Beyond 5G RIS mmWave Systems: Where Communication and Localization Meet

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RESEARCH ARTICLE

Beyond 5G RIS mmWave Systems: Where Communication and Localization Meet

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ABSTRACT Upcoming beyond fifth generation (5G) communications systems aim at further enhancing key performance indicators and fully supporting brand-new use cases by embracing emerging techniques, e.g., reconfigurable intelligent surface (RIS), integrated communication, localization, and sensing, and mmWave/THz communications. The wireless intelligence empowered by state-of-the-art artificial intelligence techniques has been widely considered at the transceivers, and now the paradigm is deemed to be shifted to the smart control of radio propagation environment by virtue of RISs. In this paper, we argue that to harness the full potential of RISs, localization and communication must be tightly coupled. This is in sharp contrast to 5G and earlier generations, where localization was a minor additional service. To support this, we first introduce the fundamentals of RIS mmWave channel modeling, followed by RIS channel state information acquisition and link establishment. Then, we deal with the connection between localization and communications, from a separate and joint perspective.

INDEX TERMS Channel modeling, millimeter wave, simultaneous localization and communications, radio localization, reconfigurable intelligent surface.

I. INTRODUCTION

As the demand on the quality of services (QoSs) keeps rapidly growing, upcoming beyond fifth generation (B5G) systems are envisioned to meet more stringent requirements, which are beyond those enabled by the ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC) in the current 5G system. In addition, B5G will also need to support diverse industry vertical applications, e.g., autonomous driving and industry 4.0. Hence, more challenges are brought on physical layer (PHY) transmissions, multi-access, network design, and resource management technologies. A plethora of disruptive techniques, e.g., holographic multiple-input multiple-output (MIMO),

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reconfigurable intelligent surface (RIS), artificial intelligence (AI) enabled communications and networking, mmWave/THz communications, and simultaneous localization and communications (SLAC), are under active investigation to fulfil the targeted QoS requirements for B5G [1]–[3]. SLAC is a special case of the wider field of integrated sensing and communication (ISAC) [4]. In particular, SLAC is limited to bi-static operation (communication and sensing and localization of connected devices), while ISAC also considers monostatic operation. While the focus of this paper is limited to SLAC, RIS is also expected to play an important role in ISAC, as shown in, e.g., [5]–[8].

In order to push data rates, interests towards high-frequency bands, e.g., millimeter wave (mmWave) and even THz, keep increasing [9], [10]. At these frequencies, the transceivers need to be equipped with a large array of antennas, often called as massive MIMO (mMIMO), to

compensate for severe free-space path loss through substantial beamforming gains. Due to the usage of high-resolution analog-to-digital converters (ADCs), a vast amount of power is consumed [11]. When the direct path between transmitter and receiver is blocked, received power drops drastically, adversely affecting QoS. Hence, there is a need for a low-power technology that can overcome link blockages. The introduction of RIS to perform analog beamforming towards dedicated users [1], [12], [13] aims to address this need. An RIS is a surface or often a thin covering of a surface with controllable electromagnetic properties. The impedance values of the RIS elements can be controlled so that it realizes an array of phase shifters, thereby modifying the reflection properties and redirecting the impinging wave. Other possible ways to realize smart surfaces are by metasurfaces, groups of strongly coupled meta-atoms, and holographic surfaces [14]. In addition to reflection, an RIS also has other operational functionalities, e.g., diffraction, refraction, polarization, and absorption, which together makes the intelligent control of wireless propagation channels feasible with enhanced spectral efficiency (SE), energy efficiency (EE), security, and network coverage [1], [15].

RISs have several characteristics that distinguish them from typical analog arrays. For instance, RISs usually possess a large aperture and a massive number of elements, so the users are likely in the near field. Also, mutual coupling exists among the RIS elements when sub-half-wavelength inter-element spacing is considered [14]. To keep the cost down, a passive RIS (with no radio frequency (RF) chains) is usually made of inexpensive components with severe hardware limitations. Hence, when combined with high channel losses and many channel coefficients to be estimated, channel estimation (CE) becomes extremely challenging, and may lead to prohibitive training overhead. On the other hand, directional high-gain antennas and a small number of multipath components lead to a sparse geometric channel with lower delay spread and higher coherence bandwidth, which should be exploited during CE. Due to the low-rate change of the geometric parameters (user location and orientation), it becomes natural and necessary to harness location information to reduce CE overheads and predict link blockages. Furthermore, an RIS provides a low-cost means to localize users as it is an additional location reference that enables time and angle measurements [16]. Hence, the RIS itself provides the localization solution to solve the communication challenges. Two exemplary scenarios are unmanned aerial vehicle (UAV) and autonomous driving systems, depicted in Fig. 1, where data transfer between the base station (BS) and mobile station (MS) and radio localization can be simultaneously enabled by RISs.[1] *While there have been a large number of magazines and technical papers on the benefits of RIS for communication and localization separately, their intimate connection via SLAC has been largely ignored. In addition,*

localization and sensing play a more and more important role in future cellular networks. The study in this paper is closely aligned with the recent emerging techniques, ISAC and (cellular) network as a sensor. However, sensing is a much broader concept. Thus, we have a special focus on localization, and offer some insights between localization and communications.

