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Reconfigurable Intelligent Surface-Assisted Localization: Technologies, Challenges, and the Road Ahead

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ABSTRACT Owing to the breakthrough of artificial meta-materials, the emergence and evolution of reconfigurable intelligent surface (RIS) have drawn a novel blueprint for the development of the sixth-generation (6G) wireless networks, through the creation of smart radio environment to meet the requirement of ubiquitous connectivity. Meanwhile, the vision for the 6G illuminates the integration of sensing and communication, bringing out a demand for both high-quality communication and high-precision localization. Therefore, regarding the future wireless localization, the potential of RIS to tag the signals provides additional degrees of freedom. To this end, to fulfil the increasing demands for positioning, RIS has drawn a growing amount of research both from academia and industry. In this paper, we first introduce the emerging investigations and development of RIS, and we give a concise summary of the localization principles. Then we explain the potential of RIS in localization, and provide a comprehensive survey of the current state of research on RIS-assisted localization. Finally, we discuss the most significant research challenges to tackle for RIS-aided localization in the future.

INDEX TERMS Reconfigurable intelligent surface, smart radio environment, localization, positioning, sixth-generation (6G).

I. INTRODUCTION

ALONG with the commercialization and popularization of the fifth-generation (5G) networks, the increase of network performance opens new application scenarios, such as the extended reality (XR), the intelligent plant, the Internet of Vehicles (IoV) and so on. It is expected that the capacity of wireless networks will expand a thousandfold in the next decade, and ubiquitous wireless connection will become a reality. However, future networks will confront significant challenges, including strong reliability, massive device access, extremely complicated networks, high-cost hardware, and rising energy consumption [1]. For example, a large number of base stations (BSs) in a super-dense network, increase the cost of hardware and maintenance and encounter serious network interference. Meanwhile, the expansion of the spectrum from sub-6G to millimeter-wave (mmWave) and even terahertz (THz) necessitates more complex signal processing capabilities and more expensive power-consumed hardware. In particular, high-precision localization has been given high expectations in future mobile communications due to the rapid development of the Internet of Things (IoT) that contributes to the explosive growth of intelligent devices [2]. Conventional time-based localization techniques [3], i.e., time-of-arrival (ToA) and time-difference-of-arrival (TDoA), tend to adopt the signals from the Global Position System (GPS) or cellular BSs, relying on high synchronization accuracy; angle-based localization, namely, angle-of-arrival (AoA) or angle-of-departure (AoD), requires massive antenna arrays for higher precision; and the accuracy of receive-signal-strength (RSS)-based approaches is limited by propagation loss modeling or the granularity of RSS fingerprints. Meanwhile, the auxiliary positioning signals often suffer from a dead zone indoors due to obstacles and an abundant multipath effect owing to non-light-of-sight (NLoS) propagations. Toward the rising demand for positioning, a certain number of advanced technologies have been put forward, including ultra-wideband (UWB) [4], time-reversal [5], wireless sensor network [6], virtual anchors [7], and so on.

Nevertheless, the sixth-generation (6G) wireless networks that aim to construct global seamless access, are facilitating the development of automated driving, holographic communication, etc., which claims for the increasing requirements for target identification, imaging, and tracking. Therefore, the vision of the 6G is also inspiring academics to seek possible breakthrough technologies. In especial, a revolutionary technology named reconfigurable intelligent surface (RIS) nowadays, propelled by the emergence of artificial meta-materials, has received significant attention in the industry [8]. In essence, RIS is composed of massive and low-cost electromagnetic elements whose capacitance, inductance, and resistance can be adjusted instantaneously, thus manipulating the amplitude, phase, and even polarization of the signals travelling through them. Owing to its potential to intelligently reconfigure the wireless environment, RIS has been conjectured as a promising candidate technology to establish a smart radio environment (SRE) for future mobile communications, alluring researchers to exploit it in wireless networks for signal enhancement, capacity improvement, spectrum and energy efficiency promotion, and so on.

In the localization domain, the superiority of RIS may be attributed to two aspects: novel degrees of freedom (DoFs) on the channel and low hardware cost. More precisely, RISs can act as additional anchors to provide extra channel DoFs by artificially shaping the travelling signals, which enables the receiver to be aware of partial electromagnetic environments. When the line-of-sight (LoS) link between the BS and the user equipment (UE) is obstructed, the two-hop BS-RIS-UE links will extremely conduce, which is especially helpful in the single access point (AP) positioning scheme. On the other hand, in a GPS-denied environment, the easy deployment of RIS allows to avoid the use of a dedicated localization infrastructure, usually made of multiple anchors, indicating less hardware cost. Recently, wireless localization with RIS has won increasing attention, where RIS acts either in the receiver mode [9] or in the reflector mode [10]. When operating in the receiver mode, RIS is assumed to be equipped with sensing circuits or RF chains, hence the entire continuous surface for receiving radiating signals scales up beyond the typical concept of the massive antenna array. When acting in the reflector mode, RISs can be treated as extra anchors, where both time and angle-based techniques can be adopted [11], [12], while exploiting the reconfiguration of RIS coefficients to acquire different RSS maps is another type of approaches [13]. Owing to its quasi-passive characteristics, i.e., it is not that practical for RIS to be equipped with large-scale circuits, RIS performing in the second mode has received more attention. Depending on the emphasis, current works in this field could be separated into four types: i) tutorials and surveys, ii) theoretical bound derivations, iii) practical localization algorithms, and iv) RIS optimization approaches.

In this context, we provide a comprehensive overview of current state-of-the-art studies on RIS-assisted localization (RISL) and discuss the most significant research issues to tackle in the future. To this end, the remainder of this paper is organized as follows.

- In Section II, the concept, evolution, and application domains of RIS are introduced, along with a generic model of RIS-assisted communication.
- In Section III, a brief overview of current localization principles is given.
- In Section IV, the potential of RIS in localization is presented.
- In Section IV, a comprehensive survey of the current state of research on RIS-assisted localization is provided.
- In Section V, the most significant challenges worth future tackling are discussed.
- In Section VI, a brief conclusion is drawn.

