is non-concave. As a result, extra relaxations are needed to further relax the resulting subtractive-form objective function which may degrade the convergence and optimization performance. To address this issue, we reformulate (10) as a parametric subtractive-form problem by exploiting the quadratic transform technique proposed in \cite{23}, i.e.,

\[
\max_{w, W_{RF}, F, u_r, u_k} \mathcal{F} \left( w^{(t)}, W_{RF}^{(t)}, F^{(t)}, u_r^{(t)}, u_k^{(t)} \right) \quad \text{s.t.} \quad (10a)-(10c),
\]

where

\[
\mathcal{F} \left( w^{(t)}, W_{RF}^{(t)}, F^{(t)}, u_r^{(t)}, u_k^{(t)} \right) = F_R \left( w^{(t)}, W_{RF}^{(t)}, F^{(t)}, u_r^{(t)} \right) + \min_{k \in [1, K]} \mathcal{F}_k \left( F^{(t)}, u_k^{(t)} \right),
\]

with

\[
\mathcal{F}_k \left( F, u_k \right) = 2 \kappa_c \Re \left( u_k h_{c,k}^H f_{c,k} \right) - \kappa_c |u_k|^2 \left( |h_{c,k}^H F R|^2 + \sum_{i \neq k} |h_{c,i}^H f_{c,i}|^2 + \sigma_c^2 \right). \tag{14}
\]

Here, \( u_r \) and \( u_k \) are two auxiliary complex variables. To solve this problem, an iteration process based on AO is given as follows

\[
w^{(t+1)} = \arg \max_w \mathcal{F}_R \left( w^{(t)}, W_{RF}^{(t)}, F^{(t)}, u_r^{(t)} \right), \quad \text{s.t.} \quad (10a), \tag{15a}
\]

\[
W_{RF}^{(t+1)} = \arg \max_{W_{RF}} \mathcal{F}_R \left( W_{RF}^{(t+1)}, W_{RF}^{(t)}, F^{(t)}, u_r^{(t)} \right), \quad \text{s.t.} \quad (10c), \tag{15b}
\]

\[
F^{(t+1)} = \arg \max_F \mathcal{F}_R \left( F^{(t+1)}, W_{RF}^{(t+1)}, u_r^{(t)} \right), \quad \text{s.t.} \quad \mathcal{F}_k \left( F^{(t+1)}, u_k^{(t)} \right) \geq \zeta^{(t)}, k \in [1, K], \tag{15c}
\]

\[
u_r^{(t+1)} = \frac{\sigma_r F^{(t+1), H} A_R^H W_{RF}^{(t+1)} w^{(t+1)}}{\mathcal{P}_Q \left( w^{(t+1)}, W_{RF}^{(t+1)}, F^{(t+1)} \right)}, \tag{15d}
\]

\[
u_k^{(t+1)} = \frac{f_{c}^{(t+1), H} h_{c,k}}{\left| h_{c,k}^H F_{R}^{(t+1)} \right|^2 + \sum_{i \neq k} \left| h_{c,i}^H f_{c,i}^{(t+1)} \right|^2 + \sigma_c^2}, \tag{15e}
\]

\[
\zeta^{(t+1)} = \min_{k \in [1, K]} \kappa_c \gamma_k (F^{(t+1)}). \tag{15f}
\]
We have the following proposition regarding the convergence of the proposed algorithm.

**Proposition 1:** The iteration in (15) creates a non-decreasing sequence

\[
\mathcal{L}^{(t)} = \mathcal{L} \left( w^{(t)}, W_{RF}^{(t)}, F^{(t)} \right) = \mathcal{F} \left( w^{(t)}, W_{RF}^{(t)}, F^{(t)}, u_r^{(t)}, u_{k_r}^{(t)} \right),
\]

which converges to the stationary point of (10), i.e., \( \mathcal{L}^* = \mathcal{L} (w^*, W_{RF}^*, F^*) \).

**Proof:** See Appendix A.

Proposition 1 guarantees the convergence of the iteration in (15), and the next issue is to solve (15a)-(15c).

### A. Update \( w^{(t+1)} \)

First, we reformulate (13) w.r.t. \( w \) as

\[
\mathcal{F}_R (w|W_{RF}, F, u_r) = 2\kappa_r \Re \left( w^H a_w \right) - \kappa_r \|u_r\|^2 w^H B w + \text{const},
\]

where

\[
a_w = \sigma_t W_{RF}^H A R_F, \quad B_w = \sum_{l=1}^L \sigma_{c,l}^2 W_{RF}^H A_{c,l} F F^H A_{c,l}^H W_{RF} + \sigma_n^2 W_{RF}^H W_{RF}.
\]

Then the problem in (11) is reformulated as the maximization of (17). This problem can be efficiently solved by the Lagrange multiplier method. Specifically, we introduce a penalty function to reformulate the problem in (17) as an unconstrained optimization problem that minimizes

\[
L_w^{(t)}(w) = -\mathcal{F}_R \left( w|W_{RF}^{(t)}, F^{(t)}, u_r^{(t)} \right) + \gamma_w \left( w^H w - 1 \right),
\]

where \( \gamma_w \geq 0 \) is the Lagrange penalty coefficient. Note that (19) is convex w.r.t. \( w \). The minimizer of (19) can be obtained by solving \( \nabla_w L_w^{(t)}(w) = 0 \), i.e.,

\[
w^{(t,\ast)} = \frac{1}{\|u_r^{(t)}\|^2} \left( B_w^{(t)} + \gamma_w I \right)^{-1} a_w^{(t)}.
\]

Note that \( w^{(t,\ast)} \) depends on \( \gamma_w \). Therefore, in the rest of this subsection, we focus on determining \( \gamma_w \). By performing the eigen-decomposition \( B_w^{(t)} = V_w A_w V_w^H \) and based on the complementary Karush–Kuhn–Tucker (KKT) condition, we have

\[
w^{(t,\ast),H} w^{(t,\ast)} = a_w^{(t),H} V_w (A_w + \lambda_{w,1} I)^{-2} V_w^H a_w^{(t)} = \sum_{i=1}^{N_{RF}} \frac{|v_{w,i}^{H} a_w^{(t)}|^2}{(\lambda_{w,i} + \gamma_w)^2} = 1,
\]

where \( v_{w,i} \) denotes the \( i \)th column of \( V_w \) and \( \lambda_{w,i} \) is the \( (i, i) \)th entry of \( A_w \). It is easy to check that \( \text{tr} \left( w^{(t+1)} w^{(t+1),H} \right) \) is monotonic w.r.t. \( \gamma_w \). We thus utilize the bisection method to find a suitable \( \gamma_w \) to make \( \|w^{(t,\ast)}\| = 1 \). We then update \( w^{(t+1)} = w^{(t,\ast)} \).
B. Update $\mathbf{W}^{(t+1)}_{RF}$

