Beam Training and Alignment for RIS-Assisted Millimeter-Wave Systems: State of the Art and Beyond

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Abstract
Reconfigurable intelligent surface (RIS) has recently emerged as a promising paradigm for future cellular networks. Specifically, due to its capability in reshaping the propagation environment, RIS was introduced to address the blockage issue in millimeter-wave (mmWave) or even terahertz communications. The deployment of RIS, however, complicates the system architecture and poses a significant challenge for beam training (BT)/beam alignment (BA), a process that is required to establish a reliable link between the transmitter and the receiver. In this article, we first review several state-of-the-art beam training solutions for RIS-assisted mmWave systems and discuss their respective advantages and limitations. We also present a new multidirectional BT method, which can achieve decent BA performance with only a small amount of training overhead. Finally, we outline several important open issues in BT for RIS-assisted mmWave systems.

Introduction
Millimeter-wave (mmWave) communications have been considered as an enabling technology for beyond 5G (B5G) or 6G systems to accommodate the exponentially increasing demand of wireless data services. Nevertheless, millimeter-wave mmWave signals suffers severe path loss (e.g., 100 dB/100 m at 28 GHz) [1, 2]. To compensate for such path loss, large antenna arrays and beamforming techniques are utilized at the transceiver to provide adequate link budgets. Directional beamforming, however, makes mmWave communications vulnerable to blockage. For instance, it was reported in [3] that the mmWave link can easily be blocked by a small obstacle such as a person’s arm. Hence, blockage is considered a major issue that hampers the deployment of mmWave communications in cellular networks.

To alleviate the blockage problem, reconfigurable intelligent surface (RIS), also known as metasurface and large intelligent surface, has recently emerged as a promising paradigm to establish a virtual line-of-sight (LoS) path when the direct link is blocked by obstructions [4, 5]. Specifically, RIS is a planar surface consisting of a massive number of low-cost and passive reflecting units. Each unit or element can induce an adjustable amplitude and phase shift to reflect the incident electromagnetic waves with the aid of a smart controller [6]. RIS-assisted systems can thus help reshape the wireless propagation environment via software-controlled reflection.

Recent progress has shown the great potential of RIS as an auxiliary device in boosting spectral efficiency, mitigating interference, enhancing physical security, and so on [7]. In particular, since RIS only passively reflects the impinging signals, it can be operated in an energy-efficient way without the need for radio frequency (RF) chains, and can thus reduce the energy consumption by orders of magnitude compared to traditional active antenna arrays. Also, due to its passive characteristics, RIS is free of self-interference and antenna noise amplification. Recent theoretical analyses reveal that RIS-assisted systems can achieve a quadratic scaling law in the receive signal power, which scales quadratically with the amount of passive units [4, 7]. All these amiable features make RIS an appealing solution for overcoming blockage and improving coverage in mmWave communications.

Channel state information (CSI) acquisition is a prerequisite to realize the full potential of RIS-assisted mmWave systems. Nevertheless, obtaining the full CSI of the base station (BS)-RIS (B-R) link and the RIS-user (R-U) link is very challenging since RIS cannot receive or transmit signals and lacks signal processing capabilities. Moreover, the CSI acquisition requires a large amount of training overhead because of the giant size of antenna arrays at the transceiver as well as the large number of passive elements at the RIS. It should be noted that some recent efforts (e.g., [8–10]) attempted to exploit the inherent sparse nature of the cascade BS-RIS-user mmWave channel and formulate the channel estimation problem into a compressed sensing (CS) framework. CS-based methods, however, are expensive to implement due to their excessive computational complexity.

On the other hand, many channel measurements [11] indicated that mmWave channels exhibit sparse scattering characteristics. In particular, it was reported that the power of the LoS path is much higher (about 13 dB higher in mmWave...
bands and 20 dB higher in THz bands) than the sum of the power of non-line-of-sight (NLoS) paths. Therefore, instead of obtaining the full CSI, an alternative option is to identify only the dominant path, and align the transmitter’s and receiver’s beams to provide sufficient beamforming gain for mmWave communications. The procedure devised for identifying one or several dominant paths for initial access is referred to as beam training (BT) or beam alignment (BA). For RIS-assisted mmWave systems, BT aims to simultaneously identify the best BA for both the B-R link and the R-U link. As RIS is a passive device that cannot transmit/receive signals, BT for RIS-assisted mmWave systems is more challenging than that for conventional mmWave systems.

