

NetBeam: Networked and Distributed 3-D Beamforming for Multi-user Heterogeneous Traffic

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Abstract—The paper presents theoretical development and a system implementation of NetBeam, a framework for fully programmable, reconfigurable and distributed beamforming. NetBeam allows for joint mechanical antenna steering, grouping of a network of individual transmitter radios for specific target receivers, as well as digital beamforming that satisfies higher layer application demands. We make the following theoretical contributions: (i) We utilize, for the first time, a machine learning approach that uses Kriging for predicting antenna gains for arbitrary 3-D placements of transmitter - receiver pairs. NetBeam efficiently exploits fine-grained and accurate antenna gain predictions of the model, while estimating the uncertainty at unexplored locations through a Gaussian distribution. (ii) We allocate antennas to receivers by formulating the scenario as a bipartite graph, followed by perfect matching strategies that maximize the channel gain. (iii) We leverage the CSI computed in stage (i) to compute the optimum digital beamforming weights by trading off SINR and power consumption that meets application requirements using semidefinite optimization. Our implementation addresses many practical aspects of distributed beamforming including achieving fast frequency, time, and phase synchronization. NetBeam minimizes the gap to optimal channel gain in a 3-D space, and reduces the total transmit power up to 60%, while still managing to provide the required SINR.

Index Terms—3D-beamforming, Distributed Systems, Antenna orientation, Machine Learning

I. INTRODUCTION

Network densification is a promising approach for solving the grand challenge of achieving 1000x throughput increase in future wireless deployments. Here, a large number of base stations (modeled as software defined radios or SDRs in this work) are arbitrarily placed in a given area, which must coordinate their actions to serve a large number of users that have heterogeneous application needs. Such networks must operate in rich interference-prone environments, rapidly converge on optimal parameter settings, and efficiently use both power and spectrum. In this paper, we present a systems architecture and theoretical framework of NetBeam that coordinates multiple SDRs for distributed beamforming, a critical operation that concentrates RF energy towards users and regions of interest.

Distributed and Collaborative beamforming (DCBF) and Distributed Array System (DAS) are two different approaches that can be used to provide N^2 fold gain in the received signal strength (RSS) using N transmitters [1]. DCBF increases the wireless capacity using cooperation among independent radios [2], while DAS requires a central unit connected to multiple spatially separated antennas [3]. NetBeam involves a network

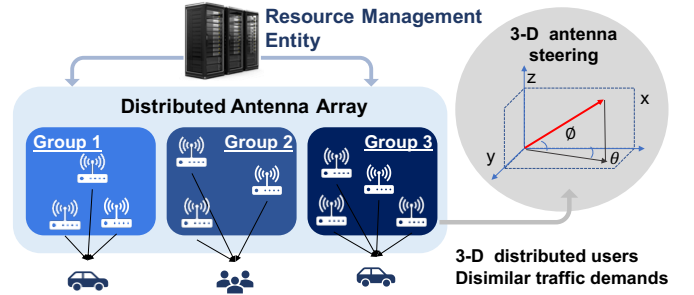


Fig. 1: Distributed beamforming using SDRs with steerable antennas in azimuth (θ) and elevation (ϕ) angles. Edge cloud runs ML and antenna grouping algorithms.

of radios that broadcast information locally to each other, and then jointly transmit to a remote receiver. NetBeam approaches the problem from a systems viewpoint under the DCBF model, recognizing that SDRs can be placed at arbitrary locations and heights. Furthermore, it assumes that antennas fixed on the SDRs may also be mechanically controlled, along with the regular function of pure beamforming (often called as phase synchronization). The goal of the latter is to primarily focus on optimizing the transmission beampattern to direct energy towards the desired receiver (see Fig. 1). With multiple independent SDRs, individual processing latencies may not allow the exact same start of the transmission, even if the same data packet is replicated across all of them. NetBeam intelligently uses receiver feedback to introduce controlled latencies within selected transmitters to operate them all in a lock-step fashion.

A. Need for a different systems approach

Experimental testbeds have previously shown the feasibility and benefits of DCBF using COTS devices. Some examples are the one bit-feedback (1BF) phase synchronization, a Kalman filter-based frequency synchronization or the zero-feedback (0F) blind beamforming [4]. Even though 1BF is fully distributed, its suitability to indoor environments is compromised due to the high convergence time and the adverse scattering and fading conditions. In addition, it does not exploit Channel State Information (CSI) at the receiver, which limits the performance. A CSI-aware set of transmitters can optimally identify which of them are most effective for beam-

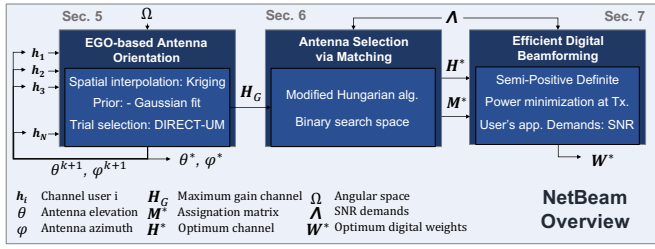


Fig. 2: NetBeam block diagram for Multi-user Heterogeneous traffic

forming to specific receivers [5]. This allows the transmitter group to reduce both, the co-channel interference and transmit power, while still guaranteeing a desired SINR at the receiver. To the best of our knowledge, NetBeam is the first open-source distributed beamforming implementation that uses full CSI information.

B. Joint hardware-software 3D beamforming

Previous works assume a restricted 2-D topology, where transmitters and receivers are located in the same plane. This is growing interest in new beamforming techniques that also accounts for the elevation plane of the antenna resulting in 3-D beamforming (3DBF) or so called Full Dimension Beamforming (FD-BF). 3DBF has proven to mitigate the inter-cell interference [6] and to improve upon multiuser beamspace transmission (MUBT) using the user's angular space information [7]. NetBeam takes the important first step of demonstrating distributed 3-D beamforming using a mixed mode operation: software-driven digital beamforming as well as antenna orientation with low resolution (1 degree) in a wide-angular span (azimuth and elevation), as shown in Fig.1.

C. Fast convergence with machine learning

The antenna orientation needs to keep up with the variations of the channel. Though an exhaustive search would always provide with the optimum elevation and azimuth angles, this becomes unrealistic in real deployments given the high computational time. We leverage recent results from machine learning that address the following question: *how to achieve the optimum in an unknown objective function while minimizing the number of trials to achieve it.* We select the so called Efficient Global Optimization (EGO) approach, which combines modeling and trial selection via acquisition functions. NetBeam uses a novel acquisition function, so-called DIRECT-UM, that splits its operation into Off-line and On-line learning stages. The Off-line stage selects angular trials in a deterministic fashion. The On-line stage relates the sampled and unsampled points in the angular domain using Gaussian Processes, and benefits from the computed variance to select the next trial. This process is done via the Kriging method, which interpolates over the unknowns using the spatial correlation as a Prior. We prove that the combination of DIRECT-UM and Kriging is suitable for our communication scenario, providing the closest solution to optimal within a reduced number of trials.