Note that $\mathcal{P}_Q$ is dependent on $\mathbf{W}_{RF}$. Therefore, we first simplify the formulation in (13). Defining the vectorization of $\mathbf{W}_{RF}$ as $\mathbf{w}_{RF} = \text{vec} (\mathbf{W}_{RF})$, the objective function in (13) w.r.t. $\mathbf{w}_{RF}$ is then reformulated as

$$
\mathcal{F} (\mathbf{w}_{RF} | \mathbf{F}, \mathbf{u}_r, \mathbf{u}_k) = 2 \kappa_r \Re \left( \mathbf{w}_{RF}^H \mathbf{a}_{w_{RF}} \right) - \kappa_r \| \mathbf{u}_r \|^2 \mathbf{w}_{RF}^H \mathbf{B}_{w_{RF}} \mathbf{w} + \text{const},
$$

(22)

where

$$
\mathbf{a}_{w_{RF}} = \sigma_t \text{vec} \left( \mathbf{A}_{RF} \mathbf{F} \mathbf{u}_r \mathbf{w}^H \right), \quad \mathbf{B}_{w_{RF}} = \mathbf{w}^* \mathbf{w}^T \otimes \left( \sum_{l=1}^L \sigma^2_{c,l} \mathbf{A}_{c,l} \mathbf{F} \mathbf{F}^H \mathbf{A}_{c,l}^H + \sigma_n^2 \mathbf{I} \right).
$$

(23)

From (15b), we can observe that the objective function is convex w.r.t. $\mathbf{w}_{RF}$, whereas the feasible set $\mathcal{M}^{N_r N_{RF}^T \times 1}$ is still non-convex. Fortunately, $\mathcal{M}^{N_r N_{RF}^T \times 1}$ is known as the complex circle manifold (CCM) so that (15b) can be addressed by the manifold-based method.

The manifold-based method updates the variable within the tangent space $\mathcal{T} \mathcal{M}$. By updating along the tangent space with a small enough step, the new point is almost within $\mathcal{M}$. For the manifold in (10c), its corresponding tangent space is given as

$$
\mathcal{T}_{w_{RF}} \mathcal{M}^{N_r N_{RF}^T \times 1} = \{ \mathbf{x} \in \mathbb{C}^{N_r N_{RF}^T \times 1} | \Re (\mathbf{x} \circ \mathbf{w}_{RF}) = 0 \}.
$$

(24)

Resembling the gradient-based method, the manifold-based method will find a direction from the tangent space where the objective function decreases most steeply (for minimization problems), i.e., the negative Riemannian gradient direction. For the manifold $\mathcal{M}^{N_r N_{RF}^T \times 1}$, the Riemannian gradient at $\mathbf{w}_{RF}$ is a tangent vector given as the orthogonal projection of the Euclidean gradient $\nabla \mathcal{G}_w^{(t)}(\mathbf{w}_{RF})$ onto the tangent space [35], i.e.,

$$
\eta(\mathbf{w}_{RF}) = \text{grad} \mathcal{G}_w^{(t)}(\mathbf{w}_{RF}) = \nabla \mathcal{G}_w^{(t)}(\mathbf{w}_{RF}) - \Re (\nabla \mathcal{G}_w^{(t)}(\mathbf{w}_{RF}) \circ \mathbf{w}_{RF}) \circ \mathbf{w}_{RF},
$$

(25)

where

$$
\nabla \mathcal{G}_w^{(t)}(\mathbf{w}_{RF}) = -2 \kappa_r \mathbf{a}_{w_{RF}}^{(t)} + 2 \kappa_r \| \mathbf{u}_r^{(t)} \|^2 \mathbf{B}_{w_{RF}}^{(t)} \mathbf{w}_{RF}
$$

(26)

denotes the Euclidean gradient. The Riemannian gradient in the tangent space is the optimization direction that shifts the manifold the least. In practice, a retraction is needed to remap the
Algorithm 1 Proposed Manifold-based Method to obtain $w_{RF}^{(t, \ast)}$

**Input:** An initial point $w_{RF}^{(t,0)} = w_{RF}^{(t)}$ and $d^{(0)} = -\eta \left( w_{RF}^{(t,0)} \right)$.

**Repeat**

1) Compute $\beta^{(m)}$ via the Armijo line search step [35, Definition 4.2.2].
2) Update $w_{RF}^{(t,m+1)} = \mathcal{P} (\beta^{(m)} d^{(m)})$ via (27).
3) Compute the Riemannian gradient $\eta \left( w_{RF}^{(t,m+1)} \right)$ via (25).
4) Update the optimization direction $d^{(m+1)} = -\eta \left( w_{RF}^{(t,m+1)} \right)$.
5) $m \leftarrow m + 1$.

**Until** Convergence criterion is met.

**Output:** The optimal solution $w_{RF}^{(t, \ast)}$.

updated points from the tangent space onto the manifold. The retraction of a tangent vector $\beta d \in T_{w_{RF}} \mathcal{M}^{N_r N_{RF} \times 1}$ at $w_{RF}$ is

$$
\mathcal{P} : T_{w_{RF}} \mathcal{M}^{N_r N_{RF} \times 1} \rightarrow \mathcal{M}^{N_r N_{RF} \times 1}
$$

$$
\beta d \rightarrow (w_{RF} + \beta d) \circ \frac{1}{\|w_{RF} + \beta d\|_e},
$$

(27)

where $\frac{1}{\|x\|_e} \in \mathcal{R}^{N_r N_{RF} \times 1}$ denotes a vector whose $i$th entry is $1/|x_i|$, and $\beta$ represents the Armijo step [35, Definition 4.2.2].

To solve (15b), we propose the manifold-based method summarized in Algorithm [1] whose convergence is guaranteed by [35, Theorem 4.3.1]. Algorithm [1] provides the update $w_{RF}^{(t+1)} = w_{RF}^{(t, \ast)}$.

