2) Multi-stage Localization: The multi-stage localization procedure divides direct localization into a geometry information estimation stage and a position/orientation estimation stage, which reduces the complexity of calculating all the unknowns from the received data. More specifically, the measurement vector $\boldsymbol{\gamma}$ is first estimated and then the state vector is extracted from it [60], [69]. Similar to (80), a multi-stage localization problem can be formulated as

$$\begin{aligned}\hat{\mathbf{s}}_{\text{multi-stage}} &= \arg\max_{\mathbf{s}} p(\hat{\boldsymbol{\gamma}}|\mathbf{s}) \\ &= \arg\min_{\mathbf{s}}[(\hat{\boldsymbol{\gamma}} - \boldsymbol{\gamma}(\mathbf{s}))^H \boldsymbol{\Sigma}_{\hat{\gamma}}^{-1}(\hat{\boldsymbol{\gamma}} - \boldsymbol{\gamma}(\mathbf{s}))],\end{aligned} \tag{81}$$

where $\boldsymbol{\Sigma}_{\hat{\gamma}}$ is the covariance matrix of the measurement vector and $\hat{\boldsymbol{\gamma}}$ is the estimated measurement vector from channel estimation. Multi-stage approaches are inherently sub-optimal [168] and usually inferior to direct localization. However, by considering all multipath components, multi-stage localization can reduce the performance gap with direct localization, and it is hence pursued in many works [60], [69].

In multi-stage localization, the parameter vector $\boldsymbol{\gamma}$ needs to be estimated first. Each element in $\boldsymbol{\gamma}$ (e.g., AOA/AOD, channel gains, and signal delay for each path) can be obtained independently or jointly. The channel gain can be estimated by solving a least-squares (LS) problem [60]. AOA/AOD can be estimated using subspace-based methods (e.g,. MUSIC) [186], compressed sensing (CS) [187], deep learning (DL) [188], or Bayesian inference [87]. TOA can be estimated using correlation-based [189] or energy-based methods [190]. The channel parameters can also be estimated jointly using multidimensional channel parameter estimation via rotational invariance techniques (MD-ESPRIT) [191], [192]. In general, the performance of AOA/AOD estimation depends on the array size of the device, while TOA estimation benefits from synchronization and wideband signals. In addition, the error in different stages propagates and may affect the localization performance, which should be considered in system design for a better tradeoff of processing time and performance.

3) Practical Algorithms for Geometry-based Localization: With the geometry information $\hat{\boldsymbol{\gamma}}$ obtained from channel estimation, multi-stage localization problems can be formulated using (81) (direct localization only requires $\hat{\mathbf{Y}}$ as in (73)). An analytical closed-form solution might be obtained by setting the derivative of an objective function equal to zero and solving for the position parameters. However, this approach is impractical considering the non-convexity of the cost function. We discuss two practical categories of optimization algorithms: convergent iterative methods and heuristic methods [48], [193].

- Convergent iterative methods: If the gradient information from the signal model is known, gradient- or Hessian-based algorithms can be implemented. Other iterative algorithms such as alternative projection [194] and expectation-maximization [60] are also practical solutions to reduce the computational burden. Within a few iterations, such deterministic algorithms converge to an optimum of the objective function. The convergence depends on the formulation of objective functions and iteration parameters (e.g., step size), where local solutions can be reached.
- Heuristic/metaheuristics methods: Heuristic methods are capable of dealing with non-differential nonlinear objective functions and reaching near-optimal solutions faster. Popular algorithms include swarm intelligence, tabu search, simulated annealing, genetic algorithms, and so on [55], [195], [196].

Given the sparsity of high-frequency channels and a large number of measurements (due to large bandwidth and array sizes/RFCs), we expect that multi-stage localization will be favored in THz localization. However, for applications that require high localization accuracy, a practical approach is to determine an initial position via multi-stage algorithms and then refine it using direct localization. Next, we discuss learning-based localization.

D. Learning-based Algorithms

In the previous subsection, we discussed geometry-based localization. In challenging environments where geometric models cannot be formulated (e.g., many non-resolvable NLOS paths), or when geometry-based localization cannot handle the processing speed requirements of the system, learning-based methods can be used. In this subsection, we briefly describe the implementations of ML-based localization algorithms in two categories, namely, direct localization and multi-stage localization. Then, practical ML-based algorithms will be discussed.

1) Direct Localization: ML-based localization involves two phases, offline training of the model $f(\cdot)$ and online processing of the observation to obtain a position estimation $\hat{\mathbf{p}} = f(\mathbf{y})$. During the training phase, a training data set $\mathcal{D} = \langle \mathcal{D}_{\mathbf{y}}, \mathcal{D}_{\mathbf{p}} \rangle$ (including $|\mathcal{D}|$ signal-position pairs $\langle \mathbf{y}_i^{\text{train}}, \mathbf{p}_i^{\text{train}} \rangle$, $(1 \le i \le |\mathcal{D}|$, $\mathbf{y}_i^{\text{train}} \in \mathcal{D}_{\mathbf{y}}$, $\mathbf{p}_i^{\text{train}} \in \mathcal{D}_{\mathbf{p}})$ is needed to train the model $f(\cdot)$ (optimize the parameters of this function) in order to reduce the loss function $\mathcal{L}(f(\mathbf{y}^{\text{train}}), \mathbf{p}^{\text{train}})$. Take the mean squared error (MSE) cost function for example, we can have

$$\mathcal{L}(f(\mathcal{D}_{\mathbf{y}}), \mathcal{D}_{\mathbf{p}}) = \sum_{i}^{|\mathcal{D}|} \|f(\mathbf{p}_i^{\text{train}}) - \mathbf{p}_i^{\text{train}}\|^2. \tag{82}$$

After the training, the model $f(\cdot)$ can be used to output end-to-end location information by taking the raw observation data as the input.

Fingerprinting (or pattern matching) is an approach that utilizes a database of fingerprints to find the best position match for a particular signal measurement [6]. The channel state information (CSI) and RSS could be used as the entries to construct the database. While RSS suffers from limited accuracy and CSI requires high computational power, spatial beam SNRs are adopted as a mid-grained intermediate channel measurement [176]. For the retrieval process, deep learning methods such as deep neural networks (DNN) and convolutional neural networks (CNN) are valuable tools to obtain effective models for location estimations [167], [176].