D. NetBeam Operational Overview

The proposed NetBeam system comprises of three main stages: 1. Antenna orientation, 2. Antenna Allocation, and 3. Centralized 3D Beamforming (Fig. 2). First, the optimal antenna orientation for each transmitter-receiver pair is obtained as described previously (Sec. V). This is followed by antenna grouping and allocation with a max sum-rate policy (Sec. VI), and a fast and optimum beamforming weight computation obtained via Semidefinite programming (SDP) with a min. power policy. This results in an efficient 3DBF approach that leverages CSI from users, allowing NetBeam to serve users with the required SINR while minimizing the overall transmit power (Sec. VII).

Our main contributions are summarized as follows:

- 1) We present the design and systems implementation of NetBeam, which is a fully programmable, distributed beamforming approach. In building this testbed, we identify practical challenges in using COTS hardware and address many synchronization issues (time, frequency, starting instant of transmission).
- 2) We propose a 3-D beamforming approach with both digital beamforming and antenna orientation. We use machine learning to efficiently search the feasible parameter space for a given tx-rx pair, through the Kriging model and a Gaussian process that estimate both the signal gain and uncertainty in estimation.
- 3) We devise a transmitter antenna to user matching algorithm based on the observed CSI and the application demands in terms of the SINR. Using heterogeneous QoS requirements to form groups of SDRs that target distinct receivers differentiates our work from previous approaches such as [5], [8].
- 4) We formulate the distributed beamforming problem of antenna weight allocation using the SDP method. This method includes in the formulation the interference caused to other users within the network through SINR constraints, and solves the problem in a convex form, despite the non-convexity of these constraints [9].

II. RELATED WORK

Antenna orientation, antenna selection, energy-efficient beamforming and synchronization are the key components of a distributed antenna system. In this section we review existing works in each of these areas and highlight the differences with the NetBeam approach.

Antenna orientation: In [10], the authors evinced the benefits of base station antenna tilt in the elevation angle to reduce the inter-cell interference. Moreover, a detail analysis of the impact of antenna orientation on the RSSI is experimentally studied in [11] and [12]. Even though [12] mentions a lower impact of antenna (omnidirectional) orientation, our experimental study shows that antenna orientation can considerably improve receiver SINR in indoor and outdoor environments.

Antenna selection: The study of optimum antenna allocation in a single-user communication has been extensively

covered in [13]. Recently, there is growing interest for multi-user scenarios, where channel correlation between users can potentially degrade the performance. [14] details the optimum computation of the beamforming weights to maximize the individual user subchannels (antenna pairs). [15] reduces the complexity of the system via channel decoupling. [5], [8] further reduces the complexity applying the bidirectional branch and bound algorithm to find the optimal channel matrix. These works focus on the physical layer, and do not accommodate dissimilar QoS requirements of users. NetBeam aims to reduce the complexity for antenna allocation while still accounting for each user's demands.

Beamforming in distributed systems: Beam pattern optimization aims to either reduce the beamwidth [16] or minimizing the sidelobe level (SLL) [17]. For the later, metaheuristic solutions have proven to tackle the NP-Hard problem and effectively minimize the maximum SLL [17]. These systems rely on general knowledge of either the network topology and radio locations [17] or available CSI at the transmitters [18]. Location awareness, however, imposes a big restriction on the system. Moreover, beam pattern optimization does not deal with channel effects, i.e. scattering, making it incomplete. A more realistic approach is found in [18], which targets lifetime maximization in a wireless sensor network while considering SNR and battery constraints.

III. PROBLEM STATEMENT & OVERVIEW

We consider N SDR transmitters, $j \in \mathcal{T}$, equipped with N_{tx} antennas and operating in Time Division Multiplexing (TDD) mode to serve and satisfy the data needs of M users, $i \in \mathcal{R}$, each of which is equipped with a single antenna. The signal is expected to experience flat fading due to a reduced transmission bandwidth, allowing for a simplified and fast channel estimation and equalization.

The transmitters are clustered into disjoint subsets with the aim to combine efforts and increase the data rate at the receiver. For instance, $\mathcal{G}_i \in \mathbb{R}^{|\mathcal{G}_i| \times 1}$ is the subset of $|\mathcal{G}_i|$ transmitters assigned to receiver i , where $|\cdot|$ denotes the cardinal or size of a set. It naturally follows that $\cup_{i \in \mathcal{R}} \mathcal{G}_i \subseteq \mathcal{T}$. Thus, the communication channel between any set of transmitters and receivers follows a Multiple Input Single Output (MISO) structure, given by $\mathbf{y}_i = \mathbf{h}_i \cdot \mathbf{x}_i + \mathbf{n}$. The channel matrix is represented by $\mathbf{h} \in \mathbb{C}^{|\mathcal{G}_i| \times 1}$. The information to be delivered to user i is captured in $\mathbf{x}_i \in \mathbb{C}$, while $\mathbf{n}$ is independent Additive White Gaussian Noise (AWGN). Under these conditions, the capacity is bounded following Shannon's formula $C_{MISO}^{max} = \log(1 + \frac{P \cdot \|\mathbf{h}\|^2}{\sigma^2})$, where P is the maximum transmit power and σ^2 is the noise power.

Users run heterogeneous applications, each with a distinct throughput and latency demand that maps to a required SINR, noted in Λ_i . We envision multi-user links where users are served concurrently by transmitter groups $\mathcal{G}_i \forall i$ operating with mutual interference. For instance, the received frame at user i is $\mathbf{y}_i = \mathbf{h}_i \cdot \mathbf{x}_i + \sum_{k \in \mathcal{R} \setminus i} \mathbf{h}_k \cdot \mathbf{x}_k$. The devices perform equalization at transmission time during beamforming, while

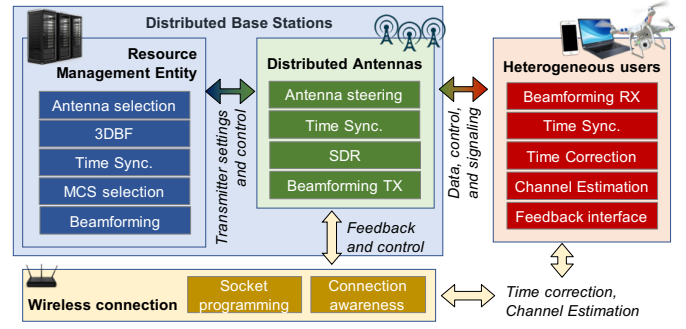


Fig. 3: NetBeam system architecture for heterogeneous users using distributed SDR transmitters.

trying to meet user's demands. This is done while minimizing the interference generated to others, so called inter-user interference (IUI). Thus, the received frame is modified to $\mathbf{y}_i = \mathbf{h}_i \cdot \mathbf{w}_i \cdot \mathbf{x}_i + \sum_{j \neq i} \mathbf{h}_j \cdot \mathbf{w}_j \cdot \mathbf{x}_j$, where $\mathbf{w}_i \in \mathbb{C}^{|\mathcal{G}_i| \times 1} \forall i$. Note that the beamforming weights and the available transmit powers are related by $\|\mathbf{w}_i\|^2 \leq P_i$. Furthermore, the antennas at the SDR transmitters can be flexibly oriented in azimuth and elevation angles in the range, $\phi \in \{0, \pi/2\}$ and $\theta \in \{0, \pi\}$, respectively.