**C. Update $F^{(t+1)}$**

We first reformulate the problem w.r.t. $F$ as a quadratically constrained quadratic programming (QCQP) which is a subclass of semi-definite programming (SDP) [36]. Define the vectorization of $F$ as $f = \text{vec} (F)$. Omitting some constants, (13) w.r.t. $f$ is rewritten as

$$
\mathcal{F}_R (f|w, W_{RF}, u_r) = 2\kappa_r \Re (a_F^H f) - \kappa_r \|u_r\|^2 f^H B_F f + \text{const},
$$

(28)

where

$$
a_F = \sigma_t \text{vec} \left( A_R^H W_{RF} w u_r^H \right), \quad B_F = I \otimes \left( \sum_{l=1}^L \sigma_{cl}^2 A_{c,l}^H W_{RF} w w^H W_{RF}^H A_{c,l} \right).$$

(29)
Then \((14)\) can be rewritten as
\[
\mathcal{F}_k (f | u_k) = 2 \kappa_c \Re (a_{F_k}^H f) - \kappa_c f^H B_{F_k} f - \kappa_c |u_k|^2 \sigma_c^2, \tag{30}
\]
where
\[
a_{F_k} = u_k^* e_k \otimes h_{c,k}, \quad B_{F_k} = ||u_k||^2 (1 - e_k) (1 - e_k)^T \otimes h_{c,k} h_{c,k}^H, \tag{31}
\]
with \(e_k = [0, \cdots, 0, 1, 0, \cdots, 0]^T\).

By substituting \((28)\) and \((30)\) into \((15c)\), the resultant problem is a typical QCQP because the objective function and all constraints are reformulated as a linear or quadratic form. This problem can be easily solved by the well-known CVX toolbox \([37]\). We then update \(F^{(t+1)}\) by rearranging \(f^{(t, \star)}\).

**Remark 1:** In general, the computational complexity of the CVX toolbox is high. Meanwhile, the performance of the AO-based method depends on the weighting coefficients \(\kappa_c\) and \(\kappa_R\), but it is hard to adjust them to meet a desired communication or sensing performance. These issues motivate us to find other methods. One option is to use other optimization methods, such as the alternating direction method of multipliers (ADMM). However, such methods also involve an internal iteration process whose computational cost is still high since the dimension of \(f\) is large. Moreover, their performance also depends on some intermediate parameters. In the next section, we derive some linear transceiver structures to reduce the complexity and reveal more physical sights.

### IV. Linear Transceiver Design

In this section, we derive two sub-optimal transceiver structures to reduce the computational cost. These methods aim to maximize the sensing performance with given communication requirements.

#### A. Linear Transmitter Design

1) **ZF Transmitter:** ZF is a well-established beamforming method. In the concerned PMN-TMT, the channel matrix for the UEs is given as
\[
H_c = [h_{c,1}, \cdots, h_{c,K}] \in \mathbb{C}^{N_t \times K}. \tag{32}
\]
Then, the zero forcing precoder can be written as

\[ F_{ZF} = \mu H_c(H_c^H H_c)^{-1} \in \mathbb{C}^{N_t \times K}, \quad (33) \]

where

\[ \mu = \sqrt{\frac{P}{\text{tr}[(H_c^H H_c)^{-1}]}}, \quad (34) \]

denotes the normalized coefficient that guarantees \( ||F_{ZF}||^2 = P \). It can be validated that

\[ h_{c,i}^H f_{ZF,j} = \begin{cases} \mu, i = j \\ 0, i \neq j \end{cases}, \quad (35) \]

where \( f_{ZF,j} \) denotes the \( j \)th column of \( F_{ZF} \), indicating that the beam for one UE will not generate interference to others.

For an ISAC system, the channel between the BS and the ST is unknown. Thus, we leverage the steering vector towards the ST. Construct the ISAC ‘channel’ matrix as

\[ H_e(\lambda_a) = [H_c, \lambda_a a_T(\phi_t)] \in \mathbb{C}^{N_t \times (K+1)}, \quad (36) \]

where \( \lambda_a \) denotes a normalized coefficient to balance the amplitude of \( a_T(\phi_t) \). Then the ZF-ISAC precoder is given as

\[ F_{ZF-ISAC} = \mu_a(\lambda_a) H_e(\lambda_a) \left( H_e^H(\lambda_a) H_e(\lambda_a) \right)^{-1}, \quad (37) \]

where \( \mu_a(\lambda_a) \) is given by

\[ \mu_a(\lambda_a) = \sqrt{\frac{P}{\text{tr}[(H_e^H(\lambda_a) H_e(\lambda_a))^{-1}]}}, \quad (38) \]

**Lemma 1:** The normalized coefficient \( \mu_a(\lambda_a) \) can be simplified as

\[ \mu_a(\lambda_a) = \sqrt{\frac{P}{C_a + \frac{1}{\lambda_a^2 C_b}}}, \quad (39) \]

where

\[ C_a = \text{tr}(H_c^H H_c)^{-1} + \frac{a_T^H(\phi_t) H_c (H_c^H H_c)^{-2} H_c^H a_T(\phi_t)}{1 - a_T^H(\phi_t) H_c (H_c^H H_c)^{-1} H_c^H a_T(\phi_t)}, \]

\[ C_b = 1 - a_T^H(\phi_t) H_c (H_c^H H_c)^{-1} H_c^H a_T(\phi_t). \]

**Proof:** See Appendix C.  

\[ \blacksquare \]
It can be checked that
\[ h_{c,i}^H f_{\text{ZF-ISAC},j} = \begin{cases} \mu_{a,i} = j, & 0, i \neq j \\ 0, & j = K + 1, \end{cases} \]
which indicates that there is no interference between sensing and communication. By substituting (37) into (5), we have the SINR for \( K \) UEs as
\[ \gamma_1 = \cdots = \gamma_K = \frac{\mu_a^2(\lambda_a)}{\sigma_c^2}. \]
To guarantee the minimum SINR for all UEs, i.e.,
\[ \min_{k \in [1, K]} \gamma_k = \frac{\mu_a^2(\lambda_a)}{\sigma_c^2} \geq \Gamma, \]
we can obtain
\[ \lambda_a = \sqrt{\frac{1}{C_b(\frac{P}{\Gamma \sigma_c^2} - C_a)}}, \]
where \( \Gamma \) is a given threshold. The transmit power on the direction of the ST is thus given by
\[ P_{ZF,tgt} \triangleq \mathbb{E} (||a_T^H(\phi_t)F_{ZF-ISAC}s||^2) = \frac{\mu_a^2(\lambda_a)}{\lambda_a^2} = (P - \Gamma \sigma_c^2 C_a)C_b. \]