In this category, all the information is maintained and will provide accurate results if the data in the implementation scenario matches the training data set. However, the drawbacks are the data collection in the training phase, and the scalability issue as one model only works for a specific scenario.

2) Multi-stage Localization: Similar to the geometry-based localization, the direct localization task can be decomposed into several sub-tasks (e.g., signal pre-processing, intermediate geometry parameters estimation, and localization). Each sub-task can be solved using learning-based methods with a much smaller training dataset. In the first stage, learning-based methods can be used to reduce the effect of the hardware impairments (HWIs) such as antenna spacing error [197], IQI [198], mutual coupling (MC) [199], and power amplifier nonlinearity (PAN) [200]. The distorted signal due to the impairments can be recovered or compensated during the data pre-processing stage. In channel parameter estimation, learning-based methods have been implemented to estimate the angle [201], [202] and delay [203], [204]. In terms of the localization stage, machine learning has shown the potential to improve localization performance via NLOS identification [205], and global fusion profile [206].

Considering the high dimension of the system parameters and the complexity of the environment, the training of an end-to-end localization model may not be practical. The design of learning-based algorithms for sub-tasks reduces the training cost. These trained models are also flexible to adapt to different scenarios (e.g., a trained model in MIMO systems may not fit a MISO system, but range or angle estimation are more general). Nevertheless, the propagation of the error caused at each stage needs to be considered while adopting learning-based methods.

3) Practical ML algorithms: Machine learning algorithms are usually classified into supervised learning (used for solving *classification* and *regression* problems) and unsupervised learning (used for *data clustering*) [38]. Other approaches, including semi-supervised learning, reinforcement learning, transfer learning, and federated learning, are designed to solve the issues faced by the supervised and unsupervised learning algorithms, which will be discussed as follows.

- Supervised Learning: Traditional machine learning algorithms, such as random forest, support vector machine, and recent popular deep learning, belong to *supervised learning*. Due to the wide application scenarios in many fields, a lot of toolboxes such as Tensorflow [207] and PyTorch [208] make the implementation simple for the researchers. However, two challenges exist. One is the data collection of the offline phase, where sufficient real data are not easy to obtain, and synthesized data may not be accurate. Another is the selection of model parameters; for example, the number of layers and neurons, as well as model structures, make deep learning often an art rather than a science.
- Unsupervised learning: Without the need for well-labeled datasets, *unsupervised learning* is widely used for clustering, and dimension reduction (or feature extraction). A novel framework called channel charting is proposed in [170], which learns CSI in a fully unsupervised manner and can map a high-dimensional point set (the channel features) into a low-dimensional point set (the channel chart). However, this category can only perform data pre-processing, and location information cannot be obtained.
- Other approaches: By combining the two above-mentioned categories, *semi-supervised learning* can train the model with partially labeled data (e.g., $|\mathcal{D}_{\mathbf{p}}| << |\mathcal{D}_{\mathbf{y}}|$ in the training dataset $\mathcal{D}$). For the scenario without a clear objective function (only a reward is known after taking action) *reinforcement learning* is preferred, which is suitable for training without a clear cost function using online data. *Transfer learning* is able to take advantage of the existing model to reduce the training time, and federated learning works in a distributed manner and hence protects user privacy. More details of ML-based localization can be found in [38]–[40], [42], [209], [210].

In summary, despite the channel at THz frequencies being more deterministic than at lower frequencies, which suits geometry-based methods well, we argue that learning-based methods still have advantages in two aspects. Firstly, processing large volumes of data (due to a wide bandwidth) necessitates faster algorithms for localization, and ML algorithms are efficient at feature extraction and hence speed up the processing. Secondly, hardware impairments are severe in high-frequency systems, and the mismatch between the theoretical and actual system models affects the performance, which needs to be mitigated by learning-based methods with onsite data.

E. Tracking and SLAM Algorithms

While this paper is focused on the snapshot localization problem, this is generally part of a wider tracking [211] or SLAM [212] routine, which the UE performs sequentially, based on its own mobility model and periodic measurements. For completeness, we briefly describe their operation in the following sections.

1) Tracking: In mobile applications, initial access is only needed for the first several frames or when the communication link is lost. Once initial access is completed, the UE goes into tracking mode. Mathematically, the model for a tracking problem can be expressed as

$$\mathbf{s}_{\mathrm{U},t} \sim p(\mathbf{s}_{\mathrm{U},t}|\mathbf{s}_{\mathrm{U},t-1}) \tag{83}$$

$$\hat{\boldsymbol{\gamma}}_t \sim p(\boldsymbol{\gamma}_t|\mathbf{s}_{\mathrm{U},t}), \tag{84}$$

where $\mathbf{s}_{\mathrm{U},t}$ is the UE state vector at time t, which depends on the previous state $\mathbf{s}_{\mathrm{U},t-1}$ via a stochastic mobility model, and $\hat{\boldsymbol{\gamma}}_t$ is the measurement vector at time t as defined in Sec. IV-A, which depends on the UE state at time t. The observation contains the estimated angles and delays related to LOS and RIS paths. In addition, a prior $p(\mathbf{s}_{\mathrm{U},0})$ is assumed to be given.

Solving the tracking problem refers to determining the posterior of the state $p(\mathbf{s}_{\mathrm{U},t}|\hat{\boldsymbol{\gamma}}_{1:t})$ given all the collected measurements up till the current time. Several filters exist to solve the tracking problem, though they are all approximate (unless the mobility and measurement models are linear and Gaussian). These filters include:

- *Filters based on the Kalman filter (KF):* the KF provides a recursive solution for linear filtering problems. For nonlinear problems, an extended Kalman filter (EKF) can

be used, which approximates the state distribution using a Gaussian random variable and propagates analytically through the first-order linearization [213]. Other extensions of the KF families include the unscented Kalman filter (UKF) and the cubature Kalman filter (CKF), where the former addresses the approximation issues of the EKF [213], and the CKF suits high-dimensional state estimation [214]. The KF-based filters generally have low complexity but are unable to cope with highly nonlinear models or multi-modal distributions.
- *Filters based on the particle filter (PF):* the PF is another widely-used filter that exploits the representation of an arbitrary probability density function (PDF) by a set of particles [215]. PFs have the advantage of dealing with highly nonlinear and non-Gaussian models, but at the cost of high computational complexity, as the number of particles grows exponentially in the state dimensionality.