$$\begin{aligned} \min_{\{\mathbf{w}_i\}_{i \in \mathcal{G}}} \quad & \sum_{i \in \mathcal{G}} Tr(\mathbf{w}_i(\phi_i, \theta_i) \cdot \mathbf{w}_i(\phi_i, \theta_i)^H), \forall i \\ \text{s.t.} \quad & \frac{|\mathbf{h}_i(\phi_i, \theta_i) \cdot \mathbf{w}_i(\phi_i, \theta_i)|^2}{\sum_{k \in \mathcal{G} \setminus i} |\mathbf{h}_k(\phi_k, \theta_k) \cdot \mathbf{w}_k(\phi_k, \theta_k)|^2 + \sigma_i^2} \geq \Lambda_i, \\ & \sum_{i \in \mathcal{G}} Tr(\mathbf{w}_i(\phi_i, \theta_i) \cdot \mathbf{w}_i(\phi_i, \theta_i)^H) \leq \mathbf{P}_{t_n} \end{aligned} \quad (1)$$

NetBeam's ultimate objective is to ensure that the user demands Λ_i are always met while the transmit power is minimized, in a distributed deployment with uncoordinated transmitters. The mathematical expression of the problem is given in (1), where $Tr(\cdot)$ represents the trace of the matrix and symbolizes the energy directed towards the intended receiver for each transmitter antenna. [19] proves that that such a formulation gives the optimum beamforming weights, while acknowledging the problems of practical implementation owing to its complexity. In addition, [9] proves that the problem in (1) is non-linear and non-convex, for which finding an optimal solution is NP-Hard. Therefore, the formulation needs to be relaxed to cope with the communication delays and expected channel coherence times.

IV. NETBEAM SYSTEM DESCRIPTION

A. Architecture

The NetBeam architecture (see Fig. 3) consists of the following key components; 1) Distributed base stations 2) Heterogeneous users and 3) Wireless connection units.

• **Distributed Base Stations:** Comprised of a resource management entity (RME) and a set of distributed SDRs with

antennas. The RME receives information of the heterogeneous needs of users using a WiFi control channel. RME consists of software modules such as: antenna selection, time synchronization, modulation and coding scheme (MCS) selection, and 3D beamforming. It identifies the best transmitter settings and communicates them to the distributed SDRs. The antennas mounted on the SDRs also have a steering module to set physical orientations.

The distributed BS are implemented using Ettus X310 USRP SDRs, each with two UBX daughterboards (see Fig. 4). The SDRs are connected to a host machine that runs the RME through high-speed Ethernet. The software stack at the host is implemented in MATLAB and Python. Each radio is equipped with VERT900 isotropic antenna at 3dBi gain with 900 MHz as operational frequency. OFDM modulated packets are created through the Communication Toolbox. These packets are pre-pended with special preamble sequences called as Gold codes and transmitted from each radio synchronously. Gold codes are generated using *preferred* pairs of sequences that have good cross- and auto-correlation properties. Therefore, these codes allow concurrent synchronization and channel estimation at multiple receivers.

NetBeam enables antenna orientation via a reconfigurable control plane. We use small-form servo motors controlled by an Arduino micro-controller, and attach them to any given omni-directional antenna for setting elevation and azimuth angles. We attach an Arduino UNO to an NRF24L01 transceiver module (master) that issues directives to the servo motors, mandated by the host computer. At the antenna, each servo motor pair is connected to an Arduino NANO equipped with a NRF24L01 receiver module (slave).

- **Heterogeneous Users:** The receiver is composed of Ettus B210 USRP SDRs connected to a host machine via USB cable. The receiver estimates the time correction by applying cross-correlation techniques and estimates the channel by employing simple Least Square (LS) fit approach. This calculated channel response is inserted in the payload for transmitter-side beam weight computation. Thus, transmitters are now able to synchronize the transmitted signals in phase at the receiver. In addition, to enable coherence reception, all radios are synchronized in frequency and time by connecting them to a common reference OctoClock-G.

B. Frame structure and CSI

The transmitted frame comprises a preamble and a payload field. The bits are modulated using the classical phase shift keying (PSK) and quadrature amplitude modulation (QAM) schemes, depending upon channel conditions. The symbols are further OFDM modulated using a 256-IFT point. We employ *Zero padding* at the OFDM modulation to avoid Inter Symbol Interference (ISI), hence ensuring symbol recovery. Finally, the symbols are adjusted according to the beamforming weights, represented by a single complex value w . This simplifies the implementation and prevents the need for multiple pilots for channel estimation. Thus, the system operates under a flat-

fading regime, with a bandwidth of 400KHz, properly ensured using interpolation, decimation and subcarrier spacing.

In order to generate a set of Gold codes, two Maximal-sequence Linear-Feedback Shift registers (MLFSR) of order $m = 11$ are used, with polynomials chosen according to the specifications in [20]. The outputs of the two MLFSRs u and v are *XOR*-ed, such that the set of output Gold codes is $G = \{u, v, u \vee v, u \vee T^1 v, \dots, u \vee T^{n-1} v\}$, where $n = 2m - 1$ is the period of the Gold code, and $T^k v$ is the k -th shift of MLFSR v . The symbol $\vee$ denotes the *XOR* operation. In this way, a set of $2m + 1$ sequences can be generated, all of which have the maximum cross-correlation property following $\theta_{max} = 2^{\lfloor \frac{m+1}{2} \rfloor} + 1$. In addition, the peak auto-correlation of every sequence in G is given as $\phi(0) = 2^m - 1$. The maximum ratio of cross- to auto-correlation is given by $r_{max} = \theta_{max} \cdot \phi(0)^{-1}$. Thus, for the set of Gold codes of order $m = 11$, there is a peak ratio of cross-to-auto-correlation of 0.03.

We obtain the CSI employing the LS approach for a generated Gold code G and a presumed received Gold code $\hat{G}$, as the receiver can easily obtain estimated channel response of $\tilde{H}$ by $\tilde{H} = \hat{G}/G$. The CSI information arrives at the transmitter with a delay of d samples, and the normalized beamforming weights can be calculated using this delayed channel estimation as $w[n-d] = \left(\tilde{H}[k-d] / \|\tilde{H}[k-d]\| \right)^{-1}$. As a result, channel estimates from the receivers are used continuously to update the transmitter-side beam weights (see Sec. VII).

C. Generating Receiver Feedback

NetBeam's CSI feedback packets are generated within the MATLAB platform and then stored in the system buffer. In the feedback packet, three main information blocks are included: 1) CSI that is estimated from channel response of each transmitter, 2) Time correction for preventing misalignment between Gold codes and ensuring each SDR transmits in lock-step, and 3) Optimized angular parameters for the orientation of each antenna. We use Python to setup a multicast connection between the receiver and multiple transmitters to deliver these packets to more than one end-point through a router via UDP.