2) Beam Synthesis Transmitter: Note that the communication signal can also be leveraged for sensing since the transmitted communication waveform is known by the TMT. Thus, although the sensing signals are not supposed to create interference to the UEs, the communication signals can be leaked to the direction of the ST. In the following, we will investigate how the above observation can be exploited by the B-syn method, which is widely utilized in radar sensing [38]. In particular, by the array response control, the beam pattern is synthesized to force the orientation and nulls of beams at the directions of the target and interference, respectively. For the given ISAC system, the B-syn precoder can be constructed as
\[ F_{\text{B-syn}} \triangleq \begin{bmatrix} f_{\text{B-syn},c,1}, \cdots, f_{\text{B-syn},c,K}, \\ f_{\text{B-syn},R,1}, \cdots, f_{\text{B-syn},R,N_s - K} \end{bmatrix}, \]
where
\[ f_{\text{B-syn},c,i} = \alpha_i f_{\text{ZF},i} + \beta_i f_{\perp}, i = 1, \cdots, K, \]
\[ f_{\text{B-syn},R,j} = \nu_j f_{\perp}, j = 1, \cdots, N_s - K, \]
denote the beamformers for the \( K \) UEs and the radar data streams, respectively. Here \( f_{\text{ZF},i} \) denotes the \( i \)th column of \( F_{\text{ZF}} \) defined in (33). Note that the beamformer to the UE includes two
parts, i.e., the ZF precoder to the $i$th UE ($f_{ZF,i}$) and the leaked communication signal towards the ST ($f_\perp$). Here, $\alpha_i$, $\beta_i$ and $\nu_j$ denote the weighting coefficients for the communication terms, the leaked communication terms, and the dedicated sensing terms, respectively. To avoid interference from sensing to communication, the term $f_\perp$ is expected to have the following property:

$$H_c^H f_\perp = 0, \quad a_T^H(\phi_t) f_\perp = 1,$$

indicating that $f_\perp$ should not impose interference to communication and should have a constant gain on the direction of the ST. We then choose $f_\perp$ as the projection of $a_T^H(\phi_t)$ in the null-space of $H_c$, i.e.,

$$f_\perp = \frac{a_T^H(\phi_t) - H_c (H_c^H H_c)^{-1} H_c^H a_T^H(\phi_t)}{1 - a_T^H(\phi_t) H_c (H_c^H H_c)^{-1} H_c^H a_T^H(\phi_t)}.$$  \hspace{1cm} (48)

It can be validated that $F_{ZF}^H f_\perp = 0$ and $||f_\perp||^2 = \frac{1}{C_0}$. From (46) and (47), we can observe the communication precoder $f_{B-syn,c,i}$ will transmit signals on the direction of the $i$th UE and the ST without interfering the other UEs. The sensing beamformer $f_{B-syn,R,j}$ will transmit signals on the direction of the ST without imposing interference to UEs. The remaining issue is how to allocate power to these component beams. By substituting (46) into (5), we have

$$\gamma_k = \frac{|\alpha_k|^2 \mu^2}{\sigma_c^2}, \quad k = 1, \cdots, K.$$  \hspace{1cm} (49)

It is desired to maximize the sensing performance with a minimal SINR for all UEs, i.e.,

$$\min_{k \in [1, K]} \gamma_k = \frac{|\alpha_k|^2 \mu^2}{\sigma_c^2} \geq \Gamma.$$  \hspace{1cm} (50)

Thus, we consider the equal-rate transmission, i.e.,

$$\alpha_1 = \cdots = \alpha_K = \alpha_s = \sqrt{\frac{\Gamma \sigma_c^2}{\mu^2}}.$$  \hspace{1cm} (51)

The remaining task is to determine $\beta_i$ and $\nu_j$. Given the sensing performance highly depends on the power of the echo back-scattered from the target, we give the following proposition for allocating power to maximize the transmitted power on the direction of ST.

**Proposition 2:** The transmit power to the ST is given as

$$P_{B-syn,tgt} \triangleq \mathbb{E} \left(||a_T^H(\phi_t) F_{B-syn} s||^2\right) = 2\alpha_s \Re(a_{tgt}^H q) + C_{tgt},$$  \hspace{1cm} (52)

where

$$a_{tgt} = \left[f_{ZF,1}^H a_T(\phi_t), \cdots, f_{ZF,K}^H a_T(\phi_t), 0, \cdots, 0\right]^T_{N_s-K},$$  \hspace{1cm} (53)
\[
q = [\beta_1, \cdots, \beta_K, \nu_1, \cdots, \nu_{N_s-K}]^T,
\]

\[
C_{tgt} = \Gamma \sigma_c^2 a_T^H(\phi_t) H_c (H_c^H H_c)^{-2} H_c^H a_T(\phi_t) + (P - \Gamma \sigma_c^2 \text{tr}(H_c^H H_c)^{-1}) C_b.
\]

**Proof:** See Appendix B.

Omitting \(\alpha_s\) and \(C_{tgt}\) which are constant relevant to the allocation of \(\{\beta_i\}\) and \(\{\nu_j\}\), the resource allocation problem to maximize \(P_{B-syn,tgt}\) is formulated as

\[
\max_q \mathcal{R}(a_{tgt}^H q) \quad \text{s.t. } ||q||^2 = P_q,
\]

where \(P_q = (P - \Gamma \sigma_c^2 \text{tr}(H_c^H H_c)^{-1}) C_b\). The constraint is obtained from (70) which indicates that the total power of \(q\), composed of \(\beta_i\) and \(\nu_j\) is fixed once \(\Gamma\) is given. This problem is to find a vector \(q\) on a sphere which has the highest correlation with \(a_{tgt}\). The solution can be obtained by the Lagrange multiplier method as

\[
q = \sqrt{P_q} \cdot \frac{a_{tgt}^*}{||a_{tgt}||}.
\]

It follows from (53) that \(\nu_j = 0, j = 1, \cdots, N_s - K\), which indicates that the optimal solution is to allocate all of the power to \(\{\beta_i\}_{i=1}^K\). By substituting (57) into (52), we can have the resultant transmit power on the direction of ST as

\[
P_{B-syn,tgt} = 2\alpha_s \sqrt{P_q} ||a_{tgt}|| + C_{tgt}.
\]

Comparing the transmit power towards the ST by ZF and B-syn, we have the following proposition regarding the improvement of B-syn over ZF.