An added advantage of tracking is that the transmitted signals and the precoders, combiners, and RIS coefficients can be optimized to account for the a priori information on the UE state. This topic will be covered in more detail in Section V.

2) SLAM: While not considered in this work, the measurements $\hat{\gamma}_t$ at each time step t also provide information about the location of the scatter points (*landmarks* in SLAM parlance), shown in Fig. 3. In turn, this knowledge can improve estimating the UE state, which is the main idea behind SLAM. SLAM has been widely applied in robotics [216], [217] and autonomous driving [2], where an agent locates itself and constructs the unknown map at the same time [173]. With the wide bandwidth and MIMO structure implemented in 5G/6G systems, this topic draws the attention of the communication community with several mmWave systems proposed. The SLAM systems can broadly be classified into two categories, infrastructure-based [173] and non-infrastructure-based systems [218]. In the infrastructure-based systems, the positions of UE and scatters are estimated from the signals transmitted from the BS, as mentioned in (64). In a situation where no BSs are deployed, the UE sends a sequence of signals and then processes the received signal reflected from the surrounding environments [218]. The SLAM problem is inherently challenging since the data association between the landmarks and measurements is unknown (i.e., which landmark generated which delay or angle measurements).

In our THz context, to infer the locations of scatter points and execute SLAM, the following modifications are needed. First of all, the channel model $\mathbf{H}_N^{(l)}$ from (25) should be expressed as a function of the scatter location, say $\mathbf{p}_{\mathrm{N}}^{(l)}$ [78], [219], [220]. Secondly, the local and global data associations between the angles and delays in $\hat{\gamma}_t$ and the landmark locations $\mathbf{p}_{\mathrm{N}}^{(l)}$ should be enumerated and their likelihoods should be calculated. This calculation should account for the hidden UE state as well as the possibility of false alarms (spurious measurements) and missed detections (landmarks without measurements at the current time). Finally, the joint posterior of the UE state and the landmark state should be computed in an iterative manner, with well-defined prediction and correction steps, accounting for all or a subset of most likely data associations. Common methods in this field are FastSLAM [221], GraphSLAM [222], belief propagation SLAM [223], and random finite set theory-based SLAM [220], [224]. These mainly differ in how the data associations are computed, how the prediction and correction steps are performed, how the UE state is represented (e.g., particles or a parametric density), and how the map is represented (e.g., parametric, grid maps, feature maps, topological maps, semantic maps, appearance maps, and hybrid maps [217]).

In summary, tracking in THz systems is challenging due to the narrow beamwidths resulting from beamforming with large array sizes. Adaptive beamwidth design could thus be adopted for different tracking scenarios (e.g., high speed, confident prior information). Nevertheless, the accuracy of both tracking and SLAM improves with narrow beamwidths resulting in a high angular resolution. Furthermore, with dense network deployments and wide bandwidths, an unparalleled SLAM performance can be achieved in THz systems.

F. Summary

In this section, we formulate the localization problems, describe the CRB, and detail some localization techniques. In particular:

- We describe the localization parameters as a state vector and a measurement vector. Different vectors can be defined based on application scenarios and algorithm selections.
- We introduce the CRB for position and orientation estimation based on the state and measurement vectors.
- We formulate geometry-based methods, namely, direct localization and multi-stage localization, and discuss several channel estimation and localization algorithms.
- We discuss several THz localization and sensing extensions, namely, learning-based localization, tracking, and SLAM. These techniques can deal with different localization scenarios and improve localization performance.

In the next section, we formulate system design and optimization problems and discuss the relationships between the variables to be optimized and the affected objectives.

V. Localization System Design and Optimization

System design and optimization are essential for determining the fundamental limits of attainable localization performance. We start by presenting the optimization problem formulation based on the desired system objectives. Then, we discuss the high-level design considerations of the system. Afterward, we detail two groups of system design problems: offline optimization and online optimization. Finally, we conclude this section with simulations and system evaluation.

A. Optimization Problem Statement

1) Motivation: Optimization is essential in communication systems to meet different objectives of signal-to-interference-plus-noise ratio (SINR), energy efficiency, maximum throughput, Etc. For localization purposes, the PEB and OEB defined in IV-B2 are used when accuracy is chosen as an objective in system design. Although this criterion is valid only when the estimator is efficient, it is still a tractable and effective tool for analyzing performance in the asymptotic region. Other objectives described in Sec. II-C are also important in certain scenarios. However, the definition of an objective is not always straightforward and is not unique; objectives need to be defined based on the application scenario. Due to different formulations of objective functions, we have to make compromises, especially when optimizing joint communication and localization systems.

In low-frequency localization systems, PRSs are broadcast by the BSs, and the corresponding system design is mainly offline (such as BS layout and antenna array design). In mmWave MIMO systems, localization performance benefits from the beamforming gain. However, beamforming requires the location knowledge of receivers. Hence, online design of precoding and combining matrices, as well as resource allocation, are of great importance. Such knowledge of transceiver locations is crucial in UM-MIMO THz systems with narrow beams. For AOSA-based THz systems, the optimization of precoder/combiner is at the SA level instead of the antenna level. Thus, in addition to the data symbols from the RFCs, the SA beamforming angles should also be well-designed. Furthermore, the optimization of RIS coefficients and resource allocation inside a dense network (possibly in near-field scenarios) requires effective algorithms. In summary, offline and online optimizations are equally important in future communication systems. We next formulate the optimization problem and discuss the effect of different variables on system objectives.

2) Problem Formulation: Different localization scenarios have different performance requirements (or objectives, such as accuracy, coverage, and so on, as defined in Sec. II-C). In most cases, these objectives are related, and tradeoffs have to be made. For example, increased coverage may increase Latency, and increased update rate may affect accuracy. A system may seek one or several objectives to be optimized while meeting other practical constraints.