II. RIS EVOLUTION, APPLICATION, AND MODELING

The concept RIS is referred to as a kind of two-dimensional artificial material, usually made up of metal, dielectric and adjustable components, which can be equivalently represented as RLC circuits. By adjusting the physical properties of electromagnetic units, such as capacitance, inductance, and resistance, the radiation characteristics of RIS can be changed accordingly, thus achieving extraordinary physical adjustment, such as abnormal reflection, negative refraction, focussing, absorption, and even polarization transformation. Compared with the traditional multiple-input multiple-output (MIMO) architecture and relays, RIS has the following core features:

Quasi-passive: RIS realizes passive control of electromagnetic waves by regulating the physical properties of artificial electromagnetic materials, but the regulation itself needs a measure of energy consumption.

Low power consumption: RIS may not possess high-power devices such as radio frequency (RF) chains.

Low thermal noise: RIS does not need amplifier to process the reflected signals, indicating low thermal noise.

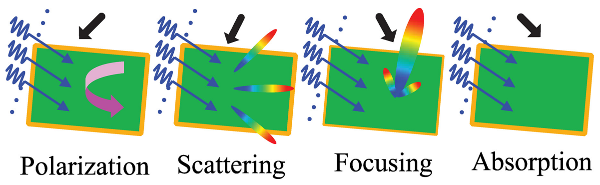


FIGURE 1. Elementary functions of RIS.

Software programmable: RIS has programmable physical characteristics, which can realize real-time and dynamic regulation of electromagnetic responses.

Easy to deploy: As a two-dimensional planar structure, RIS is easy to expand in size and to deploy on various surfaces in wireless propagation environments.

Broadband response: RIS can work in microwave band, mmWave band, THz band or even visible light band.

In a nutshell, RIS has great potentials to become a new physical platform for the simultaneous control of electromagnetic waves and digital information, as well as to build an intelligent electronic information system with a novel architecture.

A. EVOLUTION OF RIS

The emergence of RIS can be traced back to the achievement of T. J. Cui in 2014 [14], where the concept of coding/digital/programmable metamaterials was proposed, realizing the digital control of electromagnetic information. Specifically, metamaterials are constructed by metamaterial particles, each of which has two digital states "0" and "1" to represent the reflection phase response of 0 and π, thus named one-bit coding metamaterials. These metamaterial particles were composed of PIN diodes, the control is achieved by field programmable gate array (FPGA) hardware, and multi-bit metamaterials can achieve more flexible regulation. Later on, some investigation on the physical design of coding metamaterials sprang up, with the purpose of more powerful and flexible use [15], [16], [17]. For example, a carefully designed programmable metasurface was developed in [17], demonstrating that besides the reconfigurable phase, polarization control, scattering, and beam focusing are all possible through adjusting the on/off status of PIN diodes. Moving a step further, by introducing Shannon's information theory into the digital coding metamaterials, a bridge between physical space and information space was built [18], providing a brand-new system for mobile communications, imaging, radar, electronic countermeasures, and other information systems.

In June 2017, Hu et al. investigated the potential of communication with a large antenna array deployed on a large surface, which is named "large intelligent surface" [19], and further demonstrated the channel capacity for data transmission [20] and the Cramér-Rao lower bound (CRLB) for positioning [9] from the perspective of information theory. On this basis, the researchers of [21] first proposed the concept of "passive smart mirror" in 2018, pioneering the research of the two-hop BS-RIS-UE communication system. In the same year, an alternate optimization (AO) and semidefinite relaxation (SDR)-based approach was proposed to conquer the joint optimization problem of beamformer and RIS configuration [22], which provides one important optimization tool for subsequent researches. In 2019, the application of RIS in wireless communication was discussed in [8], where a detailed overview was provided, along with a discussion on the open research issues in 6G and beyond wireless networks. From then on, the research of RIS-assisted mobile communications has exploded. On the one hand, RIS has been demonstrated to enrich scattering conditions and actively enhance the multiplexing gain of wireless communication systems [23]; on the other hand, regulating the signal propagation directions, increasing the received signal intensity, and improving transmission performance between communication devices, have all been verified possible through the reconfiguration of RIS [24]. Moreover, in the prototype studies, the team of Southeast University realized real-time transmission based on RIS [25], and the RFocus system of Massachusetts Institute of Technology achieved signal-to-noise ratio (SNR) improvement for a single user [26]. Meanwhile, Tsinghua University used RIS on the transmitter to realize the real-time regulation of mmWave beam [27], whereas the ScatterMIMO system designed by the University of California, San Diego, used RIS to enhance the scattering effect in the environment and improve the spatial multiplexing gain of MIMO [28].

B. RIS APPLICATION DOMAINS

The rise of RIS has brought the new concept of SRE, where RIS transforms the physical environment space into an intelligent reconfigurable information space, bringing about a paradigm transformation in information transmission and processing, which is unimaginable in a traditional wireless network. The SRE greatly expands the scope of software-defined networks, that is, the future network will be evolved into a software-based platform through RIS, which can adapt environmental changes and provide corresponding functional services [8]. In the last few years, plenty of studies and innovative schemes related to RIS have been conducted by many researchers [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41]. On the one hand, RIS can lead to electromagnetic absorption, reflecting, scattering, and dynamically regulate wireless signals according to the required wireless functions, thus providing virtual LoS (VLoS) links, eliminating local coverage holes, and serving users at the edge of cells [29], [30], [31]. Meanwhile, when applied in existing cellular networks, RIS also has great potential for the capacity improvement [32], security assurance [33], electromagnetic pollution reduction [34], constructing a novel massive MIMO transceiver architecture [35], and reducing the hardware complexity and cost [36]. On the other hand, the massive-array characteristics of RIS also bring additional spatial information, which can