In this article, we discuss the extension of conventional BT methods to RIS-assisted mmWave systems, and elaborate the pros and cons of each approach. We also propose a novel multidirectional BT scheme for RIS-assisted systems to address drawbacks of existing BT methods. Numerical results are provided to show the efficiency of the proposed solution. Finally, future research challenges are discussed, followed by concluding remarks.

**Beam Training for RIS-Assisted mmWave Systems**

We focus on the scenario where the BS-user link is blocked due to unfavorable propagation environments. To perfectly align the beams for the three-node communication system, BT involves estimating the angle of departure to the BS and the angle of arrival (AoA) associated with the dominant path of the B-R link, and the AoD and AoA associated with the dominant path of the R-U link. Due to the cascade nature of the channel, by carefully devising its phase shift vector, RIS can form a reflecting beam pointing in a direction that is a superposition of the incident angle and a “relative reflection angle” (RRA). Therefore, instead of searching for the AoA and AoD at the RIS, we aim to find a best RRA at the RIS to achieve BA for both the B-R and R-U links. In this way, the search space can be significantly reduced.

In practice, with the knowledge of the location of the BS, RISs can be installed within sight of the BS. Hence, some existing works (e.g., [11]) assume that the BS has aligned its beam to the RIS, and focus on the BT between the RIS and the user, which can be accomplished by using conventional BT techniques. Nevertheless, the above assumption is only valid for stationary BSs and RISs. With the popularity of unmanned aerial vehicles (UAVs) and their promising potential in wireless communications, mobile BSs based on UAVs and the like are being considered for possible deployment in the near future. In such scenarios, it is necessary to simultaneously identify the best BA for both the B-R link and the R-U link. Moreover, in practice, the LoS path between the BS and the RIS may be blocked by obstacles, in which case we also need to launch joint BS-RIS-user BT to find an alternative path from the BS to the user. In the following, we first discuss the extension of conventional BT techniques to RIS-assisted mmWave systems.

**Exhaustive Search**

A natural approach to perform BT is to exhaustively search all possible beam tuples/triplets. Specifically, the BS, the RIS, and the user adopt pre-designed codebooks, $F_B$, $F_R$, and $F_U$, respectively. Each codebook, consisting of a set of narrow beams, is designed by uniformly quantizing the associated beam angle, that is, the AoD (AoA) for the BS (user) and the RRA for the RIS. The finely quantized angles are assumed to uniformly cover the whole range of the AoD/AoA/RRA angles. The best beam tuple for BA is identified by exhaustively searching all possible $|F_B||F_R||F_U|$ beam tuples based on the received signal power. Such an exhaustive search requires the RIS to scan its entire RRA angular space for each choice of beam direction on the BS side, and meanwhile requires the receiver (i.e., user) to scan its entire AoA space for every combination of AoD and RRA, as illustrated in Fig. 1.

Due to the use of pencil beams, an important advantage of the exhaustive search scheme is that the BS-RIS-user link achieves a large beamforming gain if the beam tuple aligns with the dominant path, which can help identify the best BA even in low signal-to-noise ratio (SNR) environments. The exhaustive search method, albeit simple and straightforward, entails a prohibitively large training overhead. Suppose the BS (user) is equipped with $N_B(N_U)$ antennas, and the RIS is a planar surface with $M = M_B \times M_U$ reflecting elements. To achieve the highest spatial resolution, the BS (user) needs to use $N_B(N_U)$ narrow beams to scan the entire AoA (AoD) space, and the RIS needs to use $M$ reflecting beams to search the RRA domain. The total number of beam tuples to be examined is therefore up to $N_B(N_U)N_B\times M$. Let $N_B = 32$, $N_U = 32$, and $M = 256$. Then the number of possible beam combinations is $262,144$, which would result in an excessive delay for initial access.