A general optimization problem formulation of THz localization systems, consisting of an objective function $\mathbf{f}(\mathcal{V})$ and a constraint function $\mathbf{g}(\mathcal{V})$, can be expressed as

$$\begin{aligned} \mathcal{V} &= \arg\min_{\mathcal{V}} \mathbf{f}(\mathcal{V}), \\ \text{s.t.} \quad & \mathbf{g}(\mathcal{V}) \leq 0. \end{aligned} \tag{85}$$

Here, $\mathcal{V}$ is a set of variables that could be chosen from the number of devices L_{Q}, positions $\mathbf{p}_{\mathrm{Q}}$, antennas per array N_{Q} and SA $\mathring{N}_{\mathrm{Q}}$, SA spacing Δ, AE spacing $\mathring{\Delta}$, beamforming angles $\mathring{\varphi}$, RIS coefficient $\mathbf{\Omega}$, number of transmissions $\mathcal{G}$, etc. Rather than choosing a single objective or constraint, multiple objective optimization (MOO) problems can also be considered, implying that $\mathbf{f}(\mathcal{V})$ and $\mathbf{g}(\mathcal{V})$ could comprise a set of objectives and constraints.

The objective functions depend on the system requirements for localization performance discussed in Sec. II-C, while the constraints reflect the types of variables (e.g., discrete variables or continuous variables) and the search space (e.g., positions within a specific area) of the variables to be optimized. In different scenarios, a parameter could either be an objective or a constraint. For example, localization accuracy can be used as an objective to be optimized, but it could also be accounted for as a constraint to be met (e.g., the minimum required accuracy) alongside other objectives to be optimized (e.g., energy efficiency).

TABLE VIII
OBJECTIVES OF DIFFERENT DESIGN/OPTIMIZATION CONSIDERATIONS (AND THE CORRESPONDING VARIABLES OF OPTIMIZATION)

	Considerations	Variables	Accuracy	Coverage	IA Delay	Update Rate	Stability	Scalability	Mobility	Complexity
Offline	#./Pos. of BS/RIS	L_{Q}, $\mathbf{p}_{\mathrm{Q}}$	✓	✓			✓	✓	✓	✓
	Array Size	N_{Q}, $\mathring{N}_{\mathrm{Q}}$	✓	✓				✓		✓
	Directionality	G_0	✓	✓	✓					
	Quantization	$\mathcal{Q}$	✓							✓
	Codebook	$\mathcal{C}$		✓	✓			✓		
Online	Time/ #. of Meas.	T, G	✓			✓	✓	✓	✓	
	Bandwidth	B, K	✓	✓		✓		✓	✓	✓
	Power	$P, \mathbf{s}$	✓	✓			✓	✓		
	Beamforming Angles	$\mathring{\varphi}$	✓	✓			✓	✓	✓	
	RIS Coefficients	Ω	✓	✓	✓		✓	✓	✓	

To achieve the system objectives while sustaining the constraints, we classify the system design and optimization into offline and online. The corresponding variables and the effect on the system objectives are summarized in Table VIII. Before discussing these two categories, we detail design considerations.

B. Design Considerations

When designing a localization system, we consider aspects such as the selection of network structures, the cooperative strategy, and algorithms determined by the application scenarios.

1) Network Topology: In previous sections, we described a communication system consisting of an LOS channel, an RIS channel, and multiple NLOS channels. However, multiple BSs/RISs/UEs (e.g., $L_{\mathrm{B}}/L_{\mathrm{R}}/L_{\mathrm{U}}$) should be involved as densification is one of the main features in future communication systems. THz communication system topologies can be classified into three types: centralized, distributed, and clustered. The clustered architecture is mainly seen in nanonetwork environments where short communication distances and high energy efficiency are favored [26]. For macro scenarios where the communication distance is large, centralized and distributed structures are usually used. The centralized structures can yield better overall performance with proper scheduling, while the distributed ones protect user privacy.

2) Network Structure: For macro scenarios, three structures can be considered to improve system performance:

- Heterogeneous network: Future networks are likely to be heterogeneous where different wireless (and wired) protocols coexist [225]. Such a multi-band network can sufficiently alleviate the deafness issue and reduce the initial access delay.

- RIS-assisted network: Passive RISs can reshape the channel and increase coverage. The footprints of RISs operating at THz frequencies are expected to be small due to short wavelengths, which can provide extra flexibility in deployment.
- Cell-free network: UM-MIMO systems provide beamforming gains and energy efficiency [226]. However, performance is limited by the THz channel due to its lower-rank and poorer, sparser structure of multipath propagation [31]. By adopting a distributed MIMO system with multiple BSs (probably with a smaller array size) without cell boundaries, UE could have a high coverage probability [227], and the geometrical diversity of the BSs can also improve the localization performance.

Such infrastructure enablers can improve the localization performance, assuming proper protocols, useful network management overheads, and efficient real-time processing.

3) Cooperative Strategies: Although frequent communications between the UEs cause overheads and energy consumption, cooperative localization improves the localization accuracy and the localization coverage [8]. The corresponding performance metrics should thus be defined for a reasonable tradeoff. In addition to cooperation between BSs, RISs, and UEs, other types of cooperation, including UAV-assisted localization [228] and data fusion from other types of sensors such as IMUs [229] and cameras [230], are also important.

4) Hardware Selection: In order to achieve a good tradeoff between hardware cost and system performance, hardware selection is involved in offline system design. Hardware selection considers the directionality of antennas, the quantization of phase-shifters (or RIS coefficients), and the effect of hardware imperfection. In [231], the effect of the antenna model, blockage, absorption, density on the interference, and SNR are analyzed for THz systems. This analysis provides insight into device density and antenna directionality selection for THz network design. In general, omnidirectional antennas are used at the service discovery phase, and directional antennas are used for message transmissions and localization [232]. In addition, the amplitude and phase control of RISs are not continuous in practice, where a quantized model should be considered in system design [233].

5) Signal Design: Implementing single-carrier versus multi-carrier modulation in THz systems is still not conclusive. Wideband single-carrier modulation has low complexity and could be used in scenarios with frequency-flat channels (e.g., limited multipath components). However, due to the frequency-dependent molecular absorption loss and multipath (mainly in indoor environments), multi-carrier systems are still preferred at the cost of high complexity and low power efficiency. OFDM can serve as a direct off-the-shelf solution, and discrete-Fourier-transform spread OFDM (DFT-s-OFDM) [75], [76] can be used to reduce the PAPR effect. Other multi-carrier modulations such as orthogonal time-frequency space (OTFS) modulation (suitable for highly dynamic channels) [234], hierarchical bandwidth modulations [235] (mitigate the effect of molecular absorption), spatial [236] and index modulations [237] (improve spectral efficiency) are also considered for certain scenarios. THz non-orthogonal multiple access is also being studied [238], [239]. In this work, we want to compare THz systems and mmWave systems directly; hence, OFDM modulation is assumed.