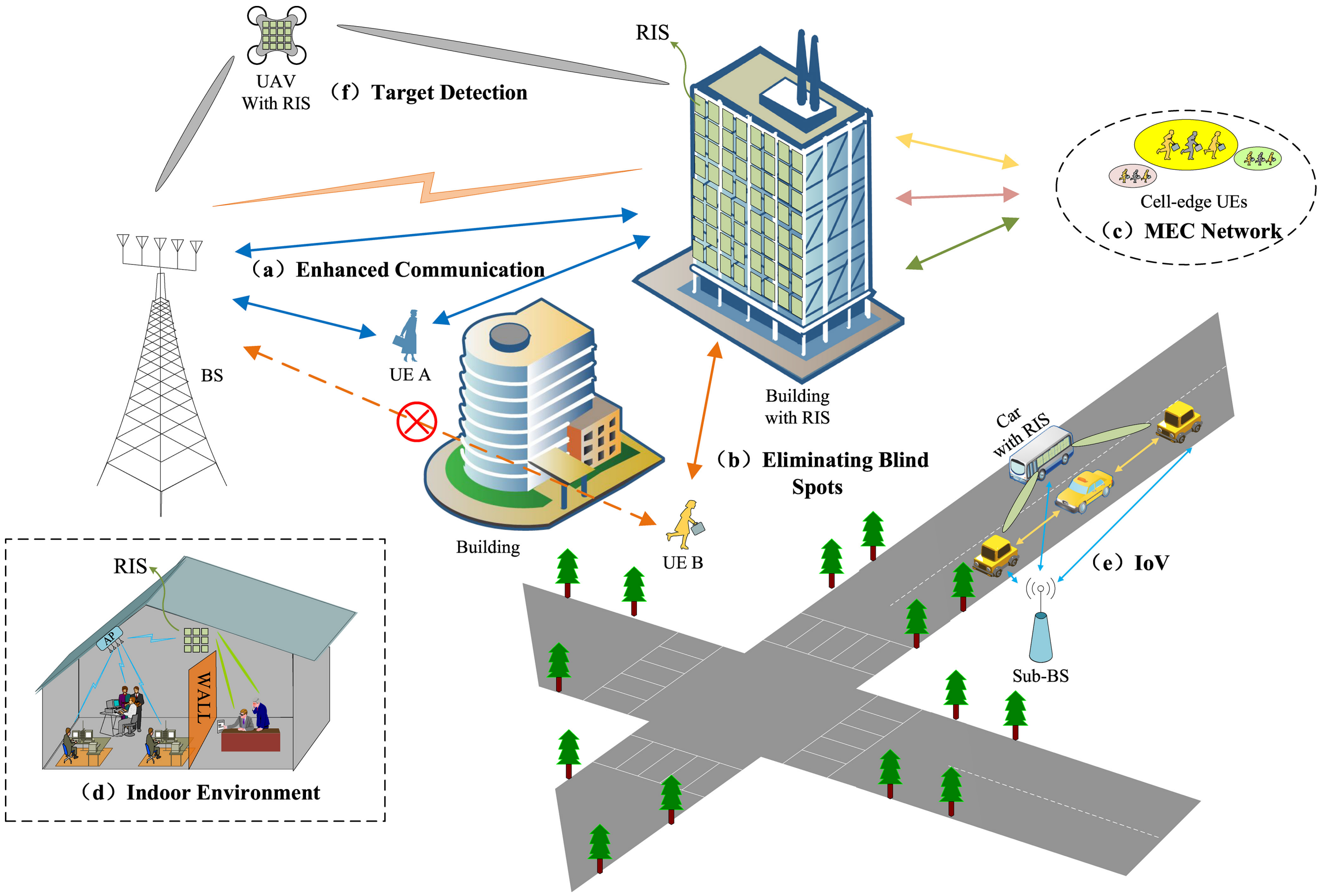


FIGURE 2. RIS application domains.

be combined with spatial modulation to improve spectrum efficiency [37]. Meanwhile, the application of RIS in simultaneous wireless information and power transfer (SWIPT) systems can provide a stable energy supply, or reflect the RF energy to target users in the dead zone [38]. Moreover, RIS also has a place in scenarios such as IoV [39], unmanned aerial vehicle (UAV) networks [40], and high-precision positioning [41]. Briefly, the future application scenarios of RIS can be divided into two main categories: one is the employment of RIS in traditional communication scenarios, and the other is the integration with novel mobile technologies.

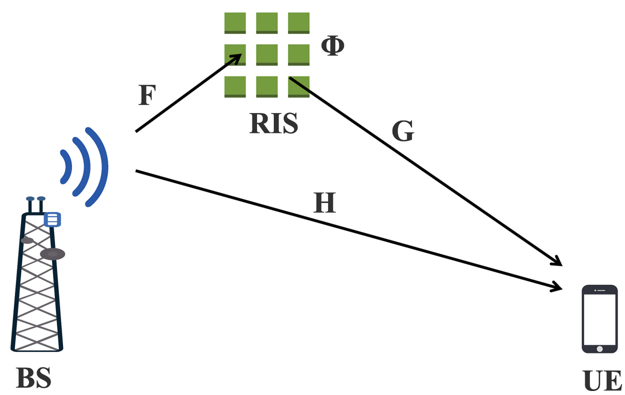


FIGURE 3. A generic system model of RIS-based communications.

C. MODELING OF RIS-BASED MOBILE COMMUNICATIONS

In this subsection, we briefly describe a generic system model of RIS-based MIMO communication. Without loss of generality, we consider a three-node downlink system consisting of an N_B-antenna BS, an N_U-antenna UE, and an RIS equipped with N_R units. As depicted in Fig. 3, the direct BS-UE channel, namely, the channel that does not include RIS, is denoted as $\mathbf{H} \in \mathbb{C}^{N_U \times N_B}$; meanwhile, the BS-RIS and RIS-UE channels are expressed as $\mathbf{F} \in \mathbb{C}^{N_R \times N_B}$ and $\mathbf{G} \in \mathbb{C}^{N_U \times N_R}$, respectively. Moreover, the RIS holds a diagonal configuration matrix

$$\Phi = \text{diag}(\boldsymbol{\phi}), \boldsymbol{\phi} \in \mathbb{C}^{N_R}, |\phi_i| \leq 1, i \in \{1, 2, \ldots, N_R\}, \quad (1)$$

to reconfigure the reflected beam due to the limits on the conservation of energy. In practice, limited by current hardware process, not all amplitude and phase values are feasible. Therefore, $|\phi_i|$ and $\angle\phi_i$ are often modeled in discrete forms, i.e., $|\phi_i| \in \{\beta_m | 0 \leq \beta_m \leq 1, m = 1, 2, \ldots, M_a, M_a \in \mathbb{N}^+\}$ and $\angle\phi_i \in \{\psi_m | 0 \leq \psi_m \leq 2\pi, m = 1, 2, \ldots, M_p, M_p \in \mathbb{N}^+\}$.