In this paper, we provide an overview of the key research directions closely related to the realization of SLAC in RIS mmWave systems: RIS channel modeling and parameter estimation, and RIS-aided localization and communications. We first briefly review the salient properties of RIS channels and then describe different approaches to CE (based on compressive sensing (CS) and data-driven deep learning (DL)). Then, in contrast to the majority of the reported works on energy- and spectrum-efficient RIS-aided communications, we specially focus on the connection between localization and communications, as well as SLAC with RISs.

II. RIS CHANNELS: MODELING AND ESTIMATION
In this section, we give an overview of the high frequency channel modeling of RISs, as well as the related challenges. Then, we show how to exploit the sparse and geometric nature of the channel when establishing links for communications and localization.

A. RIS mmWave CHANNEL MODELING
Compared to low frequency systems, the mmWave and THz band channels tend to be simpler, but suffer more from non-line-of-sight (NLoS) propagation losses and hardware challenges (phase noise, nonlinearity) [10]. The simplicity of the mmWave channel is due to small number of multipath components, in the addition to the line-of-sight (LoS) path [9]. With ongoing development of mmWave and THz, spatio-temporal channel models comprising angle of arrival (AoA), angle of departure (AoD), time-of-arrival (ToA), delay spread, and distribution of the NLoS paths, the signal processing techniques can be adapted to sparse channel conditions. RISs have mainly gained interest as a means to overcome the large losses at high frequencies by controlling the radio propagation environment [12]–[14]. Similarly, under optimized phase control, they can provide additional measurements of AoA, AoD, ToA, independent of the uncontrolled multipath, thus enabling or boosting localization and sensing capabilities [16].

1) MATHEMATICAL MODEL
An illustration of a system with an RIS is given in Fig. 2, where the BS and MS are equipped with multiple antennas connecting to both phase shifters and power amplifiers while the RIS has multiple elements made of phase shifters only. The shapes of the antenna (element) array can be uniform linear array (ULA), uniform planar array (UPA), uniform rectangular array (URA), and even uniform circular arrays (UCA). In the system, some components affect the end-to-end BS-MS MIMO channel matrix. These include amplitude

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[1]Here, we focus on the outdoor scenario. In general, the study can also be applied to the indoor scenario, where the type of users differs.
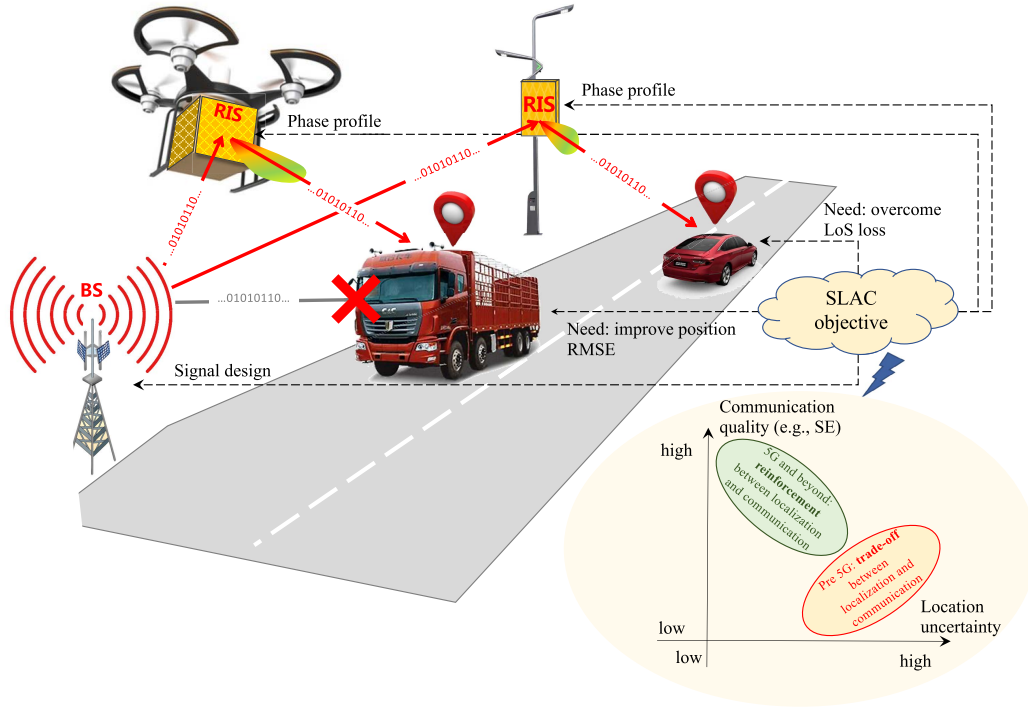
FIGURE 1. Typical applications for SLAC with RISs. A UAV serves as a mobile location reference and high-gain communication relay, which is configured to meet the red truck's SLAC requirements. When the LoS is blocked, the RIS can be reconfigured to provide a strong backup path to the red self-driving car. Different from previous generations, localization and communication will reinforce each other, rather than compete for resources.
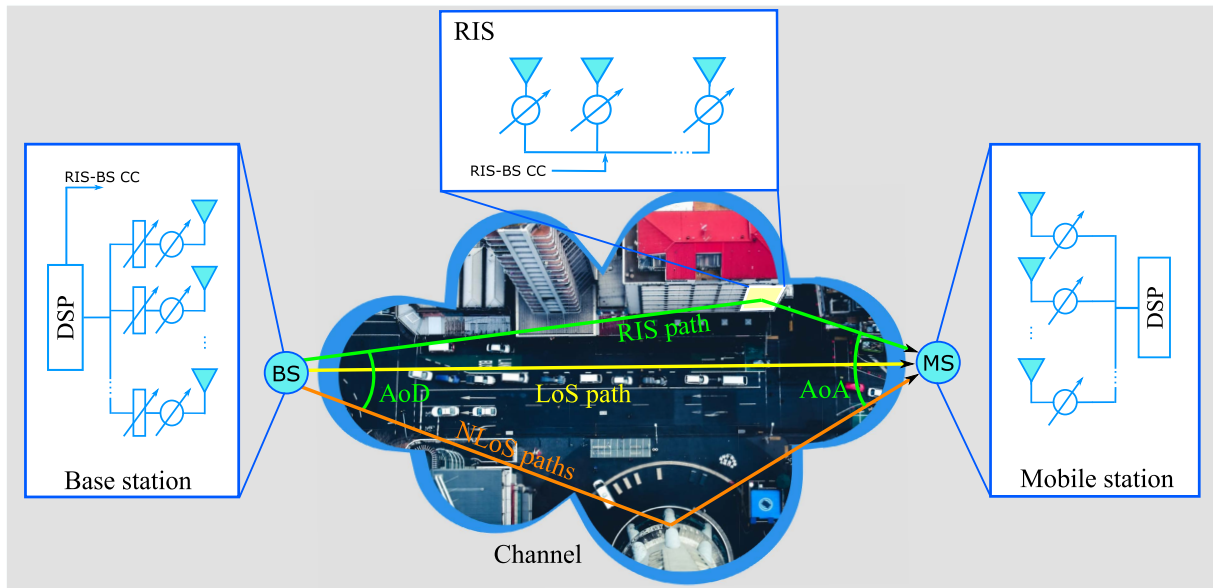
FIGURE 2. An illustration of an RIS system model with BS and MS antenna arrays and some LoS, NLoS, and RIS-aided channels, as well as AoA and AoD ranges of all possible paths. A control channel (CC) is established between the BS and RIS.