From a communication point of view, the selection of signal parameters, such as carrier frequency, bandwidth, and packet length, affects the data rate or spectrum efficiency. These parameters are also crucial for localization to obtain specific objectives. A large bandwidth is helpful to separate paths in the delay domain, but the increased sampling rate and data size should not exceed the hardware limit. The packets should be long enough to capture enough energy but short enough to meet delay constraints, especially in mobile scenarios. The design considerations directly affect the performance of a localization system; we evaluate some signal parameters via simulations in Sec. VI.

C. Offline Optimization

In an offline design, no knowledge of the position/orientation information of UEs is available. However, the surrounding environment information could be available. The offline design includes layout optimization, array design, and codebook optimization.

1) Layout Optimization: If the number of BSs/RISs/UEs is determined, their positions can be optimized based on the CRB derived using a predefined codebook. Environmental information (e.g., the geometry of the detection area and position of the blockage) can also be used to optimize the layouts and achieve the best localization performance. For the BSs with antenna arrays or directional antennas, the orientation should also be optimized.

2) Array Design: Increasing the number of antennas in an array yields higher angular resolution and beamforming gains. However, more antennas indicate higher system complexity and power cost. When adopting an AOSA structure, the design of SA size is also important. A large number of AE per SA increases beamforming gain and improves accuracy, but narrow beamwidths reduce coverage and cause deafness issues.

3) Codebook Optimization: IA is the procedure in which a new UE establishes a physical link with a BS to switch from an idle mode to a connected mode [240]. We can treat the IA procedure as localization without UE prior information. The narrow beams in THz systems make IA challenging due to deafness (transmit-receive beams do not point to each other) and blockage (channel drop caused by obstacles, device movement, or rotation) [241]. Hence, effective initial access procedures and dedicated codebook design are needed [242].

The design of codebooks depends on the search strategies, which can be broadly classified into several categories:

- Exhaustive search: The BS/UE transmits/receives data symbols by beamforming in different directions [243].
- Iterative search: Hierarchical codebooks can be designed to transmit pilots over wider sectors at the beginning and then narrow down the beams to find the best angular space [244]–[246].
- Scene-aware search: If the position prior or environmental information is available, the beams can be learned for each partitioned area to reduce IA delay [240], [247].

For these strategies, an exhaustive search provides the best coverage and hardware feasibility, but the discovery delay grows linearly with beamforming gain [248], [249]. Iterative search reduces the discovery delay at the expense of limited coverage. Considering the potential of THz SLAM, we expect a scene-aware search to be used.

4) Offline Design Example: Consider an RIS placement problem in which we want to minimize the localization coverage area with UE's PEB greater than an error threshold ϵ (e.g., $0.1\,\mathrm{u}$), given BS locations and orientations. For each possible RIS placement (position $\mathbf{p}_{\mathrm{R}}$ and orientation $\mathbf{o}_{\mathrm{R}}$) and each possible UE location $\mathbf{p}_{\mathrm{U}}$ (assuming an omnidirectional antenna), there exist a FIM $\mathbf{J}(\mathbf{p}_{\mathrm{U}}, \boldsymbol{\eta}|\mathbf{p}_{\mathrm{R}}, \mathbf{o}_{\mathrm{R}})$ and corresponding $\mathrm{PEB}(\mathbf{p}_{\mathrm{U}}, \boldsymbol{\eta}|\mathbf{p}_{\mathrm{R}}, \mathbf{o}_{\mathrm{R}})$ that can be obtained from (70). Here, $\boldsymbol{\eta}$ contains nuisance parameters (e.g., channel gains, clock biases), which are replaced with nominal values (e.g., $\boldsymbol{\eta}(\mathbf{p}_{\mathrm{U}}, \mathbf{p}_{\mathrm{R}}, \mathbf{o}_{\mathrm{R}})$ obtained from channel models). Similar assumptions need to be made for other variables such as precoders, combiners, and RIS coefficients. We can then formulate the RIS placement problem as

$$\begin{aligned} \text{maximize} \quad & |\mathcal{R}(\mathbf{p}_{\mathrm{R}}, \mathbf{o}_{\mathrm{R}})| \\ \text{s.t.} \quad & \mathbf{p}_{\mathrm{R}} \in \mathbb{R}^3, \mathbf{o}_{\mathrm{R}} \in \mathrm{SO}(3), \end{aligned} \tag{86}$$

where $\mathcal{R}(\mathbf{p}_{\mathrm{R}}, \mathbf{o}_{\mathrm{R}}) = \{\mathbf{p}_{\mathrm{U}} \in \mathbb{R}^3 | \mathrm{PEB}(\mathbf{p}_{\mathrm{U}}, \boldsymbol{\eta}|\mathbf{p}_{\mathrm{R}}, \mathbf{o}_{\mathrm{R}}) \leq \epsilon\}$ is the localization coverage area, and $|\mathcal{R}(\mathbf{p}_{\mathrm{R}}, \mathbf{o}_{\mathrm{R}})|$ denotes the volume of the coverage area (e.g., a set of discrete UE positions). Such a problem is generally non-convex and grid-search techniques can be applied.

Offline optimization in THz systems differs from low-frequency systems in several aspects. Firstly, the precoders/combiners and RIS coefficients need to be optimized first before layout optimization. Furthermore, optimization with multiple BSs/RISs is highly non-convex, and it is thus hard to obtain globally optimal solutions. Heuristic algorithms could be alternative time-saving options to get satisfactory sub-optimal results. Note that the optimization problem formulated in (86) is a simplified case in which the antenna at the UE is assumed to be omnidirectional. In general, however, the orientation of the UE needs to be considered when optimizing the layout.

D. Online Optimization

Unlike the offline design, where no prior information is available, online optimization is performed with known UE position/orientation information (or with prior information in the tracking scenario). Online optimization can be formulated as minimizing the worst-case localization performance (e.g., PEB) [250]. We consider online optimization in three aspects: resource allocation, active beamforming optimization, and RIS coefficient optimization.

1) Resource Allocation: Resource allocation is an essential phase in the operation of a communication network serving multiple UEs or conducting multiple tasks. This subsection focuses on three types of resources: time, bandwidth, and power (the space resource is discussed in Sec. V-D2 and Sec. V-D3.