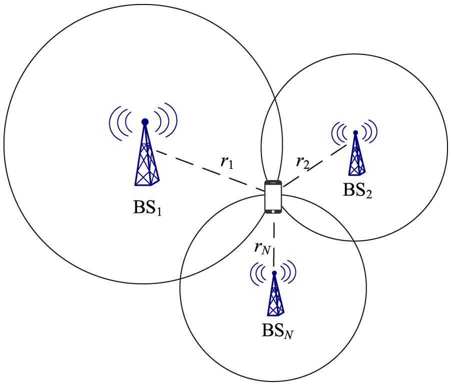


FIGURE 4. A geometrical diagram of ToA-based localization.

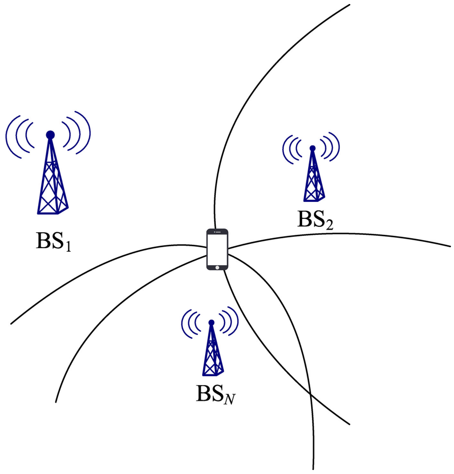


FIGURE 5. A geometrical diagram of TDoA-based localization.

Furthermore, owing to the quasi-passive nature of RIS, the thermal noise introduced by the reflective process of RIS is negligible. Thus, the received signal at UE can be formulated as

$$\mathbf{Y} = (\mathbf{H} + \mathbf{G}\boldsymbol{\Phi}\mathbf{F})\mathbf{S} + \mathbf{N}, \tag{2}$$

where $\mathbf{S} \in \mathbb{C}^{N_B \times N_S}$ is the transmitted data with N_S denoting the number of data streams, and $\mathbf{N} \in \mathbb{C}^{N_U \times N_S}$ is the Gaussian noise. A possible optimization mechanism is to design the configuration matrix of RIS, i.e., $\boldsymbol{\Phi}$, so that the transmission performance in terms of SNR, capacity, etc., can be improved, which can be given by

$$\begin{aligned} \max \quad & \mathcal{L}(\Phi|\mathbf{H}, \mathbf{G}, \mathbf{F}) \\ \text{s.t.} \quad & |\phi_{ii}| \leq 1, \forall i \in \{1, 2, \ldots, N_R\}, \\ & |\phi_{ij}| = 0, \forall i \neq j \in \{1, 2, \ldots, N_R\}, \end{aligned} \tag{3}$$

where $\mathcal{L}$ denotes a certain objective function. Similarly, this model can be straightforwardly generalized to multiple BSs, UEs, and RISs scenarios. In different application scenarios, the RIS configuration matrix should be customized to meet various requirements.

III. LOCALIZATION PRINCIPLES

As indicated in [3], any radio localization system includes three essential parts: measurements, reference systems, and estimation algorithms. Measurements, often including ToA, TDoA, AoA, and RSS, are collected from the radio signals between the transmitter and receiver through channel estimation. The reference system is the entirety of anchors, namely, the devices, reflectors, scatterers, etc., which have known positions and are geometrically related to the targets of interest. Finally, estimation algorithms help to establish the mathematical relationship between measurements and the positions of references and targets. Depending on the different types of measurements, the fundamental localization principles can be divided into the following four groups.

A. TOA/TDOA

In a literal sense, ToA and TDoA are time-based techniques, relying on measurements of propagation time between the target and anchors [42]. Assume that there are N anchors to assist positioning, with the i-th one located at (x_i, y_i), thus the distance between the target and the i-th anchor can be denoted as

$$r_i = c\tau_i, i = 1, 2, \ldots, N, \tag{4}$$

where τ_i is the corresponding ToA and c is the speed of light. Take the two-dimensional (2D) scenario as an example, the position of each anchor is the circle center, and the measured distance is the radius, namely,

$$r_i^2 = (x_i - x)^2 + (y_i - y)^2, \;\; i = 1, 2, \ldots, N. \tag{5}$$

Hence, the target position (x, y) is at the intersection of these circles, which can be formulated as

$$\begin{bmatrix} r_1^2 - R_1^2 \\ r_2^2 - R_2^2 \\ \vdots \\ r_N^2 - R_N^2 \end{bmatrix} = \begin{bmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ \vdots & \vdots & \vdots \\ -2x_N & -2y_N & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ R \end{bmatrix}, \tag{6}$$

where R_i and R are respectively defined as $R_i = \sqrt{x_i^2 + y_i^2}$ and $R = \sqrt{x^2 + y^2}$. However, considering measurement errors, the circles might not intersect at a point, i.e., the N equations in (6) might not have a feasible solution. Therefore, statistical methods like least squares (LS) and weighted least squares (WLS) are often adopted. The three-dimensional (3D) scenarios can be extended straightforwardly by introducing the z-axis, and the circles are replaced by spherical surfaces. For ToA-based localization, the strict requirement for synchronization is a typical weakness, since the uncertainty about the starting time leads to time offsets for ToA measurements, which restricts its application. Therefore, it is usually used in GPS, Beidou, and other global navigation satellite systems with a high-precision synchronization controlling and clock calibration system.

One possible choice to cut down the synchronization cost is to utilize the difference in ToA measurements, namely,

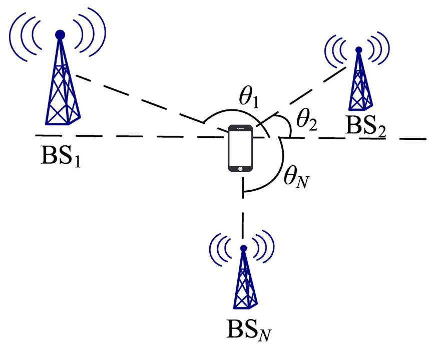


FIGURE 6. A geometrical diagram of AoA-based localization.