and phase control at the BS/MS, the gains of the BS and MS antennas, RIS phase control matrix, and LoS, NLoS and RIS paths. Mathematically, the channel at subcarrier k is expressed as

$$\boldsymbol{H}_k = \boldsymbol{H}_{k,\text{LoS}} + \boldsymbol{H}_{k,\text{NLoS}} + \boldsymbol{H}_{k,\text{RIS}}, \qquad (1)$$

where the LoS path is

$$\boldsymbol{H}_{k,\text{LoS}} = \alpha_{\text{LoS}} \boldsymbol{a}_{\text{MS}}(\boldsymbol{\theta}_{\text{LoS}}) \boldsymbol{a}_{\text{BS}}^{\top}(\boldsymbol{\phi}_{\text{LoS}}) e^{j 2\pi k \Delta_f \tau_{\text{LoS}}} \qquad (2)$$

for LoS path gain α_{LoS}, AoA $\boldsymbol{\theta}_{\text{LoS}}$, AoD $\boldsymbol{\phi}_{\text{LoS}}$ and ToA τ_{LoS}, where Δ_f is the subcarrier spacing, and $\boldsymbol{a}_{\text{MS}}(\cdot)$ and $\boldsymbol{a}_{\text{BS}}(\cdot)$ is

the MS and BS response vector, respectively. Similarly, the NLoS part of the channel is the superposition of M paths:

$$
\begin{aligned}
&\boldsymbol{H}_{k,\mathrm{NLoS}} \\
&= \sum_{m=1}^{M} \alpha_{m,\mathrm{NLoS}} \boldsymbol{a}_{\mathrm{MS}}(\boldsymbol{\theta}_{m,\mathrm{NLoS}}) \boldsymbol{a}_{\mathrm{BS}}^{\top}(\boldsymbol{\phi}_{m,\mathrm{NLoS}}) e^{J 2\pi k \Delta_f \tau_{m,\mathrm{NLoS}}},
\end{aligned}
$$

where each path may be a single-bounce or multiple bounce path, $\alpha_{m,\mathrm{NLoS}}$, $\boldsymbol{\theta}_{m,\mathrm{NLoS}}$, $\boldsymbol{\phi}_{m,\mathrm{NLoS}}$, and $\tau_{m,\mathrm{NLoS}}$ are the NLoS path gain, AoA, AoD, and ToA associated with the mth path, respectively. Final part of the channel related to the RIS is

$$
\begin{aligned}
\boldsymbol{H}_{k,\mathrm{RIS}} = {} & \alpha_{\mathrm{RIS}} e^{J 2\pi k \Delta_f \tau_{\mathrm{RIS}}} \\
& \times \boldsymbol{a}_{\mathrm{MS}}(\boldsymbol{\theta}_{\mathrm{RIS}}) \boldsymbol{a}_{\mathrm{RIS}}^{\top}(\boldsymbol{\vartheta}_{\mathrm{RIS}}) \boldsymbol{\Omega}_k \boldsymbol{a}_{\mathrm{RIS}}(\boldsymbol{\varphi}_{\mathrm{RIS}}) \boldsymbol{a}_{\mathrm{BS}}^{\top}(\boldsymbol{\phi}_{\mathrm{RIS}}),
\end{aligned}
$$