**Proposition 3:** The improvement of the transmit power towards the ST by B-syn over ZF can be obtained from (44) and (58) as

\[
P_{B-syn,tgt} - P_{ZF,tgt} = 2 \sum_{i=1}^K |\alpha_s a_T^H(\phi_t) f_{ZF,i}|^2 + 2\alpha_s \sqrt{P_q} ||a_{tgt}||
\]

\[
= \frac{2\Gamma \sigma_c^2}{\mu^2} ||F_{ZF}^H a_T(\phi_t)||^2 + 2 \sqrt{\frac{\Gamma \sigma_c^2 P_q}{\mu^2}} ||F_{ZF}^H a_T(\phi_t)|| \geq 0.
\]

**Remark 2:** The improvement by B-syn over ZF will be zero only when
1) \( \Gamma = 0 \), indicating that the required communications performance is zero. Then all power will be allocated to the sensing.

2) \( \mathbf{F}_\text{ZF}^H \mathbf{a}_T(\phi_t) = 0 \). Recalling (33), it is equivalent to \( \mathbf{H}_c^H \mathbf{a}_T(\phi_t) = 0 \), implying that the ST already falls into the null space of \( \mathbf{H}_c \).

In the above cases, B-syn is equivalent to ZF. On the other hand, the performance gap between B-syn and ZF will become larger if \( ||\mathbf{F}_\text{ZF}^H \mathbf{a}_T(\phi_t)||^2 \) is larger. Note that \( \mathbf{F}_\text{ZF}^H \mathbf{a}_T(\phi_t) \) denotes the power of \( \mathbf{F}_\text{ZF} \) on the ST direction. In general, if the ST is closer to one UE, the correlation between them gets larger and it is more efficient to leak power from that UE to the ST.

**Remark 3:** The computational cost of B-syn and ZF is only about \( O(N_t^2 + N_{RF}^3) \) whereas that of the AO for updating \( \mathbf{F} \) is about \( O((N_t N_{RF})^{3.5}) \). This indicates that the proposed B-syn and ZF methods can significantly reduce the computational cost. Meanwhile, B-syn and ZF can update the precoder with a given communication requirement. ZF transmits a dedicated sensing data stream to the ST and there is no interference between the dedicated sensing signal and the communication signals. In contrast, B-syn leaks energy from the communication signal to ST. From (59), we can observe that, it is better to leak communication energy to the ST direction than designing a dedicated sensing signal. In particular, B-syn uses less data stream to achieve a better sensing performance than ZF.

### B. Receiver Design

In the above, we give two methods to design the transmitter. With a given transmitter structure, to maximize the SCNR, the design of the receiver \( \mathbf{w}_{\text{eff}} \) is given by

\[
\max_{\mathbf{w}_{\text{eff}}} \text{SCNR}(\mathbf{w}_{\text{eff}}) = \frac{\sigma_t^2 P_{tgt} \left| \mathbf{w}_{\text{eff}}^H \mathbf{a}_R(\phi_t) \right|^2}{\mathbf{w}_{\text{eff}}^H \mathbf{R}_{\text{CN}} \mathbf{w}_{\text{eff}}},
\]

where \( P_{tgt} \) denotes the power transmitted to the ST and \( \mathbf{R}_{\text{CN}} = \sum_{l=1}^{L} \sigma_{c,l}^2 \mathbf{A}_{c,l} \mathbf{F}_C^H \mathbf{A}_C^H + \sigma_n^2 \mathbf{I} \). This problem is the classic MVDR beamforming problem, whose solution is given by [39]

\[
\mathbf{w}_{\text{eff}} = \frac{\mathbf{R}_{\text{CN}}^{-1} \mathbf{a}_R(\phi_t)}{\mathbf{a}_R^H(\phi_t) \mathbf{R}_{\text{CN}}^{-1} \mathbf{a}_R(\phi_t)}.
\]

Then we can adopt the fast optimization method in [40] to obtain \( \mathbf{W}_{RF} \) and \( \mathbf{w} \) from \( \mathbf{w}_{\text{eff}} \). Assembling the MVDR receiver with B-syn and ZF yields two linear transceiver structures, i.e., ‘B-syn + MVDR’ and ‘ZF + MVDR’.
V. SIMULATION

In this section, we show the performance of the proposed PMN-TMT with different transceiver structures. In the simulation, we consider a mmWave system operating at a carrier frequency of 28GHz. We model the small-scale fading as Rician, where the Rician factors of the UE is set as 7dB for LOS and 0dB for NLOS. The BS employs a ULA with \( N_t = 128 \) antennas. Unless specified otherwise, we also set \( N_r = 128 \) and \( N_{RF} = 4 \). In this paper, we fix the distance between the BS and TMT as 110m. The distances between the BS and UEs are set as a random variable uniformly distributed in \([19, 21]\)m. The AOD and AOA of the ST, UEs and clutter patches are set as random variable uniformly distributed in \([-\frac{\pi}{2}, \frac{\pi}{2}]\). The noise power at UEs and TMT are \( \sigma_c^2 \) and \( \sigma_n^2 \), respectively. We set \( \sigma_c^2 = \sigma_n^2 = -90\)dBm, \( \sigma_l^2/\sigma_n^2 = 20\)dB and \( \frac{1}{L} \sum_{i=1}^{L} \sigma_{c,l}^2/\sigma_n^2 = 30\)dB. Recalling (2), the channel between the BS and \( k \)th UE is modeled as

\[
h_{c,k} = \sqrt{\frac{N_t}{N_p} \sum_{i=1}^{N_p} \beta_{k,i}^{(t)} a_T(\phi_{k,i}^{(t)})},
\]

where \( \beta_{k,i}^{(t)} \sim \mathcal{CN}(0, 10^{-0.1\kappa}) \) denotes the complex gain of the LOS path and \( \kappa \) is the path loss given as \( \kappa = a + 10b \log_{10}(d) + \epsilon \) with \( d \) denoting the distance between the BS and the \( k \)th UE and \( \epsilon \sim \mathcal{CN}(0, \sigma_\epsilon^2) \) \([25]\). Following \([25]\), we set \( a = 61.4, b = 2, \sigma_\epsilon = 5.8\)dB. \( \beta_{k,i}^{(t)} \sim \mathcal{CN}(0, 10^{-0.1(\kappa+\mu)}) \) denotes the complex gain of the NLOS path and \( \mu \) is the Rician factor \([41]\). Here, we set \( N_p = 4 \).

We assume that the ISAC system serves 3 single antenna UEs and 1 ST. For the manifold optimization, we set the maximum number of iterations as 200. The tolerance for the norm of the gradient between two iterations is \( 10^{-4} \). To terminate the iteration, the tolerance for the objective function between two iterations is \( 10^{-2} \) and the maximum number of iterations is 20.