- Time Resource: For single-user communication, a trade-off between transmission time and overhead needs to be made. Intuitively, more transmissions/measurements yield better localization accuracy at the cost of increasing the latency and overhead. The allocation strategy should also consider UE speed and channel coherence. The allocation of time slots (or transmissions) for multiple users aims at meeting the positioning quality-of-service (QoS) within the served area.
- Frequency Resource: Due to the variation of vapor absorption coefficients at different frequencies, the THz spectrum is divided into a set of distance-varying spectral windows [130]. The size of the effective bandwidth window gets smaller with increasing link distance. In THz communications, the effective bandwidth is expected to support hierarchical bandwidth modulation [235], optimizing device density to maximize capacity [251]. From a localization point of view, suitable subbands and sub-carriers need to be selected and assigned to the UEs at different distances.
- Power Allocation: For most applications, localization accuracy is a constraint rather than an objective to be optimized. For example, an accuracy of, say $1\,\mathrm{cm}$ is sufficient for a mobile user to know its location inside an office building. Hence, there is no reason to increase the transmission power to achieve an accuracy of $1\,\mathrm{mm}$. With proper power allocation, different performance requirements of different UEs can be met with minimal resource utilization.

Resource allocation is usually expressed as constraints for active and passive beamforming optimizations, as we describe shortly.

2) BS/UE Beamforming Optimization (Active Beamforming): With prior location information, setting the beamforming angles to point to the receiver increases the power of the received signal, which is beneficial for communication. However, this SNR increment does not guarantee an improvement in localization performance. More practical solutions utilize the CRB as an indicator. Given the uncertainty range of the target directions, the optimal precoders for tracking the DOA and DOD are derived in [252] by solving a formulated convex optimization problem. With multiple measurements, iterative location estimation and beamforming optimization can also be performed [253].

By implementing AOSA structures and directional antennas, space resource allocation reduces the assignment of beams (SAs). The optimization of the analog beamforming angles directly affects the accuracy and coverage of the system. For scenarios with multiple UEs, the SAs need to be assigned wisely to different UEs, completing both the localization and communication tasks. The SA selection is especially important in localization, where accuracy depends on the array layout. For a communication network with multiple BSs, joint beamforming optimization is also needed to achieve a better overall system performance.

3) RIS Coefficients Optimization (Passive Beamforming): The optimization of RIS coefficients is as crucial as active beamforming at the BS/UE arrays to enhance signal gain in RIS-assisted systems. When the UE position is unknown, multiple transmissions with random symbols or beamforming angles can be used for localization purposes. With prior information of the UE position/orientation, beamforming angles at the BS/RIS/UE can be jointly optimized.

The coefficients of RIS elements can be optimized to serve communication or localization purposes [250]. The elements in an RIS can be optimized to maximize the SNR at the receiver for a higher data rate. However, a high SNR does not indicate a lower CRB. By analyzing the FIM, [250] optimizes the RIS elements in a 2D SISO localization system to reduce the PEB. However, the optimization algorithms for 3D MIMO systems are not yet available.

4) Online Optimization Example: We again consider the case with RIS, where we aim to optimize the RIS phase profiles $\boldsymbol{\Omega}_1, \dots, \boldsymbol{\Omega}_{\mathcal{G}}$ for different transmissions, given a certain precoder at the UE and a combiner at the BS. We assume that the UE location is known to be in some region with $\mathbf{p}_{\mathrm{U}} \in \mathcal{R}^* \subset \mathbb{R}^3$. By introducing $\boldsymbol{\omega}_g = \mathrm{diag}(\boldsymbol{\Omega}_g) \in \mathbb{C}^{N_{\mathrm{R}} \times N_{\mathrm{R}}}$ and using $\boldsymbol{\eta}$ to indicate the estimated values of other nuisance parameters, we can compute the FIM $\mathbf{J}(\hat{\mathbf{p}}_{\mathrm{U}}, \boldsymbol{\eta} | \boldsymbol{\omega}_1, \dots, \boldsymbol{\omega}_{\mathcal{G}})$ and its corresponding PEB. An online optimization can then be formulated as

$$\begin{aligned} \text{minimize} \quad & \varepsilon \\ \text{s.t.} \quad & \mathrm{PEB}(\mathbf{p}_{\mathrm{U}}, \boldsymbol{\eta} | \boldsymbol{\omega}_1, \dots, \boldsymbol{\omega}_{\mathcal{G}}) \leq \varepsilon \\ & \mathbf{p}_{\mathrm{U}} \in \mathcal{R}^* \\ & |\omega_{r,g}| = 1, \forall r, g. \end{aligned} \tag{87}$$

This problem can be solved by first removing the unit norm constraint so that a convex problem can be obtained. Then the solution needs to be projected onto the appropriate manifold.

In THz systems with wide bandwidths, more time-frequency blocks will be available. These resources need to be allocated wisely to serve a large number of users with different communication and localization performance requirements. In addition, joint beamforming optimization for BS/RIS/UE is crucial since THz systems are expected to rely heavily on RISs due to severe blockage. Furthermore, the optimization at the SA level in an AOSA structure is different from the optimization at the antenna level in traditional MIMO systems. Consequently, novel online optimization algorithms are called for in THz systems to assist in accurate tracking.

E. Summary

In this section, we formulate the optimization problems and discuss several aspects of localization system design and optimization, which can be summarized as follows:

- We start by motivating system optimization and formulating the optimization problem with a set of variables related to different objective functions.
- We discuss high-level system considerations such as network topology, network structure, cooperative strategy, hardware selection, and signal design, which is dependent on the application scenario.
- We divide system design into offline design and online optimization, and discuss the challenges for THz systems compared with low-frequency systems.