TDoA. TDoA determines the position of the target by detecting the time differences among the signals from different anchors rather than the absolute flight time. According to the mathematical relationship, the distance difference between the target and any two anchors is a constant; thus, the position of the target must be on the hyperbola with these two points as the focus, namely

$$\Delta r_i = r_i - r_0, \tag{7}$$

where the subscript 0 denotes the benchmark anchor. Hence, the target position is obtained by calculating the intersection of these hyperbolas, which can be formulated as

$$\begin{bmatrix} l_1 \\ l_2 \\ \vdots \\ l_N \end{bmatrix} = \begin{bmatrix} x_1 - x_0 & y_1 - y_0 & \Delta r_1 \\ x_2 - x_0 & y_2 - y_0 & \Delta r_2 \\ \vdots & \vdots & \\ x_N - x_0 & y_N - y_0 & \Delta r_N \end{bmatrix} \begin{bmatrix} x \\ y \\ r_0 \end{bmatrix}, \tag{8}$$

where $l_i = (R_i^2 - R_0^2 - \Delta r_i^2)/2$. The 3D scenarios can also be extended straightforwardly by replacing hyperbolas with hyperbolical surfaces. Since there is no need to detect signal transmission time, the TDoA-based system greatly reduces the synchronization requirement between the target and anchors, due to the fact that the synchronization among anchors is much easier to achieve than that between the target and anchors. However, every coin has two sides; the subtraction of ToA measurements also leads to correlated noise in TDoA-based positioning [43]. TDoA-based localization is usually applied in cellular networks, since current air interfaces can only provide a synchronization capability at the microsecond level, which will lead to hundred-meter-level positioning errors if adopting ToA.

B. AOA/AOD

By utilizing the information about the direction rather than the distance to neighboring anchors, angle-based measurements provide localization information complementary to the time-based measurements discussed above. Considering that the angle between the x-axis and the bearing line formed by the i-th anchor and the target is θ_i, i.e.,

$$\tan\theta_i = \frac{y - y_i}{x - x_i}, \tag{9}$$

the target is at the intersection of these lines, yielding

$$\begin{bmatrix} y_1 - x_1\tan\theta_1 \\ y_2 - x_2\tan\theta_2 \\ \vdots \\ y_N - x_N\tan\theta_N \end{bmatrix} = \begin{bmatrix} \tan\theta_1 & 1 \\ \tan\theta_2 & 1 \\ \vdots & \vdots \\ \tan\theta_N & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}. \tag{10}$$

AoA/AoD-based localization is completed by antenna arrays, and the multiple signal classification (MUSIC) algorithm, provided in [44], is of wide application for estimating the angles of incoming signals. However, 3D positioning is more difficult to achieve since the angle is represented by the azimuth and elevation angles, respectively, resulting in non-linear equations. Due to the use of massive antenna arrays, AoA/AoD-based positioning schemes are introduced for the first time in 5G networks.

C. RSS

Sometimes, time and angle-based measurements are not directly available; thus other methods should be adopted. Localization based on RSS is another way to translate radio signals into a position estimate [45], exploiting distance information like ToA and TDoA, or comparing all measured RSS values with RSS fingerprints and then giving the most matching position. Traditional researches on RSS were based on the classic radio propagation path loss model [46], which is formulated as

$$\bar{P}(d) = P_0 - 10\alpha \lg \frac{d}{d_0}, \tag{11}$$

where P_0 is the received signal power (in dBm) at a reference distance d_0, and α is the path-loss exponent usually between 2 and 4. In the real transmission environment, the measured received signal power $P(d)$ and its ensemble average $\bar{P}(d)$ is typically modeled as log-normal, based on a wide variety of measurement results [47], [48], [49] and analytical evidence [50], which yields

$$f(P(d)) = \mathcal{N}\left(\bar{P}(d), \sigma_{\text{dB}}^2\right), \tag{12}$$

where the standard deviation σ_{dB} of the received signal power is relatively constant with distance and can be as low as 4 and as high as 12 [48]. Therefore, similar to time-based methods, the target position can be obtained by solving the equations in (6) by replacing r_i with d_i.

For changing environments or unknown propagation models, the received power map is another popular RSS-based localization approach. The principle is to match the RSS measurement to the previously stored RSS map, which is also named RSS fingerprinting. For example, the authors in [51] proposed a base-station-strict approach and a particle filtering method for static and dynamic conditions, respectively. The disadvantages of fingerprinting are low precision while the database needs to be restored if the environment changes. However, RSS-fingerprinting localization is relatively low-cost and simple to implement in hardware compared with time or angle-based methods, which is an

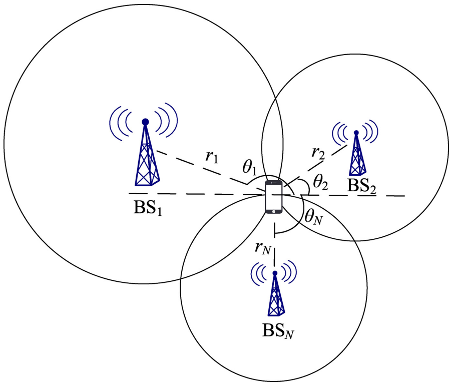


FIGURE 7. A geometrical diagram of hybrid measurements-based localization.

important topic of localization, especially in indoor environments. In fact, RSS-based positioning technologies have been widely used in WiFi and Bluetooth networks, which could achieve meter-level positioning accuracy.

D. HYBRID MEASUREMENTS

As discussed above, time-based methods require strict synchronization and angle-based ones need an antenna array, but both two kinds have higher accuracy and less cost than RSS methods. On the other hand, it is easier to obtain RSS information while RSS methods do not require specialized hardware, but the range information based on RSS is coarse and the signal strength measurements are sensitive to the channel conditions. In order to achieve better accuracy, various algorithms that utilize hybrid measurements have been proposed, and the solutions were demonstrated to have higher noise tolerance than using individual measurements. Taking the joint ToA&AoA-based approach for an example, the matrix formulation can be obtained by combining (6) and (10), i.e.,

$$\begin{bmatrix} r_1^2 - R_1^2 \\ y_1 - x_1 \tan\theta_1 \\ r_2^2 - R_2^2 \\ y_2 - x_2 \tan\theta_2 \\ \vdots \\ r_N^2 - R_N^2 \\ y_N - x_N \tan\theta_N \end{bmatrix} = \begin{bmatrix} -2x_1 & -2y_1 & 1 \\ \tan\theta_1 & 1 & 0 \\ -2x_2 & -2y_2 & 1 \\ \tan\theta_2 & 1 & 0 \\ \vdots & \vdots & \vdots \\ -2x_N & -2y_N & 1 \\ \tan\theta_N & 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ R \end{bmatrix}. \tag{13}$$

In [52], the authors proposed a closed-form estimator by constructing a new constraint between the hybrid time and angle measurements and the unknown source. Meanwhile, the authors of [53] illustrated a hybrid ToA and AoA solution using non-linear constrained optimization to realize positioning. It is worth mentioning that the approach based on hybrid measurements is quite commonly used in radar systems, where delay and angle information is gathered from the echo signals.