A. System Performance

Fig. 2 shows the average sensing performance of different transceiver structures with different levels of communication performance requirement. Here we set \( N_r = 32 \). For each curve, 800 Monte-Carlo experiments are performed. The legend ‘AO (\( \kappa_c = C \))’ denotes the AO method proposed in Sec. III with \( \kappa_c = C \). The legend ‘Beam synthesis’ and ‘ZF’ represent the proposed ‘B-syn + MVDR’ and ‘ZF + MVDR’ transceivers with a given \( \Gamma \), respectively. In particular, \( \Gamma = \Gamma_{AO, \kappa_c = C} \) means that we fix \( \Gamma \) to be the same as that of the ‘AO’ with \( \kappa_c = C \). Note
that $\Gamma_{AO,\kappa_c=0.9} < \Gamma_{AO,\kappa_c=0.999} < 50$. We have several observations regarding the performance comparison.

**AO vs. B-syn vs. ZF:** By comparing ‘AO ($\kappa_c = 0.9$)’, ‘Beam synthesis ($\Gamma = \Gamma_{AO,\kappa_c=0.9}$)’ and ‘ZF ($\Gamma = \Gamma_{AO,\kappa_c=0.9}$)’, we can observe that the performance of AO outperforms both B-syn and ZF, while B-syn is better than ZF. The same conclusion can be obtained by comparing ‘AO ($\kappa_c = 0.999$)’, ‘Beam synthesis ($\Gamma = \Gamma_{AO,\kappa_c=0.999}$)’ and ‘ZF ($\Gamma = \Gamma_{AO,\kappa_c=0.999}$)’. This is mainly due to different transceivers’ tolerance for the interference between UEs and the ST. In particular, AO does not force the beams towards different UEs and the ST to be completely orthogonal. B-syn requires the orthogonality between UEs to completely eliminate the multi-UE interference but allows leakage from the communication signal to the ST. On the other hand, ZF strictly constrains the UEs and ST not to affect each other. In particular, the sensing performance will degrade when the orthogonality constraint is stronger.

**AO vs. B-syn with Different Communication Requirements:** It can be observed by comparing ‘AO ($\kappa_c = 0.9$)’ and ‘Beam synthesis ($\Gamma = \Gamma_{AO,\kappa_c=0.9}$)’ with ‘AO ($\kappa_c = 0.999$)’ and ‘Beam synthesis ($\Gamma = \Gamma_{AO,\kappa_c=0.999}$)’ that the gap between AO and B-syn will become smaller when $\kappa_c$ increases. This indicates that when the communication requirement is high, B-syn will behave similarly as AO. This is because when the communication requirement is low, the UEs can tolerate higher interference and thus it is not necessary to completely eliminate the multi-user interference. As a result, the disadvantage of B-syn is obvious. As the communication requirement increases, the multi-UE interference is more critical and forces AO
to avoid it like B-syn. Thus, the gap is getting smaller. Under such circumstances, B-syn is preferable since it has much lower computational complexity than AO.

**B-syn vs. ZF with Different Communication Requirements:** As $\Gamma$ increases, it can be observed by comparing ‘Beam synthesis ($\Gamma = \Gamma_{AO,\kappa_c=0.9}$)’ and ‘ZF ($\Gamma = \Gamma_{AO,\kappa_c=0.9}$)’ with ‘Beam synthesis ($\Gamma = 50$)’ and ‘ZF ($\Gamma = 50$)’ that the gap between B-syn and ZF will become larger. Note here $\Gamma = 50$ corresponds to a higher communication requirement than $\Gamma = \Gamma_{AO,\kappa_c=0.9}$. This indicates that, compared with ZF, B-syn can achieve better sensing performance with the same communication requirement, and as the communication requirement $\Gamma$ increases, the power improvement in (59) becomes larger.

![Fig. 3: Effect of $N_s$ for AO.](image)

**Energy Leaking:** In Sec. IV, we proved that it is more efficient to leak communication energy to the ST than sending a dedicated sensing signal, i.e., B-syn outperforms ZF. For AO, it is hard to prove this property. In Fig. 3, we show the sensing performance of AO with different number of data streams $N_s$ when $\kappa_c = 0.9$. Note that the case $N_s = K$ means there are $K$ communication data streams and no dedicated sensing signal, while the case $N_s = K + C$ indicates that there are $C$ data streams for sensing. It can be observed that, as $N_s$ increases, the performance of AO becomes slightly worse, implying that the dedicated sensing signal is also less efficient for AO.

**B. Physical Insights**

In this section, we reveal some physical insights by looking into the beam patterns with different transceiver structures.
Fig. 4: Transmitted beam pattern for different data streams. (a) Data stream 1 for UE 1 (10°); (b) Data stream 2 for UE 2 (15°); (c) Data stream 3 for UE 3 (40°).

**Interference Management:** In Fig. 4, we show how interference management and power allocation between sensing and communication are achieved by different transmitter structures, which further explains the performance difference shown in Fig. 2. For ease of display, we fix the direction of the ST, the UEs and the clutter patches at 45°, {10°, 15°, 40°} and {50°, 60°}, respectively. Parts (a), (b) and (c) in Fig. 4 illustrate the beam pattern for each UE, together with their corresponding energy leakage to the ST. The beam pattern for the $i$th communication data stream is defined as $P_i(\phi) = ||a_i^H(\phi)f_{c,i}||^2$. Here we set $\kappa_c = 0.9$.

It can be observed that both ZF and B-syn eliminate the multi-user interference, but AO allows
a low level of interference. In terms of the power leakage from communication to sensing, both B-syn and AO leak a certain amount of energy from the UEs to the ST, but ZF does not. Furthermore, with AO, the transmit power on the ST direction from data streams 1, 2, and 3 are about 16.2448dB, 16.2579dB and 16.3768dB, respectively, where the total power is about 21.0648dB. The corresponding numbers for B-syn are 4.7378dB, 11.0259dB and 20.4939dB, respectively, and the total power is about 21.0615dB. This agrees with (57), which indicates that \( \beta_i \) is proportional to the \( i \)th entry of \( a_{tgt} \), i.e., \( a_H(\phi_t) F_{ZF,i} \) and it is more efficient to leak energy to the ST from UEs closer to the ST (higher channel correlation).