**Hierarchical Search**

To expedite the BA process, hierarchical multi-resolution beam search approaches were proposed for conventional mmWave systems [12]. The hierarchical search scheme can readily be extended to the RIS-assisted systems, where the BS, the RIS, and the user employ their respective multi-layer beamforming codebooks for joint spatial scanning. For hierarchical codebooks, a lower-layer codebook consists of wider beams in comparison to higher-layer codebooks. The spatial resolution rises as the number of layers increases. The hierarchical search scheme consists of multiple stages. At each stage, the corresponding layer’s codebooks/subcodebooks are used for spatial scanning. The scanning procedure is similar to that of the exhaustive search scheme, except that here we only need to search the range that is identified in the earlier stage. The user then examines the received signal power to find the best beam tuple. This information is fed back to the BS and RIS to adaptively choose higher-resolution subcodebooks for the next stage’s scanning. The above process continues until the required spatial resolution is achieved, which is depicted in Fig. 2.

The hierarchical search can effectively reduce the amount of training overhead. Consider a typical binary-tree search. At each stage, the search...
range at each node is halved by two beams, and the required number of layers for hierarchical search is determined by \(\log_2\max(N_r, M, N_t)\). Let \(N_r = 32\), \(N_t = 32\), and \(M = 256\). We will need \(\log_2 256 = 8\) layers to complete the hierarchical search. There are \(2^8 = 8\) beam tuples to be examined for each of the first five stages. For the last three stages, the beams at the BS and the user are fixed, and we only need to search the RRA at the RIS. Thus, the total number of beam tuples to be examined throughout the whole process is given by \((5 \times 8) + (3 \times 2) = 46\), which is far less than that required by the exhaustive search scheme.

Despite the substantial training overhead reduction, a major drawback of hierarchical beam search is that the use of wide beams at early stages results in low beamforming gains. As a result, spatial scanning at lower levels may fail to identify the correct beam tuple in low SNRs and eventually miss detecting the dominant path. The situation gets worse for RIS-assisted mmWave systems due to the severe product-path-loss of the cascade channel. Also, the hierarchical beam search scheme involves frequent feedback from the user to the BS/RIS, which exerts an extra burden on the training process. Lastly, since hierarchical beam search needs the BS/RIS to interact with each user individually, the extension to multi-user scenarios requires careful global coordination, presenting another challenge for such systems.

### MultiDirectional Beam Training Scheme

To overcome difficulties faced by existing BT approaches, in this section, we propose a multidirectional BT scheme for RIS-assisted mmWave systems by leveraging the sparse characteristics of mmWave channels. The idea is to let each node in the system simultaneously form multiple directional beams to probe its associated angular (i.e., AoA, AoD, RRA) space. Specifically, the angular space can be divided into a number of disjoint spatial intervals via beams formed by a discrete Fourier transform (DFT) matrix. To develop a multidirectional BT scheme for RIS-assisted mmWave systems, we first discuss how to simultaneously generate multiple DFT beams at each node of the system.

### Generating MultiDirectional Beams

In mmWave systems, a hybrid analog and digital beamforming/combining structure is usually employed at the BS/user to reduce the cost/energy consumption. We assume that a fully connected (FC) hybrid structure is used at the BS/user, where each RF chain is connected to all antennas. For a fully connected hybrid structure, the BS (user) can simultaneously form \(R_{BS}(R_{UE})\) directional beams by simply letting the hybrid precoder (combiner) be a linear combination of \(R_{BS}(R_{UE})\) columns of an \(N_r \times N_t\) \((N_r \times N_t)\) DFT matrix. Here, \(R_{BS}(R_{UE})\) denotes the number of RF chains at the BS (user).