E. SOPHISTICATED APPROACHES

As described above, the fundamental nature of localization lies in the extraction of position-related measurements, i.e., ToA, TDoA, AoA, and RSS, comprised in the LoS paths from the anchors to the target. Thus, the cornerstone is the receiver's ability to accurately estimate the arrival time of the LoS signals. The most popular way to cope with the NLoS condition is to filter NLoS signals and localize with LoS ones. For example, the author of [54] adopted a residual test to determine the LoS dimension and identify the LoS signals, and further estimate the position through a maximum likelihood (ML) estimator. State-of-the-art approaches also explore the NLoS components in association with known or partially known objects and scatterers, which is especially of great use indoors due to the complicated multipath environment [55].

IV. OVERVIEW OF RIS-ASSISTED LOCALIZATION

As discussed in the previous section, due to the ability of artificially regulating the electromagnetic waves passing through it, RIS naturally has the potential in high-precision localization. In this section, we give an overview of current works on RIS-based localization, to illustrate how the geometric relationships of RIS channels and the electromagnetic controlling capabilities of RIS can be exploited to locate terminals and improve positioning accuracy. These papers are divided into four categories depending on their emphasis, i.e., i) tutorials and surveys, ii) theoretical bound derivations, iii) localization algorithms, and iv) RIS optimization approaches; the main features of ii)-iv) are also summarized in Tables 1, 3, and 5.

A. TUTORIALS AND SURVEYS

Since the first attempt of using RIS in positioning, there have been very limited survey and tutorial papers in this field, except for [41] and [56], [57], [58]. In [41], the authors described the main challenges and prominent research questions in RIS-based localization and mapping, along with potential avenues to handle these issues. Meanwhile, the authors of [56] discussed wave fingerprinting-based radio localization in rich scattering environments from an information flow perspective with a focus on the use of an RIS-equipped propagation environment. Some important issues about potential limitations were also discussed, and artificial neural networks were considered as a potential solution. In [57], the authors focused on the connection between localization and communications, and argued that RIS-enabled beyond 5G (B5G) systems will rely on a synergy between communications and localization. Most recently, [58] discussed using RIS to improve the radio location of IoT devices and summarized current works on RIS-IoT positioning. Albeit so, there is no comprehensive survey of the research activities on RIS-based localization.

Fig. 8 provides a schematic diagram of the potential of RIS in future wireless localization. Owing to the easy deployment, plenty of objects could be equipped with RIS, such as walls, the surface of buildings, UAVs, and even buses. According to existing articles, RISs could work in two ways: one is as a receiver while the other is as a reflector. When

TABLE 1. Overview of RISL on theoretical performance limits.

References	RIS Model Types	Signal Types	Dimensions	Transceiving Types	Special Characteristics
[9]	Receiver	\	3D	\	\
[10]	Reflector	OFDM	2D	MIMO	\
[11]	Reflector	OFDM	2D	SISO	Multiple RISs
[12]	Reflector	UWB	2D	SIMO	\
[13]	Reflector	\	2D	SISO	RSS-ranging
[59]	Receiver	\	3D	\	Discrete amplitude and phase
[60]	Receiver	\	3D	\	Continuous and discrete RISs
[61]	Reflector	\	3D	MIMO	NLoS
[62]	Reflector	OFDM	3D	SISO	\
[63]	Lens	\	3D	SISO	Near field
[64]	Reflector	OFDM	3D	MIMO	Near field; synchronous&asynchronous
[65]	Reflector	Multi-carrier	3D	SISO	Near field
[66]	Reflector	Wideband	3D	SISO	\
[67]	Reflector	mmWave	3D	SISO	Near field; phase-dependent amplitude
[68]	Reflector	mmWave	3D	SISO	Transceiving hardware impairments
[69]	Reflector	mmWave OFDM	2D	MISO	Transceiving hardware impairments
[70]	Reflector	UWB	2D	SIMO	Quasi-static and dynamic modes
[71]	Reflector	\	3D	MISO	Continuous RIS