**Overall Beam Pattern:** Fig. 5 shows the overall beam pattern, i.e., \( P(\phi) = ||a_H(\phi) F||^2 \). Comparing AO with B-syn, we can observe that they achieved the same communication performance by different strategies, i.e., AO delivers a higher power to the UEs while allowing interference between UEs, but B-syn forces the interference to zero while sending a lower power to different UEs. On the other hand, the transmit power towards the ST by two schemes is similar, which agrees with Fig. 2. When comparing B-syn with ZF, we notice that they achieved the same gain for the UEs but B-syn obtained a higher transmit power towards the ST, because leaking energy from communication to sensing is more efficient than forming a dedicated sensing signal, which agrees with (59). Furthermore, we can see that AO transmits extremely low (but non-zero) power on the direction of the clutter patches, i.e., \( \{50^\circ, 60^\circ\} \). As will be shown later, this will give more freedom to the receiver design.

**Which UE Leaks More Energy?** Fig. 6 shows the beam pattern where the relative location
between the UEs and the ST are different and we set $\Gamma = 600$. In general, the ST can obtain more gain from the closer UEs. The B-syn and ZF methods can always avoid multi-UE interference.

**Impact of Communication Requirement:** Fig. 7 shows the beam pattern with different $\Gamma$s. The directions of the ST and UEs are set as 45° and (48°, 51°, 54°), respectively. The transmit power to the ST by B-syn is larger than that of ZF owing to the power improvement in (59). When $\Gamma$ is reasonably large, the gap becomes larger. This is because, with a large $\Gamma$, the power improvement will be more significant as more energy has been used for communication.
Receive Beam Pattern: Next, we show the beamforming performance of the TMT, i.e.,
\( P(\phi) = \|w^H W_{RF}^H a_R(\phi)\|^2 \). For ease of illustration, we fix the direction of the ST and the clutter patches at 54° and (30°, 35°, 40°), respectively. Fig. 8 shows the received beam pattern with different number of the receive antennas \( N_r \). Overall, the mainlobe of all scenarios can focus on the ST while the responses on the clutter direction are all less than −20dB. Comparing ‘B-syn + MVDR’ and AO, we can observe that the MVDR receiver suppresses the energy from
the direction of clutter patches while AO does not need to. This is because AO can suppress the transmit power towards the clutter patches, which leaves more freedom for the receiver.

VI. CONCLUSION

In this paper, we proposed a novel perceptive mobile network structure with distributed target monitoring terminals. The system design problem was formulated as the maximization of the weighted average between sensing and communication performance, and solved by an AO method. We further derived linear transceiver structures, which reduced the computation complexity and revealed interesting physical insights regarding the interplay between sensing and communication. Specifically, it is more efficient to leak communication energy towards the sensing target than forming a dedicated sensing signal. Furthermore, the amount of energy leakage depends on the channel correlation between the communication user and sensing target, which is determined by their locations. Simulation results validated the effectiveness of the proposed methods and illustrated the physical insights regarding interference management and resource allocation between sensing and communication.

APPENDIX A

PROOF OF PROPOSITION 1

To simply the notation, we first denote

\[ a_{u_r}^{(t+1)} = F^{(t+1),H} H^{(t+1),H} W_{RF}^{(t+1)} w^{(t+1)}, \quad B_{u_r}^{(t+1)} = P_Q \left( w^{(t+1)}, W_{RF}^{(t+1)} F^{(t+1)} \right). \]  

Hence, (15d) can be rewritten as \( u_r^{(t+1)} = a_{u_r}^{(t+1)} B_{u_r}^{(t+1)} \). By substituting (63) into (13), we have

\[ F_R \left( u_r^{(t)} \mid w^{(t+1)}, W_{RF}^{(t+1)}, F^{(t+1)} \right) = 2\kappa_r R(a_{u_r}^{(t+1),H} u_r^{(t)}) - \kappa_r \| u_r^{(t)} \|^2 B_{u_r}^{(t+1)}. \]

Thus, we can obtain

\[ F_R \left( u_r^{(t+1)} \mid w^{(t+1)}, W_{RF}^{(t+1)}, F^{(t+1)} \right) - F_R \left( u_r^{(t)} \mid w^{(t+1)}, W_{RF}^{(t+1)}, F^{(t+1)} \right) = \frac{\kappa_r}{B_{u_r}^{(t+1)}} \| a_{u_r}^{(t+1)} - a_{u_r}^{(t)} \|^2 \geq 0. \]
It indicates that the objective function $\mathcal{F}_R$ increases after the update of $u_t$. Then we have

$$
\text{SCNR}^{(t+1)} = \text{SCNR}(w^{(t+1)}_r, W_{RF}^{(t+1)}; F^{(t+1)}) = \frac{\mathcal{F}_R(w^{(t+1)}, W_{RF}^{(t+1)}, F^{(t+1)}, u_r^{(t+1)})}{\kappa_r} \geq \cdots \geq \frac{\mathcal{F}_R(w^{(t)}, W_{RF}^{(t)}, F^{(t)}, u_r^{(t)})}{\kappa_r} = \text{SCNR}^{(t)}.
$$

(64)

Similarly, we have

$$
\mathcal{F}_k(u_k^{(t+1)}, F^{(t+1)}) - \mathcal{F}_k(u_k^{(t)}, F^{(t+1)}) = \frac{\kappa_c}{B_{u_k}^{(t+1)}} \left\| \alpha_{u_k}^{(t+1)} - B_{u_k}^{(t+1)} u_k^{(t)} \right\|^2 \geq 0.
$$

where

$$
\alpha_{u_k}^{(t+1)} = f_c H_{c,k}^{(t+1)}, \quad B_{u_k}^{(t+1)} = \sum_{i \neq k} |h_{c,k}^{H} f_{c,i}|^2 + \left\| h_{c,k}^{H} F_R \right\|^2 + \sigma_c^2.
$$

(65)

Denote $k^* = \arg\min_{k \in [1, K]} \gamma_k(F^{(t+1)})$. We have

$$
\min_k \gamma_k(F^{(t+1)}) = \frac{\mathcal{F}_{k^*}(u_{k^*}^{(t+1)}, F^{(t+1)})}{\kappa_c} \geq \frac{\mathcal{F}_{k^*}(u_{k^*}^{(t)}, F^{(t+1)})}{\kappa_c} \geq \frac{\mathcal{F}_{k^*}(u_{k^*}^{(t)}, F^{(t+1)})}{\kappa_c} \geq \min_k \gamma_k(F^{(t)}),
$$

(66)

where (a) comes from the constraint in (15c).

From (64) and (66), the sequence $L^{(t)} = \kappa_R \text{SCNR}^{(t)} + \kappa_c \min_{k \in [1, K]} \gamma_k(F^{(t)})$ is monotonically increasing with more iterations. According to the monotone convergence theorem [42], the increasing sequence $L^{(t)}$ will converge to a stationary point $L^*$ as $t$ increases.