where $\boldsymbol{\Omega}_k$ is a diagonal matrix that describes the RIS control (in phase and amplitude), $\boldsymbol{\varphi}_{\mathrm{RIS}}$ and $\boldsymbol{\phi}_{\mathrm{RIS}}$ are the AoA and AoD for the channel between the BS and RIS, while $\boldsymbol{\theta}_{\mathrm{RIS}}$ and $\boldsymbol{\vartheta}_{\mathrm{RIS}}$ are the AoA and AoD for the channel between the RIS and MS, and τ_{RIS} is the corresponding ToA. Note that the path gains $\alpha_{m,\mathrm{NLoS}}$ and α_{RIS} may be random, if each path corresponds to an unresolved cluster of paths.

2) MODELING CHALLENGES

The RIS channels are modeled as compound channel between BS-RIS and RIS-MS with the phase control at the RIS. The channel models of the compound link depend on the environment, mobility of users and other network elements, and the frequency band. The phase control at RIS modifies the behavior of the compound link to maximize the channel gains. The RIS (phase) control depends on various aspects, but predominantly the type of the RIS itself and its limitations (element spacing, element gains, phase shifter resolutions, etc.). Models for RIS control should account for these limitations [17], as well as possible frequency selectivity [18]. As a low-cost RIS will be HW-limited, each of these limitations must be carefully modeled. For instance, realistic models for *mutual coupling* are needed when RIS elements are spaced less than half a wavelength apart [19]. An additional modeling challenge stems from the large aperture of the RIS, which pushes the far field of the array far away from radiation source, leading to wavefront curvature [20]. This *near field* region can be handled with beamforming algorithms via CE, but may result in decreased channel gains compared to far field operation. There are many different types of RISs whose physical properties have impact on the control algorithms. The two most common in literature are phased reflective arrays and metasurface-based RISs [14]. The most commonly utilized RIS models in literature are phased reflective arrays as those allow easy way to model and modulate the phase shifts, and subsequently, the beamforming at the RIS.

In summary, the RIS channel models can be composed by combining the conventional static and mobile channel models with specific RIS hardware models and RIS control algorithms. There are many research challenges ahead to physically and algorithmically understand the behavior of the RISs and channels with RISs, how to estimate the channel, how to
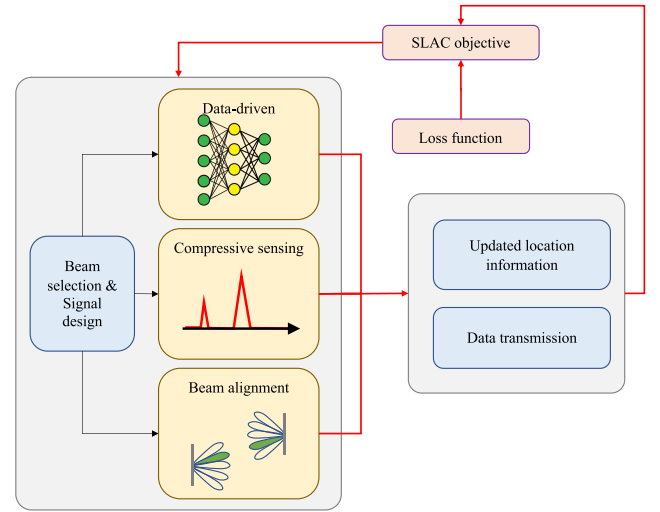
FIGURE 3. A systematic framework for CS-aided RIS CE, RIS beam alignment, and deep neural network (DNN) based data-driven approaches for RIS joint active and passive beamforming, channel parameters extraction, and even MS localization. The beam training matrix design is also of great importance for the above tasks, and can be enhanced by prior location information on MS and environmental objects. As for different SLAC objectives, a variety of loss functions can be considered accordingly.

steer beams efficiently, and ultimately, how to simultaneously maximize the communication and localization performance.

B. RIS CHANNEL ESTIMATION

RISs possess several fundamental limitations that affect CE capabilities: (1) a large number of elements but no or limited number of RF chains; (2) low computational power and small storage space; (3) severe hardware issues such as phase quantization and mutual coupling. All these properties should be taken into consideration when designing and developing efficient yet effective RIS-aided communication and localization protocols. A systematic framework is sketched in Fig. 3, containing three approaches: pilot-based approaches relying on CS [21]–[23], blind beam alignment relying on pre-designed beam codebook [24], and data-driven approaches [25]–[27]. These are described now in detail.