D. Phase, Frequency and Time synchronization

NetBeam compensates for the phase offset of initially uncoordinated SDRs by using the cross-correlation property of Gold codes to estimate channel response for each tx-rx pair. Depending on the received CSI, the transmitted signal is multiplied with the beamforming weights at the transmitter-side. In addition, NetBeam compensated for the frequency offset by means of a common reference clock, generated using the *Octoclock-G*. This unit distributes 10 MHz and 1 PPS signals generated from an external source and is connected via wires to the transmitters. Time synchronization is ensured using the correlation indexes for each Gold sequence at the receiver. A mismatch reveals a lack of time synchronization and triggers the time correction procedure. The receiver notifies the RME of the node that is ahead of the rest, requesting it to defer its transmission by the difference in the correlation indexes.

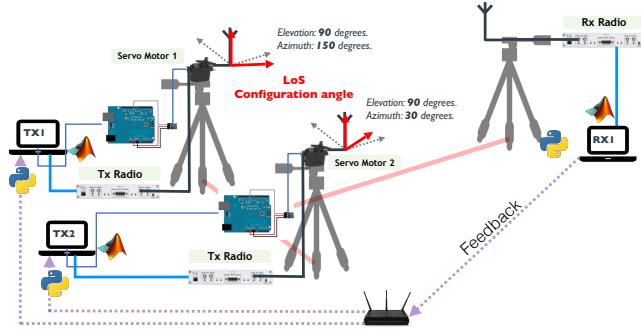


Fig. 4: Two X310 and one B210-USRP, acting as transmitter and receiver, respectively.

E. Preliminary studies and motivation

We aim at characterizing the channel for different physical antenna orientations to validate the following claim: despite the popularity of pure-digital beamforming solutions, a joint software-hardware implementation is needed. We employ a reduced setup described in Fig. 4, exploring the complete angular range of orientations in steps of 1 degree in both, azimuth and elevation. The Gold sequences from Sec. IV-B enable frame-detection and channel estimation. We use the channel feedback described in Sec. IV-C to notify transmitters of the new orientation angles.

The results are shown in Fig. 5, for indoor- and outdoor-communication. The key observation is that the orientation between antenna pairs impacts on the maximum achievable channel gain in the order of 10x. More interestingly, the LoS rarely offers the maximum gain in indoors, while it does so for outdoor scenarios. The multipath effect and rich scattering indoors creates constructive and destructive interference with low correlation with the LoS path. Thus, simple location-based orientation leads to suboptimal gain and, in turn, a lower achievable capacity.

We are thus motivated to devise a more advanced antenna orientation mechanism to utilize the full capacity of the channel. The presence of multiple local maximum and the lack of convexity in the general channel gain plots advocate for a new approach. In the next section, we present our proposed antenna orientation scheme, where we minimize (i) the gap to optimum antenna orientation, and (ii) minimize the number of trials required to achieve this level.

V. ANTENNA ORIENTATION

In this section, we propose a method for finding the optimal antenna orientation for each transmitter-receiver pair, i.e. $\phi_{j,i}$ and $\theta_{j,i}$, $\forall i \in \mathcal{R}, \forall j \in \mathcal{T}$.

We approach the problem using Bayesian theory and cast it as a sequential decision problem, where the set of feasible angular choices is minimally explored. This is important because the cost associated with computing the gain function $G(\phi, \theta)$ at any given ϕ and θ is non-negligible for real-time systems. Ultimately, NetBeam returns the tuple (ϕ^*, θ^*) that

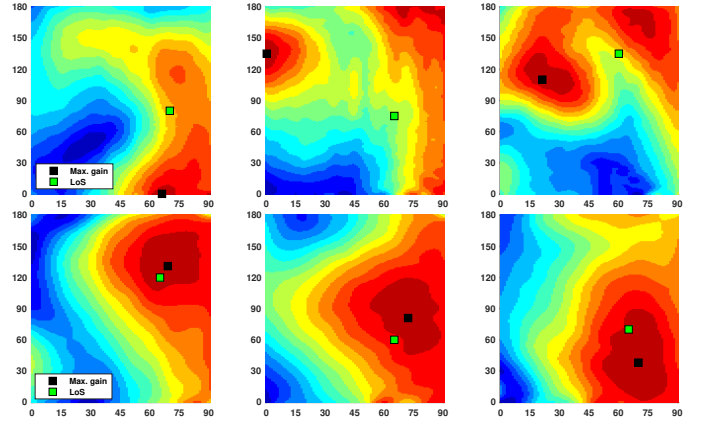


Fig. 5: Empirical gain for *indoor* (top) and *outdoor* (bottom) using the testbed in Fig. 4. The results reveal a non-trivial optimum and a non-negligible gain difference from LoS to optimum. X and Y axis map to Azimuth and Elevation angles.

maximizes the gain G and gives also the loss associated with the choice $\lambda(\phi^*, \theta^*)$, the latter obtained via the Bayesian formalism of the problem. We use a Kriging-based approach to model the environment due to its unique inclusion of spatial autocorrelation between the inferred and empirically measured data [21].

Section V-A provides a brief insight of Kriging and how Gaussian Processes (GP) are used to infer the probability of maximum channel gain at each exploration point. Section V-B proves that the empirical data actually meets the Kriging data pre-requisites. Section V-C describes the overall procedure to find the next angles to be analyzed, i.e. $(\phi^{k+1}, \theta^{k+1})$, the stopping criteria δ and the consequent final optimum orientation (ϕ^*, θ^*) .

A. GP and the Kriging model

GP can be treated as a generalization of the multivariate normal distribution, where $\mathbf{t}$ represents the bidirectional collection of indexes $\{\phi_{i,j}, \theta_{i,j}\}$. The yet-to-be visited points in the set are characterized by (2), where I represents the prior knowledge of the spatial distribution. Given the Gaussian nature, I is modeled with mean vector μ and covariance matrix $\mathbf{C}(\mathbf{y}, \mathbf{y}')$, also referred as Kernel $\mathbf{K}(\mathbf{x}, \mathbf{x}')$.

$$P(\mathbf{y}|\mathbf{x}, \mu, \mathbf{C}) = \mathcal{N}(\mathbf{y}|\mathbf{x}, \mu, \mathbf{C}) = \frac{1}{(2\phi)^2 |\mathbf{C}|} \cdot e^{\frac{1}{2}(\mathbf{y}-\mu)^H \mathbf{C}^{-1}(\mathbf{y}-\mu)} \quad (2)$$

This way, $P(\mathbf{y}|\mathbf{x}, \mu, \mathbf{C})$ reveals the most probable value for each point in the angular space to return the maximum channel gain, i.e. μ , and how gains from different angles correlate, i.e. $\mathbf{C}$. Conversely, we can write $\mu(\mathbf{x}) = E[(\mathbf{y}|\mathbf{x})]$ and $\mathbf{K}(x, x') = \text{Cov}(P(\mathbf{y}|\mathbf{x}), P(\mathbf{y}|\mathbf{x}'))$. For instance, if we wish to predict $y|x$ with $y \sim \mathcal{N}(\mu, \mathbf{C} = \mathbf{K}(x, x))$, we would use the previously computed value x^0, y^0 to get the joint probability distribution $P(\mathbf{y}, \mathbf{y}^0)$ as in (3), where $\mathbf{C}_* = \mathbf{K}(x, x^0)$. Bayes rule gives us the conditional probabilities for these two samples as shown in (4). Thus, the mean and variance in the

posterior distribution represent the prediction and the value of uncertainty, respectively.