**APPENDIX B**

**PROOF OF PROPOSITION 2**

The transmit power to the ST is formulated as

$$
P_{B,\text{syn},t} = \mathbb{E} \left( ||a_T^H(\phi_t)F_{B,\text{syn}}||^2 \right) = \mathbb{E} \left( \left\| \sum_{i=1}^{K} \alpha_i a_T^H(\phi_t) f_{ZF,i} s_{c,i} + \sum_{i=1}^{K} \beta_i s_{c,i} + \sum_{j=1}^{N_s-K} \nu_j s_{R,j} \right\|^2 \right)
$$

$$
= \sum_{i=1}^{K} \sum_{m=1}^{K} \alpha_i^2 a_T^H(\phi_t) f_{ZF,i} (a_T^H(\phi_t) f_{ZF,m})^* \mathbb{E} (s_{c,i} s_{c,m}^*) + \sum_{i=1}^{K} \sum_{m=1}^{K} \beta_i \beta_m^* \mathbb{E} (s_{c,i} s_{c,m}^*)
$$

$$
+ \sum_{j=1}^{N_s-K} \sum_{n=1}^{N_s-K} \nu_j \nu_n^* \mathbb{E} (s_{R,j} s_{R,n}^*) + \sum_{i=1}^{K} \sum_{m=1}^{K} 2\alpha_i \Re \left( \beta_m^* a_T^H(\phi_t) f_{ZF,i} \mathbb{E} (s_{c,i} s_{c,m}^*) \right)
$$

$$
+ \sum_{i=1}^{K} \sum_{j=1}^{N_s-K} 2\alpha_i \Re \left( \nu_j^* a_T^H(\phi_t) f_{ZF,i} \mathbb{E} (s_{c,i} s_{R,j}^*) \right) + \sum_{i=1}^{K} \sum_{j=1}^{N_s-K} 2\Re \left( \beta_i \nu_j^* \mathbb{E} (s_{c,i} s_{R,j}^*) \right),
$$

where $a_T(\phi_t)$ is the transmitted signal at the ST, $s_{c,i}$ is the signal from the $i$-th user to the ST, and $s_{R,j}$ is the signal from the $j$-th user to the ST.
where we utilized the property $a_i^Hf_\perp = 0$. Here, $s_{c,i}$ and $s_{R,j}$ denote the $i$th and $j$th entry of $s_c$ and $s_R$, respectively. Recalling that $\mathbb{E}(s^Hs) = I$, we have

$$P_{B\text{-syn},tl} = \sum_{i=1}^K |\alpha_i a_i^H(\phi_t) e_{ZF,i}|^2 + \sum_{i=1}^K 2\alpha_i \Re(\beta_i^* a_i^H(\phi_t) f_{ZF,i}) + \sum_{i=1}^K |\beta_i|^2 + \sum_{j=1}^{N_s-K} |\nu_j|^2. \quad (67)$$

Next, we further simplify this formula. First, by the definition of $F_{ZF}$ and $\alpha_\ast$, we have

$$\sum_{i=1}^K |\alpha_i a_i^H(\phi_t) e_{ZF,i}|^2 = \alpha_\ast^2 a_\ast^H(\phi_t) F_{ZF} F_{ZF}^H a_T(\phi_t) = \Gamma \sigma_c^2 a_\ast^H(\phi_t) H_c (H_c^H H_c)^{-2} H_c^H a_T(\phi_t). \quad (68)$$

Then to meet the transmit power constraint, we have

$$P = \sum_{i=1}^K ||f_{B\text{-syn},c,i}||^2 + \sum_{j=1}^{N_s-K} ||f_{B\text{-syn},R,j}||^2 = \sum_{i=1}^K (\alpha_\ast^2 ||f_{ZF,i}||^2 + ||\beta_i||^2 ||f_\perp||^2) + \sum_{j=1}^{N_s-K} ||\nu_j||^2 ||f_\perp||^2. \quad (69)$$

It is equivalent to

$$\sum_{i=1}^K ||\beta_i||^2 + \sum_{j=1}^{N_s-K} ||\nu_j||^2 = \frac{P - \alpha_\ast^2 ||F_{ZF}||^2}{||f_\perp||^2} = \frac{(P - \Gamma \sigma_c^2 \text{tr}(H_c^H H_c)^{-1}) C_b, \quad (70)$$

where we used the property $||F_{ZF}||^2 = P$ and $||f_\perp||^2 = \frac{1}{C_b}$. It requires that $P - \Gamma \sigma_c^2 \text{tr}(H_c^H H_c)^{-1} \geq 0$, i.e., $\Gamma \leq \frac{P}{\sigma_c^2 \text{tr}(H_c^H H_c)^{-1}}$. Substituting (70) into (67) yields (52).

**APPENDIX C

PROOF OF LEMMA 1**

For ease of illustration, we denote $H_c(\lambda_a)$ as $H_c$ hereafter in this proof. Recalling (36) and applying the block matrix inversion lemma [30], we can show that

$$(H_c^H H_c)^{-1} = \begin{bmatrix} H_c^H H_c & \lambda_a H_c^H a_T(\phi_t) \\ \lambda_a^2 a_T^H(\phi_t) H_c & \lambda_a^2 & \lambda_a^2 \end{bmatrix}^{-1} \begin{bmatrix} (H_c^H H_c)^{-1} & 0 \\ 0^H & 0 \\ A_1 & A_2 & A_3 \end{bmatrix}, \quad (71)$$

where

$$A_1 = \frac{\lambda_a^2 (H_c^H H_c)^{-1} H_c^H a_T(\phi_t) a_T^H(\phi_t) H_c (H_c^H H_c)^{-1}}{\lambda_a - \lambda_a^2 a_T^H(\phi_t) H_c (H_c^H H_c)^{-1} H_c^H a_T(\phi_t)},$$

$$A_2 = \frac{\lambda_a (H_c^H H_c)^{-1} H_c^H a_T(\phi_t)}{\lambda_a^2 - \lambda_a^2 a_T^H(\phi_t) H_c (H_c^H H_c)^{-1} H_c^H a_T(\phi_t)},$$

$$A_3 = \frac{1}{\lambda_a^2 - \lambda_a^2 a_T^H(\phi_t) H_c (H_c^H H_c)^{-1} H_c^H a_T(\phi_t)}.$$

Thus, we have

$$\text{tr}(H_c^H H_c)^{-1} = \text{tr}(H_c^H H_c)^{-1} + \text{tr}(A_1) + A_3. \quad (73)$$

By substituting (73) into (38), we have (39).
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