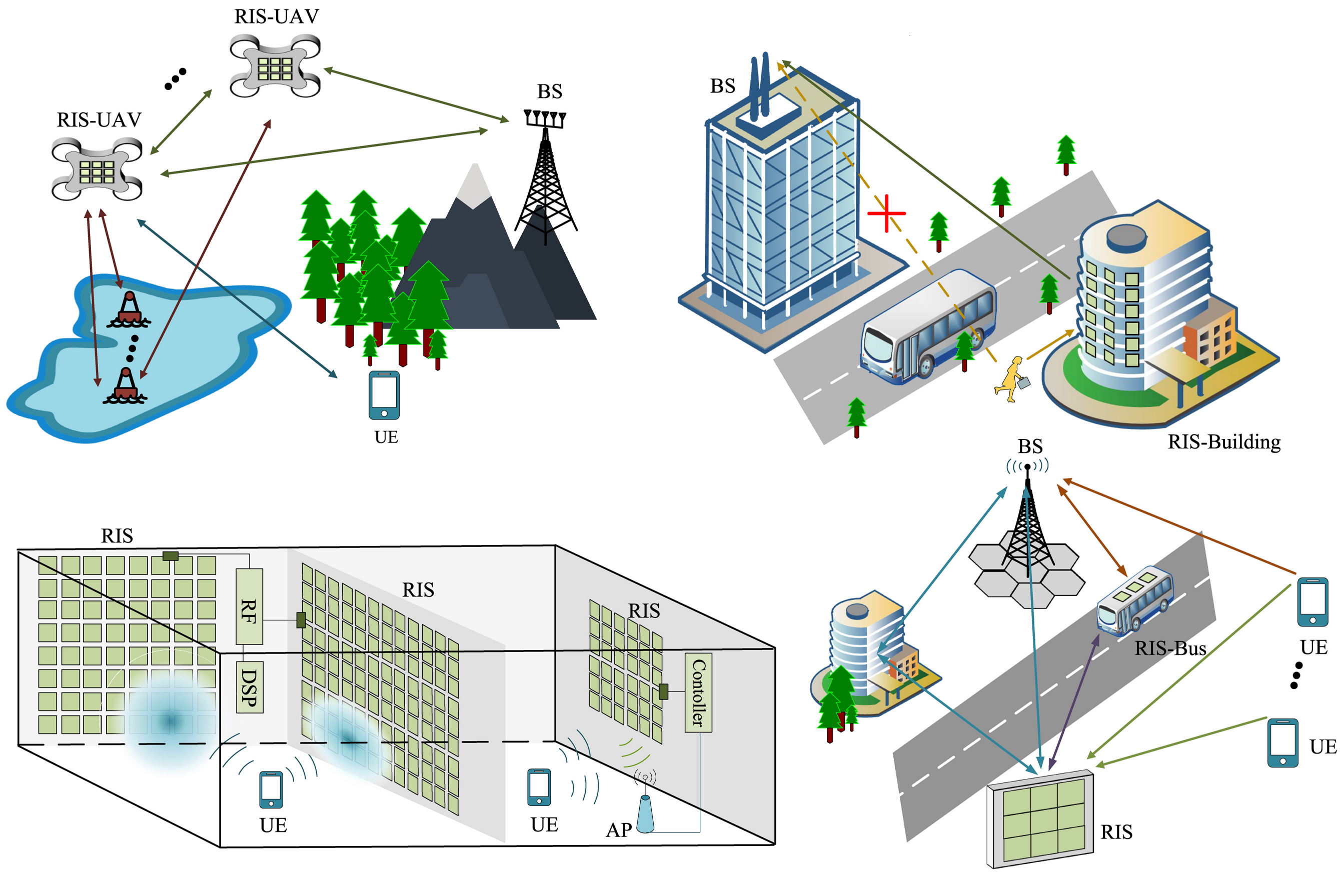


FIGURE 8. Potential of RIS in wireless localization.

operating as a receiver, the whole continuous RIS surface could be equivalent to a massive phased array that does not require conventional phase shifters, but demands for RF chains and digital signal processors (DSPs) to demodulate signals. When acting as a reflector, RISs could be considered as additional anchors to provide extra channel DoFs and spatial resolution. On condition that the LoS link between the BS and the UE is obstructed, the two-hop BS-RIS-UE links will contribute a lot in providing robust positioning services.

B. ON THEORETICAL PERFORMANCE LIMITS

The theoretical performance bounds can play an important role in enabling us to evaluate the localization potential and guide the development of localization and optimization algorithms. Therefore, one essential field is the derivation

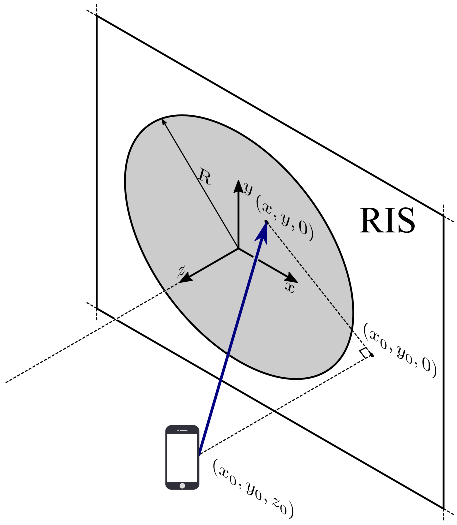


FIGURE 9. The radiating model of transmitting signal to the RIS [9].

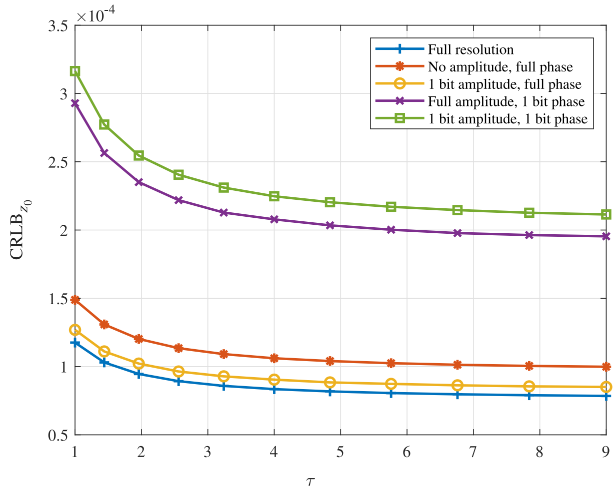


FIGURE 10. CRLB_{z_0} with respect to τ under different quantization resolutions and SNR = 10 dB, where a single antenna user is located at (x_0, y_0, z_0) with $z_0 > 0$ and a circular RIS extends throughout the xy-plane and centered at (0,0,0) [59].

of bounds of theoretical positioning performance in various scenarios, in terms of Fisher information matrix (FIM) or CRLB.

1) AS A RECEIVER

Tracing back the development of RIS-based localization, the potential of RIS-assisted localization was firstly discussed in [9], where the RIS acts as a receiver radiated by an interested terminal. More specifically, the authors treated RIS as a large contiguous surface for receiving signals, and gave the formulation of the radiated signal at any point on the surface. Fig. 9 gives an example of the radiating model of the transmitting signal to the RIS utilized in [9], where the transmitter is located at $\mathbf{p} = [x_0, y_0, z_0]^{\mathrm{T}}$. In this model, the received noiseless signal at $(x, y, 0)$ is denoted as

$$r(x, y, t) = \frac{\sqrt{z_0}}{2\sqrt{\pi d^3}} \exp\left(-\frac{j2\pi d}{\lambda}\right) s(t - d/c), \tag{14}$$

where

$$d = \|(x_0, y_0, z_0) - (x, y, 0)\|_2, \tag{15}$$

while λ denotes the wavelength.