1) RIS CHANNEL ESTIMATION VIA COMPRESSIVE SENSING

In order to achieve the optimal or sub-optimal joint active and passive beamforming, it is essential to get an accurate channel state information (CSI) of all the individual channels in (2)–(3) or parameters (i.e., AoAs, AoDs, and path gains) therein. As discussed earlier, there exists inherent sparsity in the mmWave MIMO channels, benefiting from the poor scattering propagation environment, which can be leveraged in the CE algorithm development via advanced CS techniques, e.g., approximate message passing (AMP) and off-the-grid atomic norm minimization (ANM) [21]. However, for the purely passive RIS architecture without any connected baseband processing units, CE can only be performed either at the BS via uplink training or the MS via downlink training,

due to the lack of observations at the RIS and its limited computation capabilities. When extending to multi-user RIS CE, a shared BS-RIS channel exists among all the users, and this fact should be considered for CE algorithm development. In order to simplify the CE, a few active sensors or anchors can be deployed at the RIS, so that CE can be performed at the RIS, by alternations of uplink and downlink training [28].
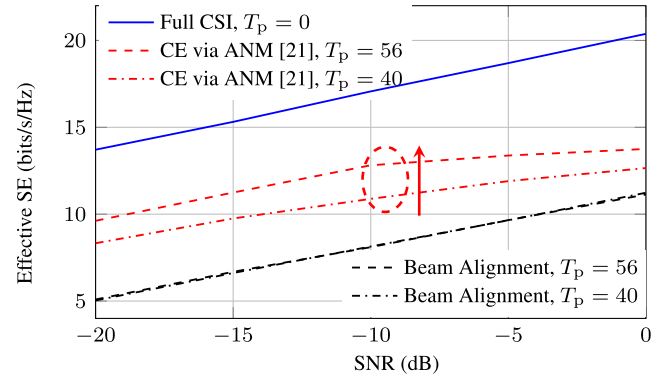
With respect to the beam training matrix, if no prior knowledge about the MS location and environmental objects, e.g., scatters, reflectors, is available, a random construction or selection from part of unitary discrete Fourier transform (DFT) matrix or array response vectors are usually considered. The prior information on MS location and environmental objects can be transformed into the prior knowledge on channel parameters, e.g., AoAs and AoDs. Thus, a better beam training matrix can be designed with higher resolution, compared to the case without any prior information [29]. This in turn brings better performance on RIS CE. On the other hand, the prior information can be used to reduce training overhead by beam selection, resulting in an increase on effective SE.

2) RIS BEAM ALIGNMENT

Beam alignment, a one-step direct approach, can intentionally skip the CE process and directly focus on the optimal or suboptimal beam pair selection. It scans and chooses the best pair of beams, one for each terminal, according to a certain criterion, for data transmission [24]. Meanwhile, a coarse MS location can be extracted from the selected beams. The criteria of choosing the best beam pair include maximizing the received power, multiple hypothesis testing, etc. These criteria work well in the high signal-to-noise ratio (SNR) regime and bring a promising performance in terms of beamforming gains and effective SE. Same as RIS CE, the prior location information can also help. The weakness lies in that the performance of beam alignment will be determined by the resolution of the predetermined beams (closely related to training overhead) and the criterion of beam selection. When the number of RIS elements is large, its overhead will be inevitably high, which might prevent its usage for RIS-aided mmWave MIMO systems in practice.

3) RIS DATA-DRIVEN APPROACHES

In practice, a huge number of low-cost RIS elements are needed in order to compensate for the severe path loss occurred in the reflection route via RIS. Under such an extreme situation, advanced CS-based CE scheme and standard beam alignment may fail to deliver a satisfactory performance due to either the inevitably high complexity or training overhead. In this regard, data-driven approaches come into effect and may play a pivotal role in CE [25], [26], joint active and passive beamforming [30], MS localization, and SLAC (see Fig. 3). In general, data-driven approaches enable us to learn a model from the huge amount of available data (usually with labels) for different purposes. After the training, the learned model is leveraged to predict the output with

new input. The commonly known data-driven approaches include DNN, convolutional neural network (CNN), deep unfolding neural network, etc. In the data-driven approaches, the dataset can be collected by fixing the beam training matrices (with reasonable sizes) at all the terminals, resulting in a reasonable training overhead. The labels include the exact (cascaded) channels or parameters therein, joint active and passive beamforming, MS location, or combinations of these. A fully connected DNN or its variant is then trained to map the received signals to the aforementioned labels. Besides, deep unfolding can also be applied with the aid of domain knowledge to mimic the conventional iterative CE algorithms, e.g., iterative reweighted method, projected gradient descent, yielding better estimation performance as well as speeding up the convergence [26]. The training procedure can be done offline with parameter fine-tuning online with a negligible effort. The SLAC loss functions include the combinations of the normalized mean square error (NMSE), SE, and position error bound (PEB). After training, the DL model is used for real-time implementation with the same fixed beam training matrices as in the channel acquisition phase to collect observations. The output of DL model can be used for multiple purposes, as various loss functions can be applied, shown in Fig. 3.

C. CASE STUDIES

To demonstrate the relative performance of the different approaches, the usefulness of exploiting sparsity, as well as different performance metrics, we have conducted two case studies. The first case study (shown in Fig. 4) compares RIS channel estimation via compressive sensing (using ANM [21]) with beam alignment, with performance measured in terms of the effective SE (i.e., accounting for the rate loss due to using T_p training signals compared to a frame time of duration $T_c = 500$). CE via ANM outperforms the standard beam alignment due to its fixed beam resolution. As the effective SE is a function of the training overhead T_p/T_c,

FIGURE 4. Case study 1: CE via compressive sensing (ANM [21]) and beam alignment in terms of effective SE, considering 16 BS and 16 MS antennas and 64 RIS elements, all with half-wavelength spacing. Each individual channel is modelled by following Section II-A, and the CE is performed at the MS via downlink training. Beam alignment is conducted by creating single-layer beam codebooks at all the terminals.