At the RIS, we can generate a number of reflecting beams simultaneously by setting the reflection vector to be a linear combination of \(Q\) distinct columns of an \(M \times M\) DFT matrix. Here, \(Q\) is a parameter of the user’s choice. Such an
Best Beam Tuple Estimation

Identifying the best beam tuple is equivalent to determining the BS’s AoD, user’s AoA, and RIS’s RRA associated with the dominant path. To this objective, one needs to search for the three-dimensional AoD-AoA-RRR space. We can imagine this three-dimensional angular space as a three-dimensional cube, which is uniformly divided into $N_tN_rm$ small blocks, where each block corresponds to a possible beam tuple and can also be viewed as a potential BS-RIS-user path. By simultaneously generating multiple DFT beams at each node of the system, the user collects signals coming from multiple (more precisely, $R_{\text{BSRISUE}}(Q)$) blocks. If the dominant path matches one of these $R_{\text{BSRISUE}}(Q)$ blocks, the user will receive a prominent measurement. Note that the best beam tuple estimation is performed at the receiver (user) side. After the best beam tuple is identified, this information will be fed back to the BS via a dedicated channel for subsequent joint beam-forming and downlink data transmission.

Specifically, we divide the three-dimensional cube into $S = N_tN_rm/(R_{\text{BSRISUE}}(Q))$ disjoint subsets, also referred to as bins, each of which consists of $R_{\text{BSRISUE}}(Q)$ blocks. Thus, we can complete scanning the entire three-dimensional angular space using $S$ successive time slots. Such scanning is called a round of batch-mode scanning. After a round of batch-mode scanning, we are able to identify which bin contains the dominant path. Nevertheless, we cannot determine which block in this bin is associated with the dominant path.

To identify the exact block associated with the dominant path, we perform a few rounds of batch-mode scanning, and for each round, we randomize the bins that fall into $S$ disjoint bins. For each round of scanning, say, the $l$th round of scanning, we denote the bin that contains the dominant path as $B_l$. Then we can retrieve the block associated with the dominant path by finding the common element (i.e., block) among the bins $(B_l)^c$. The rationale behind this intersection scheme is as follows: Since the blocks assigned to each bin at each round of scanning are randomized, it is very unlikely that, other than the block associated with the dominant path, there is another block which lies in the intersection of these bins, particularly when $L$ is large. Therefore, it is expected that we can identify the block associated with the dominant path with a high probability.

In Fig. 3, we provide an illustrative example to show how the proposed method identifies the dominant path in an efficient way. Consider a toy example where we have $N_t = 6$, $N_r = 4$, $M = 8$, $R_{\text{BS}} = 4$, $R_{\text{RIS}} = 2$, and $Q = 2$. The dominant BS-RIS-user path is associated with the block located at position $(5, 4, 2)$. The proposed method starts by dividing the three-dimensional space into $S = 16$ disjoint bins. Each bin thus collects energy from paths associated with its blocks. By examining the received signal power at the user, in each round we can identify the bin that contains the dominant path. For instance, in round 1, bin 6 is identified and highlighted with a red rectangular box, bin 10 is marked in the second round, and so on. Finally, we can identify the dominant path by finding the common element in these highlighted bins.

Discussions

Recall that the exhaustive search scheme has a sample complexity of $N_tN_rM$. As a comparison, to achieve the same spatial resolution, the sample complexity for the proposed multidirectional BT scheme is $T = SL$. Based on the probability theory, it is not difficult to derive the exact number of batch-mode scanning rounds $L$ required to attain a decent probability that the best beam tuple can be correctly identified. Specifically, it can be analyzed that the number of batch-mode scanning rounds $L$ is on the order of $O(\log(\max(N_t, N_r, M)))$, which is usually much less than $R_{\text{BSRISUE}}(Q)$. In Table 1, an example is provided to show the amount of training overhead required to attain perfect BA with a decent probability, from which we see...
that it only takes the proposed method less than 1 percent of the training overhead required by the exhaustive search scheme to achieve BA with the same spatial resolution.

We highlight some important advantages of our proposed method compared to the hierarchical search scheme. First, unlike the hierarchical search scheme, the proposed approach does not involve multiple rounds of interactions between BS/RIS and the user, and thus can be straightforwardly extended to multi-user scenarios. Also, compared to the hierarchical search scheme, the proposed method is more robust to noise due to the use of narrow beams, which helps increase the probability of identifying the best beam tuple in the low SNR regime. For clarity, in Table 2, we provide a concise overview of some key aspects of our proposed and existing BT techniques.