$$\begin{bmatrix} \mathbf{y} \\ \mathbf{y}_0 \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mu \\ \mu^0 \end{bmatrix}, \begin{bmatrix} \mathbf{C} & \mathbf{C}_*^* \\ \mathbf{C}_*^T & \mathbf{C}^0 \end{bmatrix} \right) \quad (3)$$

$$P(y|\mathbf{y}^0) \sim \mathcal{N}(\mu^0 + \mathbf{C}_*^T \mathbf{C}^{-1}(\mathbf{y} - \mu), \mathbf{C}^0 - \mathbf{C}_*^T \mathbf{C}^{-1} \mathbf{C}_*) \quad (4)$$

Therefore, GP generates the posterior distributions given our selected angle $\mathbf{x}$ and prior distributions μ^0 and $\mathbf{C}^0$. Several models are suggested to approximate the covariance matrix, also called semivariogram. We will show that a Gaussian Kernel allows for the best fit using the LS approximation [22] (more details in Sec. VIII). The model is shown in (5), where c_0 and a_0 are the hyperparameters, and h represents the distance between any pair of angles, i.e. $h = \|\mathbf{x} - \mathbf{x}'\|^2$.

$$\mathbf{K}(h|c_0, a_0) \sim c_0 \left[1 - \exp \left(-\frac{h^2}{a_0^2} \right) \right] \quad (5)$$

Kriging extends from GPs in the sense that it allows to model every single point as the sum of a weighted function, called as a *trend*, and a GP with 0 mean and variance $\mathbf{K}$, i.e. $\mathbf{g} \sim GP(0, \mathbf{K})$. Among the three different Kriging models (simple, universal or ordinary), we fit the ordinary Kriging model (OK) into our system given the stationary nature of the data, i.e. no mobility in-between angular space sampling. Therefore, the Kriging model can be expressed in (6), where the coefficients $\mathbf{W}(\mathbf{y})$ are the Kriging trends and represent the prediction value. For simplicity, we write these as $\mathbf{W}$, with their uncertainty metric captured in y , a GP centered in the prediction $\mathbf{W}^T \mathbf{x}$, added to environmental noise ϵ_x .

$$y_0(x_0|\mathbf{x}, \mathbf{y}) = \mathbf{W}^T \mathbf{x} + \mathbf{g} + \epsilon_x \quad (6)$$

$$\begin{aligned} \min_{\mathbf{W}_i} \quad & \sigma_y^2 = E[\{y - \hat{y}\}^2] = C_{00} + \mathbf{W}^T \mathbf{C} \mathbf{W} - 2\mathbf{W}^T \mathbf{C}_0 \\ \text{s.t.} \quad & \mathbf{W}^T \mathbf{1} = 1 \end{aligned} \quad (7)$$

$$\mathbf{W}^* = \mathbf{C}^{-1} (\mathbf{C}_0 - \lambda^T \mathbf{1}) \quad (8)$$

The Kriging estimate is obtained by choosing weights $\mathbf{W}$ so that the estimation variance σ_y^2 is minimized. We define the matrix of autocovariance from the sampled data as $\mathbf{C} \in \mathbb{R}^{P \times P}$, and the covariance between $\mathbf{x}$ and the spot $\mathbf{y}$ as $\mathbf{C}_0 \in \mathbb{R}^{P \times 1}$. In addition, the cumulative sum of the weights should be constant and normalized. The constrained optimization problem is defined in (7).

The Best Linear Unbiased Estimator (BLUE) has the lowest estimate variance among all other linear, unbiased estimators, under the following conditions: (i) $E(\epsilon) = 0, \forall i$, (ii) $Var(\epsilon) = \sigma^2$, and (iii) $Cov(\epsilon_i, \epsilon_j) = 0$ [21]. Since the only source of error is AWGN noise, known to have 0 mean, constant variance and independent, we conclude that BLUE will give the optimum configuration (8). The constrained problem is tackled via duality using the Lagrange Multipliers λ , leading to the solution $\lambda^* = (\mathbf{C}^T \mathbf{C}_0^{-1} - 1)(\mathbf{1}^T \mathbf{C}^{-1} \mathbf{1})^{-1}$. Note that the

Algorithm 1 Proposed DIRECT EGO-based antenna orientation

- 1: Init. angular space: $\Omega = \{\Phi, \Theta\}$, $\forall \phi \in \Phi, \forall \theta \in \Theta$
 - 2: Init. DIRECT and channel functions: $\mathbb{D}()$, $f()$
 - 3: Init. number of trials in On-line learning: K_D
 - 4: Init. candidates: $\Pi \equiv (\Phi_0, \Theta_0) \in \mathbb{R}^{K_D \times 2} \in \Omega$
 - 5: Init. stopping threshold γ and model variation Δ_K
 - 6: Populate $\mathbf{x}$ with candidates: $\mathbf{x} \leftarrow \Pi$
 - 7: Eval. channel at $\mathbf{x}$: $\mathbf{y} \leftarrow f(\mathbf{x})$ (Off-line learning)
 - 8: Compute Variogram of $\langle \mathbf{x}, \mathbf{y} \rangle$: $\mathbf{Var}(\mathbf{x}, \mathbf{y})$
 - 9: Gaussian fit to $\mathbf{Var}$: $\mathbf{K}(x, x')$, $\forall x, x' \in \Omega$ (Kernel)
 - 10: Kriging to $\mathbf{x}, \mathbf{y}$ and $\mathbf{Kr}(\mathbf{x}, \mathbf{y})$: $\mathbf{K}_p, \mathbf{K}_v$
 - 11: Select best: $\pi^* \leftarrow \arg \min_{x \in S} \mathbb{E}(\|\mathbf{K}_p\|; \mathbf{x})$
 - 12: **while** $\gamma \geq \Delta_K$ **do**:
 - 13: Sort Π , K_D best: $\Pi_s = \text{sort}(\mathbb{E}(\|\mathbf{K}_p\|; \mathbf{x}, K_D))$
 - 14: **for** $\mathbf{t}'$ in Π **do**:
 - 15: Select new trial: $x^{n+1} \leftarrow \mathbf{t}'$ (On-line learning)
 - 16: Eval. channel at x^{n+1} : $y^{n+1} \leftarrow f(x^{n+1})$
 - 17: Apply DIRECT to x^{n+1} : $\mathbf{t}_D \equiv (\Phi, \Theta) \in \Omega$
 - 18: Add $\mathbf{t}_D$ to total candidate set: $\Pi \leftarrow \Pi \cup \mathbf{t}_D$
 - 19: Remove explored configuration: $\Pi \leftarrow \Pi \setminus \mathbf{t}'$
 - 20: Update set: $\mathbf{x} \leftarrow \mathbf{x} \cup x^{k+1}$ and $\mathbf{y} \leftarrow \mathbf{y} \cup y^{k+1}$
 - 21: Update subindex n : $n \leftarrow n + 1$
 - 22: Update Variogram of $\langle \mathbf{x}, \mathbf{y} \rangle$: $\mathbf{Var}(\mathbf{x}, \mathbf{y})$
 - 23: Gaussian fit to $\mathbf{Var}$: $\mathbf{K}(x, x')$ (Kernel)
 - 24: Kriging to $\mathbf{x}, \mathbf{y}$ and $\mathbf{Kr}(\mathbf{x}, \mathbf{y})$ in: $\mathbf{K}_p, \mathbf{K}_v$
 - 25: Select best: $\pi^* \leftarrow \arg \min_{x \in S} \mathbb{E}(\|\mathbf{K}_p\|; \mathbf{x})$
 - 26: Model variation $\Delta_K = \max(\mathbf{K}_p^n - \mathbf{K}_p^{n-K_D})$
 - 27: **return** $\pi^* \equiv (\phi^*, \theta^*)$
-

solution weights depend only on the spatial covariance and the semivariogram (prior).