TABLE 1. Overview of SLAC for possible applications in RIS-aided communication. Here, ✓means that the information has limited impact, ✓✓means that the information is useful, and ✓✓✓means that the information provides significant performance benefits. We observe that location and map information can boost RIS-aided communication performance, and should themselves be provided with the aid of RIS.

Communication application	Prior location information	Prior map information	Localization and sensing application	Prior location information	Prior map information
RIS phase profile optimization [31]	✓✓✓	✓	RIS phase profile optimization [32]	✓✓✓	✓✓
Frame structure optimization [33]	✓	–	User tracking [34]	✓✓✓	✓✓✓
RIS channel estimation [23]	✓✓	✓	RIS environment mapping [35]	✓	✓
RIS link blockage prediction [36]	✓✓	✓✓	RIS object sensing [6]	✓	✓
Inter-RIS handover [37]	✓✓	✓	Dedicated region (low energy, high secrecy, etc) [38]	✓✓✓	✓
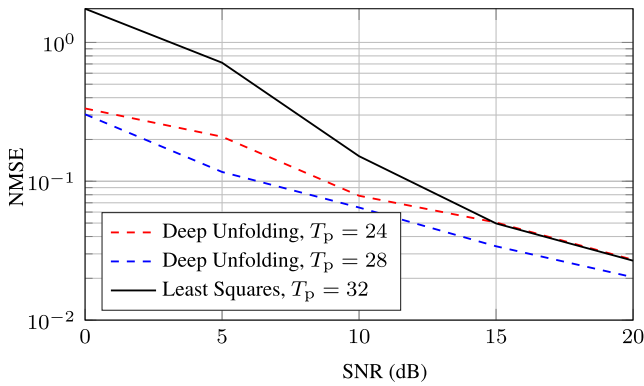
FIGURE 5. Case study 2: CE via data-driven approaches (deep unfolding) and least squares (which ignores the channel sparsity) in terms of NMSE, considering 1 BS antenna, 16 MS antennas, and 32 RIS elements, all with half-wavelength spacing. Each individual channel is modelled by following Section II-A.

we observe that the performance does not further improve when we increase the training duration from $T_{\mathrm{p}} = 40$ to $T_{\mathrm{p}} = 56$ in the beam alignment. On the contrary, performance improvement can still be seen in the CE via ANM. The second case study (shown in Fig. 5) compares cascaded channel estimation via data-driven deep unfolding with the standard least squares approach (which ignores channel sparsity), in terms of NMSE [26]. Deep unfolding mimics the gradient descent algorithm for a regularized optimization problem, where both channel rank deficiency and noise effect are considered. Deep unfolding based cascaded channel estimation is capable of offering better estimation performance in terms of NMSE compared to the least squares estimation with lower training overhead $T_{\mathrm{p}}/T_{\mathrm{c}}$.

III. RIS SIMULTANEOUS LOCALIZATION AND COMMUNICATION

Many practical applications can be enabled by virtue of RISs. The RIS mmWave MIMO channels contain the geometry information about the environmental objects and the terminals, which inextricably link the two important functionalities, i.e., communications and localization. This also

emphasizes the importance of CSI acquisition, already discussed in Section II-B, and the RIS control. An overview of how prior location and sensing information can be harnessed for communication and localization applications with RIS is provided in Table 1. For instance, prior location information can be leveraged for RIS phase profile optimization in both communication and localization applications. The two research topics are closely coupled. For this reason, we will discuss, in this section, RIS optimization for communications and localization performance separately, as well as their joint performance. We conclude with a brief remark on the use of RIS for radar-like sensing.

A. RIS FOR COMMUNICATIONS

A typical use case of an RIS in wireless communications is to use it as a reflector enabling communications "around a corner" by using directive beamforming. In mmWave communications, the path loss of the radio wave propagation is very large requiring usually a LoS connection between the transmitter and the receiver. If the direct link is obstructed, a reflected "LoS"-like link may be created by an RIS:

$$H_k = H_{k,\mathrm{NLoS}} + H_{k,\mathrm{RIS}}(\Omega_k), \qquad (3)$$

where the RIS control Ω_k can be tuned to optimize the end-to-end SNR. The reflection loss decreases the receive power level, but still it can in many cases be much higher than that caused by random scattering from uncontrolled channel, though still limited of course by physics [39]. Due to its large area, an RIS can leverage the near-field effect and create not only directional beams, but also positional beams. Such beams focus energy and provide communication quality in a specific location, rather than a specific direction, with as extreme case so-called holographic RIS [40].

The RIS operation can be interpreted by at least two ways.

- One is to see it as a mechanism to *control on the random wireless channel* realization [38]. The classical system design takes the wireless channel as it is so that the waveforms, channel codes, transmit and receive processing etc. are the functionalities that an engineer can design. The introduction of an RIS (or multiple RISs) in

the channel changes the paradigm so that one can also design the channel to optimize communication-relevant performance metrics.

- The other way to interpret the use of an RIS is to interpret it as a *passive relay station*. A true relay station amplifies the received signal directly in the amplify-and-forward (AF) protocol, or decodes and re-transmits it in the decode-and-forward (DF) one. The RIS can operate in some sense similarly to the AF relay without active power amplification or receive noise, because it is a passive element. However, similar order or even better power gains have been reported [41].