**Performance Evaluation**

Figure 4 depicts the spectral efficiency attained by respective BT schemes. Results are averaged over $10^4$ independent runs. Also, we include the performance of the joint beamforming method [8], which assumes perfect knowledge of the full CSI. Clearly, this joint beamforming method based on full CSI provides an upper bound on the achievable rate attained by any BT scheme. The Rician factors for both the B-R channel and the R-U channel are set to 13.2 dB for the LoS scenario, while for the NLoS scenario, we set the Rician factor of the R-U channel to 0 dB [1]. It can be observed that the spectral efficiency achieved by the exhaustive search scheme is only slightly lower than that attained by assuming knowledge of full CSI. Another observation is that the proposed BT method is able to obtain performance close to that of the exhaustive search scheme with substantially fewer training measurements. Specifically, the proposed method requires only 3 percent of the training overhead needed by the exhaustive search scheme. For the hierarchical search scheme, it only needs $T = 2^3 \times \log_2(M) = 64$ time slots to complete the BT process, which is the least among all three BT schemes. Nevertheless, due to the use of wide beams at early stages, it performs poorly in the low SNR regime. To make a fair comparison, we enlarge the transmission time of the hierarchical search method such that its training overhead is equal to that of our proposed method. Due to the accumulated signal power, we see that the performance of the hierarchical search scheme can be substantially improved. Nevertheless, our proposed method still presents a clear performance advantage over the hierarchical search scheme in the low SNR regime. Such an advantage is highly desirable as it brings improved signal coverage for mmWave communications.

**Open Research Issues**

BT is essential for realizing the potential of RIS-assisted mmWave systems. Despite some early stud-
ies on this subject, extensive work is still needed to investigate this challenging problem from both theoretical and practical aspects. In the sequel, we outline several important open issues in BT for RIS-assisted mmWave systems.

**Implementation Challenges**

There are several implementation challenges to be overcome for BT for RIS-assisted mmWave systems. First, due to hardware limitations, the phase shift coefficients at the RIS may only take discrete values drawn from a finite set. As a result, the generated beam based on coarsely quantized phase shifts deviates from the ideal beam pattern and affects the accuracy of BA. It is therefore of practical significance to analyze the impact of hardware constraints/imperfections on the BT performance and develop robust BT algorithms. Second, to achieve joint beam training, the BS and RIS need to be well synchronized. How to achieve accurate synchronization between the BS and the RIS is another important issue that should be addressed. Lastly, the control link between the BS and the smart controller attached to the RIS is capacity-limited. The control signal should be suppressed as much as possible without sacrificing precise signal transmission, which needs further investigation.

**Joint Localization and Beam Training**

RIS-assisted mmWave wireless systems offer great opportunities for accurate localization and sensing due to their large bandwidth and massive antenna arrays. Specifically, BT provides an estimate of the AoD and AoA associated with the LoS/virtual LoS component between the BS and the user. With the knowledge of the BS’s and RIS’s locations, localization of the user is possible based on the estimated angular parameters. On the other hand, the location information and other situation awareness techniques can be utilized to enhance the efficiency of the BT process. For example, if the BS has some coarse information about the location of the user, the angular space to be scanned at the BS/RIS can be narrowed down. Accordingly, a more efficient BT sequence can be devised to improve the BT efficiency by searching those areas of interest instead of scanning the entire angular space.

**Extension to Multi-RIS Scenarios**

As a cost-effective and energy-efficient means for reconfiguring the wireless propagation environment, it is desirable to deploy multiple RISs to more effectively overcome blockage and improve signal coverage for mmWave communications. Developing an efficient BT method
CONCLUDING REMARKS

In this article, we first discuss the extension of conventional BT methods to RIS-assisted mmWave systems. The advantages and limitations of each approach are elaborated. To address drawbacks of existing methods, we present a new multidirectional BT method. Numerical results show that the proposed method can achieve decent BA performance under low SNR environments, even with a moderate amount of training overhead which is far less than that of the exhaustive search scheme. Finally, several open research issues for RIS-assisted BT are presented.

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