B. Kriging data prerequisites

Classical Kriging provides the optimal interpolation technique if the input data meets certain criteria: First, the data needs to have a normal distribution. Second, the data needs to be stationary. Third, the data cannot have any *trends*. The second condition is met since the only disturbances in the system is the AWGN, taken into consideration in (6). Finally, we determine that the data has no *trends* by inspecting the generated dataset, containing uneven and dissimilar distributions of maximums and minimums across the space.

C. Proposed approach based on GP

The objective in the antenna orientation is two-fold: obtain the optimum combination of angles (ϕ^*, θ^*) for every antenna pair while minimizing the number of sampling points. We approach the problem using Efficient Global Optimization (EGO) theory, which considers scenarios where the objective function is undefined [23]. The solution comes from the combination of three well-differentiated aspects: (i) environment modeling, (ii) point selection and (iii) stopping criteria.

With (i) described earlier in Sec. V-A, we focus attention on (ii) and (iii). Standard EGO nomenclature refers to (ii) as

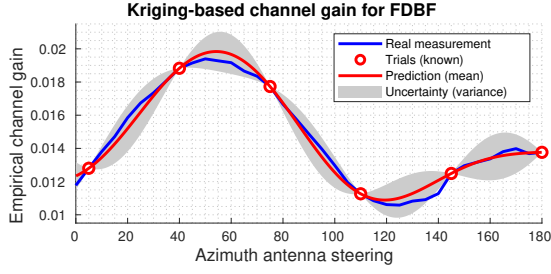


Fig. 6: Kriging modeling applied to a sample preliminary result shown in Fig. 5. Elevation is fixed and azimuth variable for better visual. Trials are limited and equidistant.

the acquisition function, which decides the way we sample our unknown function. Bayesian theory becomes critical at this stage, since it not only provides an estimation of the unknown values, but also it provides an understanding of how sure we are about each prediction, giving the so-called prediction uncertainty (Fig. 6). In other words, it allows for the exploration in areas with high prediction values, high uncertainty on the measure, or both. We want to minimize the expected deviation from the maximum $\mathbf{G}^*$ when choosing the next trial point x^{k+1} .

An extensive analysis on acquisition functions is available in [22]. The least complex approach is the so-called Probability Improvement (PI), where the next trial is selected to be the one with the highest expectation. That is, $x^{n+1} \leftarrow \arg \min_{x \in S} \mathbb{E}(\|\mathbf{K}_p\|; \mathbf{x})$. PI works well with smooth and convex objective functions but may get stuck at a local minimum, which occurs in Fig. 5. Another widely used function is the Expectation Improvement (EI), where uncertainty at each unknown combination is treated as if the predicted value was generated from a normal distribution with mean and standard deviation given by the Kriging predictor. However, this requires tuning the environmental noise ϵ that controls the exploration-exploitation phases.

We propose a method that requires no exploration-exploitation tuning and limits the search space to a confined subset, given the time limitation driven by the coherence time of the channel. To that end, we use the DIvide in REctangles (DIRECT) method, which samples the space into equidistant squares and applies a fractal procedure as samples are withdrawn from them. Thus, DIRECT generates a set of possibilities for next trial. We apply a variance minimization (VM) mechanism, selecting the point to explore that has the highest uncertainty in the Kriging model (see Sec. V-A).

Our approach, called as DIRECT-UM, alternates between environmental modeling, via Kriging, and next trial selection, via uncertainty minimization (UM). The algorithm comprises two stages: Off-line learning, where the channel is evaluated using pre-stored angles that span as much as possible the set; and On-line learning, where we employ DIRECT-UM to select the next trials. In On-line learning, the system keeps trying new antenna angles until the variation on the channel map Δ_k is below a certain threshold (Alg. 1).

VI. ANTENNA GROUPING & ALLOCATION

Next, we present the approach of grouping the transmitter SDRs together to serve different target receivers. We state the objective as: *given the channel gains y^* provided by DIRECT-UM (see Sec. V), select the best transmitters to beamform towards each user.* We attempt to maximize the MISO sum-rate so that each user perceives an interference-free environment.

The RME builds matrix $\mathbf{M} \in \mathbb{C}^{N \times M}$ containing $y_{i,j}^*, \forall j \in \mathcal{T}$ and $\forall i \in \mathcal{R}$. Noting heterogeneous QoS demands, we model the network as a bipartite graph $\mathcal{G}_r = (\mathcal{T}, \mathcal{R}, \mathbf{M})$, where the sets $\mathcal{T}$ and $\mathcal{R}$ contain the transmitters and receivers, and $\mathbf{M}$ represents the collection of $y_{i,j}^*$. The antenna assignment problem is solved using the Hungarian Algorithm [24], which finds the perfect matching for the max sum-rate in the network. Thus, every node in set $\mathcal{T}$ is linked to one node in set $\mathcal{R}$ and removed from the set $\mathcal{T}$ afterwards. Given that users are to be allocated multiple transmitters (MISO), a modified Bipartite Graph $\mathcal{G}_r$ is formed by adding dummy transmitters so that a perfect match can be found. That is, adding extra nodes in $\mathcal{G}_r$ so that a one-to-one assignment in the graph results in a multiple-to-one assignment in the real world. The Hungarian Algorithm has polynomial complexity given by $O(n^3)$ and always finds the optimum allocation in the graph $\mathcal{G}_r$.

We execute the modified Hungarian for different K , denoting the maximum number of transmitters to be allocated per user. This allows to balance available SDR resources with capacity maximization. For each K , the algorithm terminates when $\mathcal{T}$ is either an empty set or no further matches are possible, returning the matching in $\mathcal{M}$. The time complexity of the method $O(Nn^3)$ is further reduced by employing a binary search algorithm to explore the space, confining the values of K via space bisection. The stopping rule is an improvement below what is considered meaningful.

VII. EFFICIENT 3-D BEAMFORMING

Semidefinite programming allows us to solve the non-convex NP-hard problem presented in Section III in polynomial time. By solving the problem in (1), we not only take into account scattering, but also consider the interference caused to unintended receivers within the network, which is desirable for our multi-user scenario.