TABLE IX
DEFAULT SIMULATION PARAMETERS

Parameters	Simulation Values
mmWave / THz Frequency f_c	$60\,\mathrm{GHz}$ / $0.3\,\mathrm{THz}$
Transmission Power P	$10\,\mathrm{dBm}$
Noise PSD	$-173.86\,\mathrm{dBm/Hz}$
Noise Figure	$13\,\mathrm{dBm}$
Array Footprint (BS/RIS/UE)	$2{\times}2\,\mathrm{cm}^2$ / $10{\times}10\,\mathrm{cm}^2$ / $1{\times}1\,\mathrm{cm}^2$
AE Spacing $\mathring{\Delta}$	$\lambda_c/2$
Bandwidth W	$100\,\mathrm{MHz}$
Number of Transmissions $\mathcal{G}$	10
Synchronization Offset B	10 us (for Simulation D/E/F/G)
Number of Subcarriers K	10
Signal Wave Model	SWM (near-field)
Localization Scenario	2D Position, 1D Orientation
mmWave Array Dim N_{Q} (BS/RIS/UE)	4×4/ 20×20 / 2×2
THz Array Dim $N_{\mathrm{Q}}\mathring{N}_{\mathrm{Q}}$ (BS/RIS/UE)	20×20/ 100×100 / 10×10
THz SA Dim $\mathring{N}_{\mathrm{B}}$ /$\mathring{N}_{\mathrm{R}}$/ $\mathring{N}_{\mathrm{U}}$	5×5 / 1×1 / 5×5
Position $\mathbf{p}_{\mathrm{B}}$ / $\mathbf{p}_{\mathrm{R}}$ / $\mathbf{p}_{\mathrm{U}}$	$[0,0,0]^T$ / $[5,5,0]^T$ / $[10,0,0]^T$
Orientation $\mathbf{o}_{\mathrm{B}}$ / $\mathbf{o}_{\mathrm{R}}$ / $\mathbf{o}_{\mathrm{U}}$	$[0,0,0]^T$ / $[-\frac{\pi}{2},0,0]^T$ / $[\frac{5\pi}{6},0,0]^T$

The next section provides simulations to show the effect of parameters on the system CRB.

VI. SIMULATION AND EVALUATION

In this section, we provide several simulations to evaluate the effect of system parameters on localization performance. A $0.3\,\mathrm{THz}$ sub-THz system and a $60\,\mathrm{GHz}$ mmWave system in an uplink scenario are considered with the default parameters listed in Table IX. These parameters are the default setting for the rest of the simulations unless otherwise specified. Simulations A/B/C/D (Sec. VI-A to VI-D) consider only LOS channels, while the effects of RIS and NLOS channels are discussed later in simulations E/F/G (Sec. VI-E to VI-G). Matlab code is available in [254].

A. A Comparison between mmWave and THz Systems

We first compare the PEB and OEB between two systems with different array configurations. To make a fair comparison, we fix variables such as transmission power, time, and maximum footprint. A fully connected antenna array is adopted in the mmWave system, while an AOSA structure is used for the THz system. All the RFCs send different random data symbols with normalized energy.

In this comparison, the system is assumed to be synchronized [11], while for simulations D/E/F/G a synchronization offset is assumed. We also assume that no prior information of the UE is available, and hence the beamforming angles at the SA (AOSA systems) are set randomly as $\tilde{\phi}, \tilde{\theta} \in (-90^\circ, 90^\circ)$ for different transmissions. We use CRB (PEB/OEB) to evaluate the fundamental limit of the localization systems as shown in Fig. 5. This figure illustrates the potential of THz localization (lower PEB and OEB), where ∼5 (∼20) times better positioning performance without (with) prior information is expected

[11] If only an LOS channel is considered in a far-field model, synchronization between the BS and the UE is needed for delay estimation. However, if more paths are available, e.g., extra LOS paths provided by other BSs, RIS, or NLOS paths, synchronization is not a requirement. One typical example is TDOA-based localization.

interesting results observed. In this section, we would like to highlight the lessons learned from the simulations in Section VI, and discuss the future directions from the aspects of channel modeling, localization, and optimization in Sections III-V.

A. Lessons Learned

1) Deal with SWM and PWM wisely in channel modeling and performance analysis. SWM requires high computational complexity since the phase change cannot be described using a simple steering vector, and there could be amplitude variations across the array. As a result, PWM is usually preferred, with possible performance loss in the near-field. From the CRB analysis point of view, the SWM and PWM are also different. In the far-field, the local AOA and AOD can be estimated directly, whereas the UE state is integrated into the channel model as shown in (62) and (65).
2) A similar concept of AOSA can be used in the RIS channel realization. A large number of RIS elements is needed to combat the high path loss of the RIS channel. This is even more challenging in high-frequency signals (e.g., 200×200 RIS elements can be fitted into a $10 \times 10\,\mathrm{cm}^2$ area in a $0.3\,\mathrm{THz}$ system). With segmented sub-RIS and equivalent array response, the complexity can be reduced.
3) Be aware of the model mismatch. We have seen the CRB mismatch between the SWM and the PWM models. Since PWM is an approximation, the model is inaccurate in the near field and should be avoided if possible. In addition to the channel model mismatch, the mismatch caused by the mobility of the UE and HWI should also be considered. The MCRB could be used as a tool to analyze such mismatches.
4) Tradeoff between coverage and beamforming gain needs to be taken care of in system design. When designing a system, the directionality of the antenna and the size of SA should be considered to achieve a high beamforming gain. However, the gain in SNR will affect the coverage of the system, and severe misalignment will occur. These two aspects need to be well-designed depending on the application scenarios.
5) Performance (CRB) analysis is an important step for algorithm evaluation and system optimization. However, the lower bound may not be reached in some scenarios, for example, low SNR scenarios and the existence of multiple non-resolvable paths. In addition to the CRB, other types of bound such as CCRB, and MCRB are also important in different scenarios.

B. Future Directions

By moving from mmWave to THz, a better localization performance is expected. However, new issues and challenges need to be rethought to benefit from the system in this band. First, new KPIs may need to be defined for specific applications (e.g., quality of service rather than localization error). Also, position integrity[12] and availability[13] may become more important in localization, especially for the scenarios that need highly reliable position information. In addition, we need to have methods that are scalable, given a large number of antennas/RIS elements and a large volume of data. Regarding the RIS, this new enabler brings topics such as the synchronization to other network elements, information-sharing between operators, and the roles at different frequencies (should RIS operate in the same way at mmWave-band and THz-band or not). More problems will need to be tackled when we are moving to a higher frequency.