The performance metrics for the communications include the link range, SE or EE, for example [15]. The former can be characterized as the probability of outage of given data rate as a function of the distance between the transmitter and the receiver. The latter is basically the achievable rate or the sum rate in the case of multiple users. Both depend on the signal-to-noise-plus-interference ratio (SINR) at the receiver. The target of the RIS control algorithm is to adjust the phase shifts so that the SINR is maximized by coherent combining of the propagated signal given the instantaneous CSI.

B. RIS FOR LOCALIZATION

The RIS has been recognized as one of the key enabling technologies toward B5G localization [16], [42]. A typical use case on an RIS in localization, is to use it as a location reference point when the LoS connection is obstructed. The reflected LoS path created by the RIS provides an informative measurement of the user's position. When LoS is present, the RIS can provide localization improvement, by turning multipath from a foe to a friend, and moreover controlling this multipath to optimize localization performance. In particular, the RIS has great potential to improve the estimation accuracy of the channel parameters (such as AoA, AoD, ToA, phase-of-arrival (PoA), and even Doppler shifts), by optimizing the adjustment of the phase profile or the current distribution in the RIS elements. As a result, the position estimation by utilizing the geometric relationship between the measurements and positions, can be significantly improved.

More precisely, considering downlink transmission as in Figure 1, and denoting the state (3D position, 3D orientation) of MS, BS, and RIS by s_{ms}, s_{bs}, s_{ris}, and the position of physical interaction points by p_{ip}, then the different channels in (1) are functions of these geometric parameters:

$$H_k = H_{k,\mathrm{LoS}}(s_{\mathrm{ms}}, s_{\mathrm{bs}}) + H_{k,\mathrm{NLoS}}(s_{\mathrm{ms}}, s_{\mathrm{bs}}, p_{\mathrm{ip}})$$
$$+ H_{k,\mathrm{RIS}}(s_{\mathrm{ms}}, s_{\mathrm{bs}}, s_{\mathrm{ris}}).$$

Hence, by estimating the individual channels in H_k and their geometric parameters, it is in principle possible to recover the MS position and/or RIS position, provided BS state is known.

As in communications, RIS operation for localization can be interpreted in several ways.

- First, an RIS with known position and orientation serves as a *location reference* (similar to a BS) in a global coordinate system. The signal from this reference provides measurements of ToA, AoA, and AoD, which enable more accurate localization.
- A second interpretation is as a *smart object with a unique signature*, providing a distinguishable multipath component, thus aiding localization and environment mapping applications.

An RIS can operate as a reflector, a receiver, and a transmitter. For the most commonly used reflector mode, an RIS can be deployed to smartly forward the wave signals to user terminals or based station, where the multi-path propagation is fully utilized to localize users. For the receiver mode, an RIS can be configured with a nearly continuous phase profile, acting as a lens. Due to the large size of the RIS, wavefront curvature can be harnessed to localize MS and help with system synchronization [43]. For the transmitter mode, an RIS can act similarly to analog transmit beamformer and generate phase-shift keying (PSK) modulated symbols as pilots, hence the channel and position estimation can be performed.

The performance metrics for localization include root mean-square error (RMSE) of position estimation and the localization coverage. Through Fisher information analysis, the Cramér–Rao bound of position can be derived, using as the PEB for localization frameworks.

C. RIS FOR SIMULTANEOUS LOCALIZATION AND COMMUNICATIONS

With the development of 5G and beyond, emerging applications have posed *stringent constraints on both communications and localization*. For example, in autonomous driving, a large amount of information needs to be exchanged among vehicles and roadside infrastructure and decimeter-level localization accuracy at the MS side should simultaneously be achieved. In these emerging SLAC applications, the signal and algorithm designs, architecture, and standards, should be further investigated. The RIS can be a promising candidate technology in realizing SLAC applications, since, as we will see, it shows great potential in achieving high SE communications and high accuracy localization performance.

Distinct from the conventional communications or localization framework, where either the communications metrics (SE, for example) or the localization performance (PEB) are considered, RIS-assisted SLAC requires a proper trade-off between communications and localization. Particularly, the optimal adjustment of the phase profile for the RIS should be designed to meet both the communications and localization requirements. In Fig. 6, we study the trade–off between communication and localization in a SISO system equipped with a single RIS (as in [44, Fig. 1]). The coherence time is assumed to be $T_{\mathrm{c}} = 1000$ symbols, where we use $T_{\mathrm{p}} \geq 3$ symbol slots for transmitting specific pilots and the rest for communication. For each value of T_{p}, the localization and communication performance are calculated in terms of PEB and SE, and illustrated as a curve in Fig. 6. The RIS phase profile sequence can be random (when there is no a priori
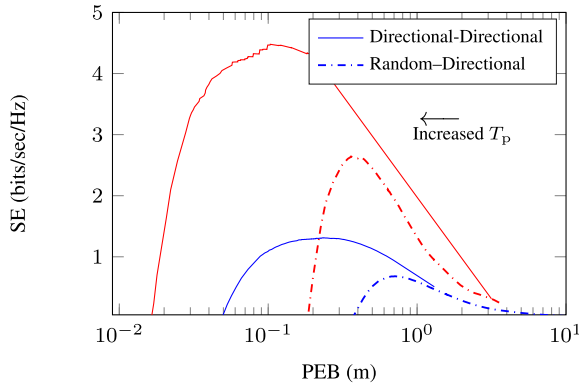
FIGURE 6. PEB vs. NLoS SE with T_p increasing from right to left, for a SISO system equipped with a single RIS of size 16×16 (blue curves) and 32×32 (red curves). The BS, RIS and the user are located at $(1, 1, 0)$, $(0, 0, 0)$, and $(5, 5, -5)$, respectively. We consider directional or random RIS profiles for localization and communication. The rest of the parameters can be found in [44, Table 1].