The non-convexity of (1) is shown in [25]. SDP relaxation is based on the inclusion of a new matrix variable defined as $\mathbf{W}_i(\phi_i, \theta_i) = \mathbf{w}_i(\phi_i, \theta_i) \mathbf{w}_i^*(\phi_i, \theta_i)$. Subsequently in this paper, we simplify the notation regarding the selected 3DBF angles, i.e. $\mathbf{w}_i = \mathbf{w}_i(\phi_i, \theta_i)$. The resulting new formulation is described in (9).

$$\begin{aligned}
& \min_{\{\mathbf{W}_i\}_{i \in \mathbb{G}}} \sum_{i \in \mathbb{G}} \text{Tr}(\mathbf{W}_i), \quad \forall i \\
& \text{s.t.} \quad \text{Tr}(\mathbf{R}_i \mathbf{W}_i) - \Lambda_i \sum_{k \in \mathbb{G} \setminus i} \text{Tr}(\mathbf{R}_k \mathbf{W}_k) \geq \Lambda_i \sigma_i^2, \\
& \sum_{i \in \mathbb{G}} \text{diag}(\mathbf{W}_i \leq \mathbf{P} \mathbf{t}_n), \\
& \mathbf{W}_i = \mathbf{W}_i^*, \\
& \mathbf{W}_i \geq 0, \\
& \text{Rank}(\mathbf{W}_i) = 1
\end{aligned} \tag{9}$$

Where $\mathbf{R}_i$ is the channel correlation matrix, the property $\mathbf{w}_i^* \mathbf{R}_i \mathbf{w}_i = \text{Tr}(\mathbf{R}_i \mathbf{w}_i \mathbf{w}_i^*) = \text{Tr}(\mathbf{R}_i \mathbf{W}_i)$ is used, and the last three constraints assure the equivalence between (1) and (9). Notice that the equality $\mathbf{W}_i = \mathbf{w}_i \mathbf{w}_i^*$ holds when $\mathbf{W}_i$ is a one-rank positive semidefinite matrix. It can be proven that when $\mathbf{W}_i$ is one-rank, $\mathbf{w}_i$ can be computed as an eigenvector associated to the only non-null eigenvalue. (9) is not a convex problem yet and requires further modifications. By removing the one-rank constraint of the weight matrix $\mathbf{W}_i$, we relax the problem and allow it to be solved efficiently. Our goal then is depicted in (10), where we employ convex optimization techniques.

$$\begin{aligned}
& \min_{\{\mathbf{W}_i\}_{i \in \mathbb{G}}} \sum_{i \in \mathbb{G}} \text{Tr}(\mathbf{A}_i \mathbf{W}_i), \quad \forall i \\
& \text{s.t.} \quad \text{Tr}(\mathbf{R}_i \mathbf{B}_i \mathbf{W}_i) - \Lambda_i \sum_{k \in \mathbb{G} \setminus i} \text{Tr}(\mathbf{R}_k \mathbf{B}_k \mathbf{W}_k) \geq \Lambda_i \sigma_i^2, \\
& \sum_{i \in \mathbb{G}} \text{diag}(\mathbf{W}_i \leq \mathbf{P} \mathbf{t}_n), \\
& \mathbf{W}_i = \mathbf{W}_i^*, \\
& \mathbf{W}_i \geq 0
\end{aligned} \tag{10}$$

The matrices $\mathbf{A}_i$ and $\mathbf{B}_i$ are multiplied by $\mathbf{W}_i$ in order to assign each antenna to a user according to the previously computed antenna allocation. The problem in (10) is solved using the interior point method approach [26]. Furthermore, given that the unitary rank constraint is relaxed, the rank of the solution $\mathbf{W}_i^*$ could be greater than unitary. [27] shows that the rank of $\mathbf{W}_i^*$ is one and thus, the optimum solution is always found.

VIII. PERFORMANCE EVALUATION

In this section, we provide a comprehensive evaluation study on our experimental testbed resented in Sec. IV to validate the claims that NetBeam (i) requires minimum trials to find the optimum orientation per antenna pairs, (ii) allocates antennas efficiently so that the network capacity bound is maximized, and (iii) reduces the emitted power while guaranteeing good SINR service. First, we generate extensive channel matrices from different deployment scenarios, ranging from several transmitters, receivers, radio locations in a 3D space. We refer



Fig. 7: NetBeam outdoor testbed with a given antenna-location configuration

to this as our *dataset*, which we divide into training and validation sets. Our setup can be further inspected in Fig. 7 and test-cases in Fig. 8.

The testbed comprises 12 USRP-X310 transmitter SDRs and 3 USRP-B210 radios as receivers. The architecture follows the description in Sec. IV. Transmitters and receivers are centrally connected to the RME, which receives the measurements from the receivers, computes the antenna orientation (Sec. V), weights (Sec. VII) and time correction (Sec. IV-D), and forward the information to the transmitters.

A. NetBeam spatial correlation

We reduce the amount of computations during modeling by considering spatial correlation in data. That is, NetBeam finds the optimum orientation using the gains associated to the visited angles and the angular distances to any un-visited angle. Distance here refers to the 2-norm between $\mathbf{x}_i$ and $\mathbf{x}_j$, $\forall i, j \in \mathcal{T}$. To that end, we employ our training data, indoors and outdoors, to compute the semivariogram, and to construct the Prior during the Kriging procedure. Fig. 9 shows the experimental semivariogram, characterizing the *sill*, i.e. the value at which the model first flattens out, and the *range*, i.e. the maximum distance for which we can still consider correlation. The *range* reveals to be approximately 100 (norm L^2), taken as a constraint in steps 4 and 12 of Alg. 1, fastening the execution and improving the efficiency.

B. NetBeam antenna orientation

In this section, we prove that our proposed trial selection in the antenna orientation procedure (Direct-UM) finds the optimum with the minimum number of trials. To that end, we implemented other common acquisition functions: variance minimization (VM), random selection (Random) and DIRECT with random sampling (Direct-RD). We use the empirical data from our data set in the indoor and outdoor deployment, shown in Fig. 8. Given the time constraint in real systems, the angular exploration is capped at 8 trials.

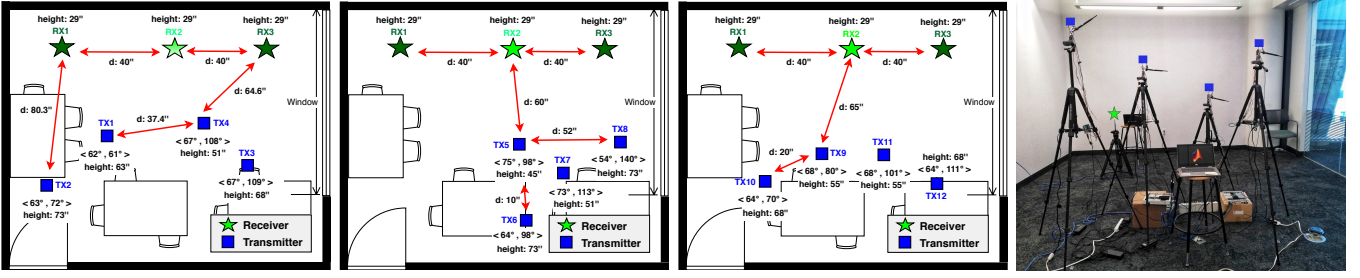


Fig. 8: Indoor test-cases. Experiments are labeled 1,2,3 (a), 3,5,6 (b), 7,8,9 (c). We employ 12 transmitters and 3 receivers with different locations and heights. Sample scenario of Experiment 1 in (d) (LoS wrt RX2).