The research on THz localization is still at the early stage, with many directions to be explored. We list a few directions from the aspects of the channel model (1-2), localization performance analysis and algorithm design (3-6), and system optimization (7-9):

1) Stochastic model analysis: We have formulated a deterministic channel model in this work. In realistic scenarios, however, the AOAs and amplitudes of scattered signals are stochastic. The effect of randomized NLOS signals needs to be modeled, and the effect of scatters on the localization performance can be evaluated. The stochastic model is also helpful for object/reflector detection and classification in sensing tasks.
2) Accurate channel modeling: Channel model is the foundation of geometry-based localization. Currently, we use an extrapolation of mmWave models by introducing features in high-frequency systems such as atmosphere attenuation, SWM, wideband effect and AOSA structure. However, the effects of HWIs and other THz-specific aspects may not be captured in the channel model (including the LOS, RIS, and NLOS channel models). These model mismatches degrade the localization performance, and thus, a more accurate channel model is important.
3) BS/RIS calibration. In most of the localization tasks, we are interested in the position and orientation of UEs by assuming the known anchor information (e.g., BS/RIS position and orientation). For the scenarios with more than one anchor, there could be calibration errors in the rest of the anchors compared to the reference anchor. In this case, jointly UE localization and BS/RIS calibration would be of great interest.
4) Doppler estimation: In addition to position and orientation, the Doppler effect of the UE is not discussed in this work, which is crucial for mobile scenarios. This additional type of channel parameter can contribute to the tracking and SLAM tasks. In addition, by introducing the Doppler effect, localization can be done within a longer integration time.
5) Cooperative localization. Coverage is one of the challenging issues in high-frequency communication and localization. As a result, D2D communication and cooperative

[12]Positioning integrity: is a measure of the trust in the accuracy of the position-related data provided by the positioning system and the ability to provide timely and valid warnings to the location service client when the positioning system does not fulfill the condition for the intended operation [255].

[13]Availability: is defined as the fraction of the time that the estimated localization error is below the alert limit [83].

localization can help even if there is an outage between the UE and the BS. As for SLAM, the collaboration between UEs can complete the mapping tasks within a shorter period of time.

6) Advanced performance analysis tools: We have discussed various types of CRBs (e.g., CRB, CCRB) for position and orientation estimation. Nevertheless, other bounds should be studied and enter more widespread use to account for phase ambiguities (e.g., in carrier phase-based localization), low-SNR operation, model mismatch, and with prior information. These advanced performance analysis tools will enable the algorithm development and system design for THz-band localization.
7) Scene-aware localization: From the SLAM algorithm, surrounding map information could be available. In addition to the map, the probability density functions of past access locations can also be used to perform scene-aware localization. Beamforming vectors at the BS/UE and RIS element coefficients can be optimized to avoid obstacles and take advantage of the strong reflectors for localization purposes. In this topic, how to maintain a map with minimum resources and update the map with time is a problem to be solved.
8) Dynamic deployment optimization. It is straightforward to optimize the deployment of static BSs for coverage or accuracy purposes. In temporal high traffic situations as in stadiums or conference halls, the BS could also be dynamically deployed, e.g., attached to UAVs. The location and route of the UAVs need to be optimized to meet the communication and localization requirements of the UEs. However, the connectivity in dynamic THz UAV networks is also challenging, which should be addressed carefully.
9) AI-based methods: Model-based methods are easy to analyze, but when unknown model mismatches exist, AI-based methods are more preferred to learn or to mitigate the effect of such mismatches. In the latter case, access to common databases is needed to compare and evaluate different approaches. Furthermore, the collection, sharing, and storage of a large amount of data, transfer a learned model into another domain to reduce the training duration, and the protection of user privacy are urgent issues that need to be solved.

In summary, we need to put more effort in three aspects in order to improve THz localization accuracy and efficiency: (a) develop a more accurate system model (directions 1, 2, 3), (b) utilize other types of information (directions 4, 5, 7, 8), and (c) develop more advanced tools for analysis and optimization (directions 6, 9).

VIII. Conclusion

This work explores the potential of the 6G THz system from a localization point of view, emphasizing comparisons with 5G mmWave localization systems. Comparisons include system and signal properties, channel modeling and assumptions, localization problem formulation, and system design and optimization. Preliminary simulations are carried out to show the potential of THz localization compared with mmWave systems, in terms of the PEB and OEB. This tutorial outlines recommendations on efficient and practical localization algorithm design for RIS-assisted AOSA-based MIMO systems, providing insights into other research directions. With joint localization and communication systems operating at the terahertz band, data-hungry and high localization accuracy demanding applications such as intelligent networks, autonomous transportation, and tactile internet are anticipated in future communication systems.

Abbreviations

3D	three-dimensional
5G	fifth generation
6G	sixth generation
ADC	analog to digital converter
ADOD	angle-difference-of-departure
AOA	angle-of-arrival
AOD	angle-of-departure
AOSA	array-of-subarray
BS	base station
BSE	beam split effect
CDF	cumulative distribution function
CKF	cubature Kalman filter
COA	curvature-of-arrival
CRB	Cramér-Rao bound
CSI	channel state information
D-MIMO	distributed MIMO
D2D	device-to-device
DFL	device-free localization
DFT-s-OFDM	discrete-Fourier-transform spread OFDM
DL-PRS	downlink positioning reference signal
EKF	extended Kalman filter
GPS	global positioning system
HWI	hardware impairment
IoT	internet of things
IQI	in-phase and quadrature imbalance
ISAC	integrated sensing and communication
KF	Kalman filter
KPI	key performance indicator
MAC	medium access control
MC	mutual coupling
MCRB	misspecified Cramér-Rao bound
MDS	multidimensional scaling
MEMS	micro-electro-mechanical system
MIMO	multiple-input-multiple-output
ML	machine learning
mmWave	millimeter wave
MPC	multipath components
NLOS	none-line-of-sight
OFDM	orthogonal frequency-division multiplexing
OTFS	orthogonal time-frequency space
PA	power amplifier
PAN	power amplifier nonlinearity
PAPR	peak-to-average-power ratio
PDF	probability density function
PDOA	phase-difference-of-arrival
PF	particle filter
PN	phase noise
POA	phase-of-arrival
PRS	positioning reference signals
PS	phase shifter
PWM	planar wave model
RF	radio frequency
RFC	radio-frequency chain

RFID radio frequency identification
RIS reconfigurable intelligent surface
RNN recurrent neural network
RSS received signal strength
RTT round-trip time
SA subarray
SLAM simultaneous localization and mapping
SOTA state-of-the-art
SPP surface plasmon polariton
SWM spherical wave model
TDOA time-difference-of-arrival
THz terahertz
TOA time-of-arrival
TOF time-of-flight
UE user equipment
UKF unscented Kalman filter
UPA uniform planar array
VLC visible light communication
VLP visible light positioning
WLAN wireless local area network

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