location information) or directional (when there is a priori location information) during pilot transmission, while it is always directional during communication, as it is based on the estimated channel from the pilots. We observe that such a priori location information can significantly boost both maximal SE (about a factor of 2) and minimal PEB (about a factor of 10). The size of the RIS has a major impact on the performance, where going from 256 elements to 1024 elements improves the maximal SE about 4 times and the minimal PEB about 2–4 times. The figure also clearly illustrates three distinct regimes: (i) communication and localization quality are bad when T_p is too small, as we obtain a poor estimation of the user position, which leads to directing the signal to an incorrect location and subsequently a low SNR. In this regime, both PEB and SE can be improved by increasing T_p; (ii) good localization performance but low rate occurs when T_p is too high, since too much of the coherence time is devoted to pilots, leading to excellent channel estimates, but no time to exploit them; (iii) a regime where both positioning and communication have good performance, near the peak of the PEB–SE curves, obtained by moderate values of T_p (about 5% overhead for the directional RIS phase profiles and 25% for the random RIS phase profiles, irrespective of the RIS size).

More generally, in the SLAC framework, the objective function involves both communication metrics (e.g., SE) and localization metrics (e.g., PEB). Considering x as the available resources, which include RIS phase profiles, power, BS beamforming, and time/frequency allocation, canonical versions of the SLAC problem are as follows.

- *Communication-centric design*: The aim is to optimize communication performance, while ensuring good enough localization quality:

$$\max_x \ \mathrm{SE}(x) \tag{4}$$

$$\text{s.t. PEB}(x) \leq \gamma. \tag{5}$$
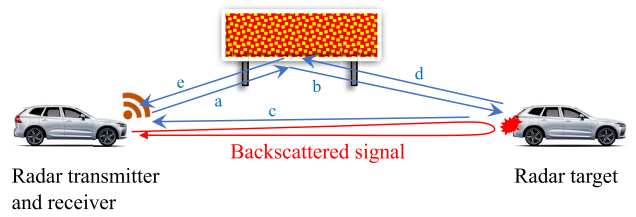
FIGURE 7. RIS for radar-like sensing, providing 2 additional propagation paths compared to the conventional backscattered signal. These two paths can boost sensing performance.

- *Localization-centric design*: The aim is to optimize localization performance, while ensuring good enough communication quality:

$$\min_x \ \mathrm{PEB}(x) \tag{6}$$

$$\text{s.t. SE}(x) \geq \gamma. \tag{7}$$

- *Multi-objective design*: The aim is to optimize both communication and localization metrics,

$$\max_x \ [\mathrm{SE}(x), -\mathrm{PEB}(x)], \tag{8}$$

where the Pareto-optimal frontier can be found by, e.g., linear scalarization:

$$\max_x \ \omega_c \mathrm{SE}(x) - \omega_l \mathrm{PEB}(x), \tag{9}$$

in which $\omega_c \geq 0$ and $\omega_r \geq 0$ are the scalarization weights.

When SE and PEB are conflicting, we have a trade-off; when SE and PEB are aligned, they will reinforce each-other. This is visible in Fig. 6, where for short pilots, SE and PEB are aligned (increasing the pilot improves both metrics), while for very long pilots, they are in a trade-off (increasing the pilot improves PEB but worsens SE). It is our vision that reinforcement will be more likely, especially when we are able to exploit data symbols for positioning, in addition to conventional pilot symbols. On the other hand, conflicting SE and PEB, which are associated with pre-5G communications, will likely become less relevant.

D. RIS FOR RADAR-LIKE SENSING

This paper was limited to RIS for SLAC, where both localization and communication rely on channel estimation, which is a form of *bistatic sensing*. RIS has also been considered for directly supporting radar-like *monostatic sensing* applications, such as target detection and tracking. An example of this is shown in Fig. 7. The conventional backscattered signal is shown in red and is used by the radar to detect and localize passive objects. The RIS provides 2 secondary paths: 'abc' and 'abde', which can be used to detect and localize the target when the backscattered signal is weak. However, overcoming the large path loss corresponding to the double bounce or triple bounce reflections requires careful design of the RIS placement and the RIS configuration. This is the focus of much ongoing work [45].

IV. OUTLOOK

We have argued that beyond 5G systems enabled by RIS will have to rely on a synergy between communications and localization, since (i) both services rely on the same physical channel; and (ii) one will rely on the other for optimized performance. This leads to the concept of SLAC, which relies on the co-design of communications and localization resources and the flexible trade-off and reinforcement between the two services. To realize SLAC, reliable geometric channel models (including RIS and their hardware effects), as well as low-complexity channel estimation and resource allocation routines must be developed. More research and development are required to address the RIS and SLAC technologies towards a wide commercial usage, e.g., in cellular communications, UAV, industry 4.0, autonomous driving, and others.

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