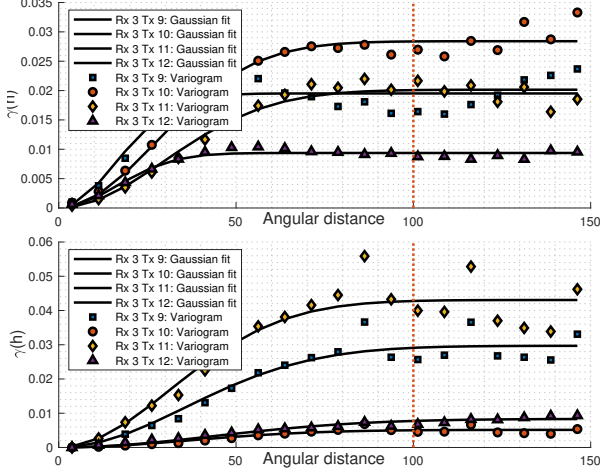


Fig. 9: Semivariogram using a Gaussian fit and BLUE for Indoor (top) and Outdoor (bottom).

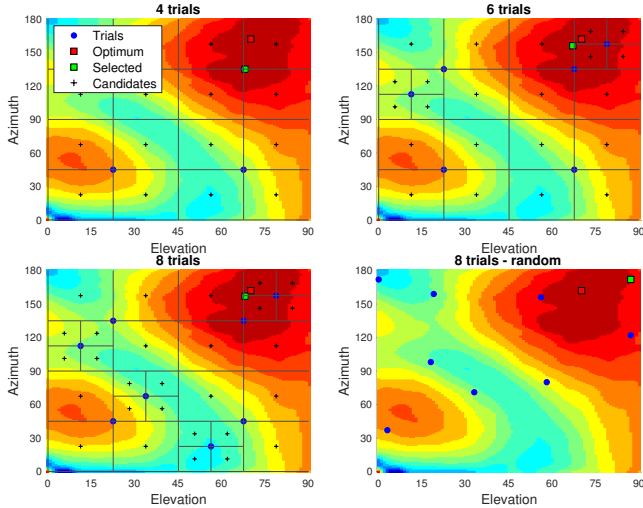


Fig. 10: DIRECT-UM partitions the space and finds the optimum within few iterations via variance minimization. Other techniques, i.e. Random search, do not search the space efficiently.

The behavior of Direct-UM is explained in Fig. 10, where the space is divided using DIRECT and the optimum ori-

entation is found within a limited set of trials. A Random strategy, however, offers a worse performance. A comparative summary of the aforementioned algorithms is included in Fig. 11. Indeed, DIRECT-UM minimizes the gap to optimality when the off-line stage is large, benefiting from the Variance in the set and selecting the points with highest uncertainty. The greedy (PI) policy is unsuitable for non-convex objective functions. DIRECT-RD, with no use of prior knowledge, manages to explore the space but always settles in a local minima. An unguided UM only exploits the exploration stage, leading to a larger gap.

C. Power minimization and required SINR

We now show that the multi-stage comprising antenna orientation using DIRECT-UM and antenna allocation produce the minimum transmit power while meeting the desired SNR. We use the empirical data from the test case shown in Fig. 8, execute the DIRECT-UM approach (Sec. V) and apply the Hungarian Algorithm (Sec. VI) on the RME. The maximum available transmit power at each node is assumed to be the same. The used power and the resulting SNR is shown in Fig. 12. As expected, the optimum antenna allocation (Modified Hungarian) combined with DIRECT-UM-based orientation requires the minimum power while still able to meet the SNR demands. An improper antenna allocation results in drastic SNR losses.

IX. CONCLUSIONS

We introduce NetBeam, a full programmable 3-D beamforming approach with both digital beamforming and mechanical antenna orientation that serves multiple users with heterogeneous application demands. First, we show the substantial channel gain when the antenna is properly oriented versus a conventional LoS or even fixed orientation. We then propose the multi-stage approach that comprises of: (i) antenna orientation, (ii) antenna allocation and (iii) efficient SDP-beamforming. Performance evaluation results show that DIRECT-UM always finds the best solution in a minimum number of angle trials, compared to other efficient acquisition functions. In addition, NetBeam minimizes the transmit power compared to conventional methods, while still meeting the applications demands. Our approach is validated using our testbed, using COTS devices deployed in indoor and outdoor conditions.

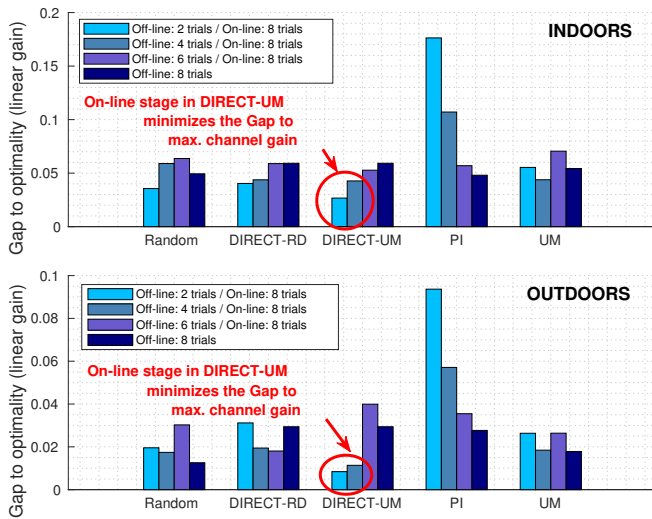


Fig. 11: Gap to optimum antenna orientation using the proposed method in Sec. V. DIRECT-UM minimizes the gap in a reduced set of trials thanks to the On-line stage.

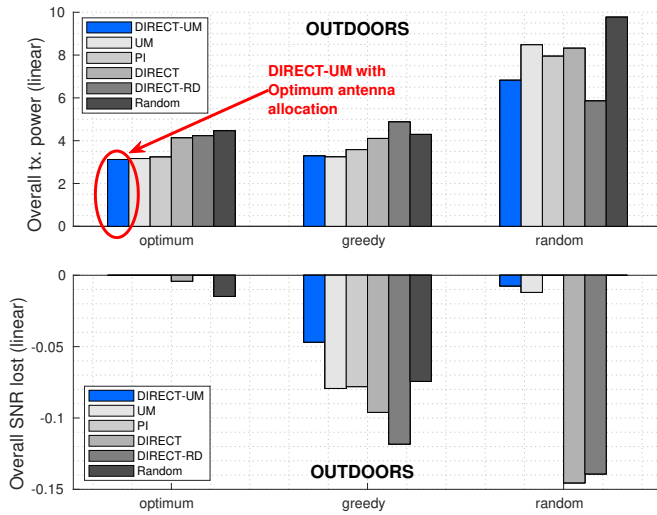


Fig. 12: Power minimization using proposed multi-stage mechanism (Sec. V, VI and VII)

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