Then, the received signal can be expressed by

$$y(x, y, t) = r(x, y, t) + n(x, y, t), \tag{16}$$

where $n(x, y, t) \sim \mathcal{CN}(0, N_0)$ is the additive white Gaussian noise with zero mean and variance N_0. Thus, the FIM of $\mathbf{p}$ can be given by the second partial derivatives of the logarithmic likelihood function $f_{y|\mathbf{p}}$, i.e.,

$$\left[\mathbf{F_p}(x, y, t)\right]_{ij} = -\mathbb{E}\frac{\partial^2 \ln f_{y|\mathbf{p}}}{\partial p_j} \partial p_i = \frac{2}{N_0} \Re \frac{\partial r}{\partial p_j} \frac{\partial r^*}{\partial p_i}, \tag{17}$$

which further yields the total FIM by taking integrals over the time and the whole area of the RIS, i.e.,

$$\mathbf{F_p} = \iiint_{x,y,t} \left[\mathbf{F_p}(x, y, t)\right]_{ij} \mathrm{d}x\mathrm{d}y\mathrm{d}t, \tag{18}$$

where $p_i, p_j \in \{x_0, y_0, z_0\}$. Therefore, the CRLB matrix can be obtained by

$$\mathrm{Cov}\big(\mathbf{p} - \hat{\mathbf{p}}\big) \succeq \mathbf{F}_{\mathbf{p}}^{-1}. \tag{19}$$

In [9], the authors gave a detailed derivation of the CRLB, demonstrating the potential of RIS in positioning acting as a receiver.

In view of practical hardware cost, the authors of [59], standing on the shoulders of [9], considered quantized amplitude and phase of receiving signals to derive the amendatory CRLBs under different quantization bits. Fig. 10 depicts CRLB_{z_0} with respect to $\tau (= \frac{D^2}{z_0^2})$ under different quantization resolutions with an RIS of radius D. Numerical results depicted that increasing the resolution of the phase is more effective than increasing the amplitude. In other words, the resolution in phase is remarkably more important than that in amplitude to approach the ideal case. Meanwhile, it is also shown that enlarging the RIS area or decreasing the vertical distance from the UE to the RIS leads to better accuracy. However, all these parameters (quantization resolutions, area, and vertical distance) are of marginal benefit.

Following the model in [9] and [59], the authors of [60] proposed a general model for RIS-aided localization and communication via both continuous and discrete RISs, which is valid for both near-field and far-field scenarios. Theoretical limits on the localization and communication performance in terms of SNR, channel capability, and FIM were all derived, and the optimal design of the phase response for RISs was also investigated.

In general, when acting as a receiver, RIS could be integrated into current transceiving structures as a new type of massive antenna array. Meanwhile, due to its unique 2D structure, RIS could be easily deployed on the surface of moving vehicles. Therefore, the receiver-mode RIS would be promising in IoV and UAV networks.

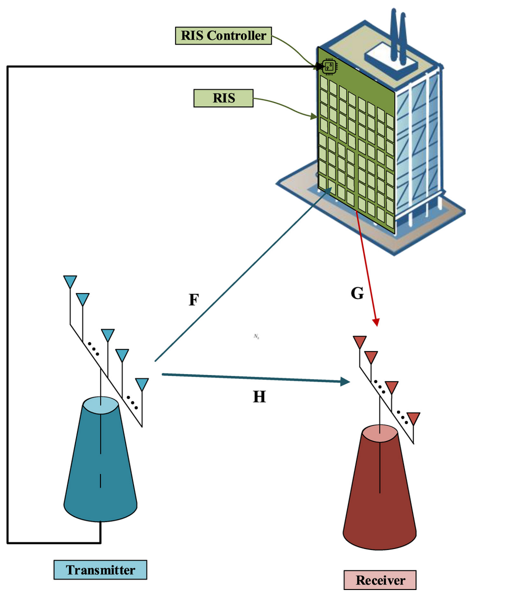
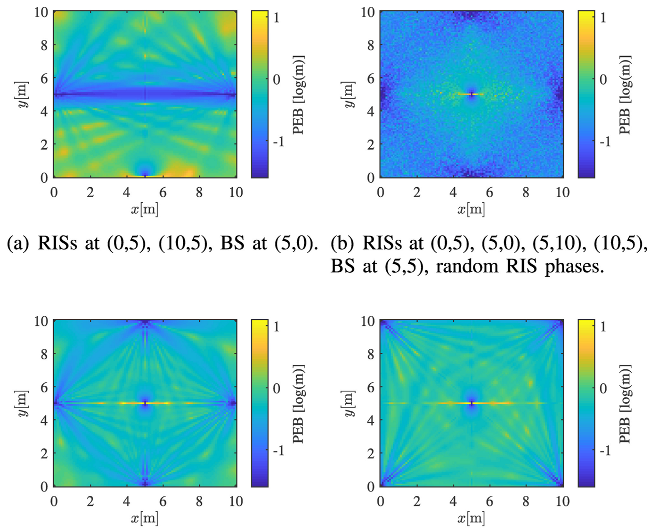


FIGURE 11. The system model of RIS-aided localization where RIS acts as a reflector.



(a) RISs at (0,5), (10,5), BS at (5,0). (b) RISs at (0,5), (5,0), (5,10), (10,5), BS at (5,5), random RIS phases.

(c) RISs at (0,5), (5,0), (5,10), (10,5), BS at (5,5). (d) RISs at (0,0), (10,0), (0,10), (10,10), BS at (5,5).

FIGURE 12. Logarithmic position error bound maps with $N_R = 16$, $\kappa_0 = -30$ dB, $\kappa_k = \kappa_k^r = 0.9$, where κ_0, κ_k, and κ_k^r denote the Rician factors of the UE-BS, UE-RIS$_k$ and RIS$_k$-UE links, and RISs are set to maximize the SNR at (5,5) in (a), (c), and (d) [70].

2) AS A REFLECTOR

However, owing to the quasi-passive characteristics of RIS, it is not that practical to equip large-scale circuits for signal receiving and processing on the RIS. Therefore, RIS performing in another mode, namely, as a reflector, has been laid more emphasis. The first attempt in this field was the work in [10], where the authors considered RIS-aided mmWave MIMO orthogonal frequency division multiplexing (OFDM) systems for localization. In this design, the RIS does not require the deployment of any active sensor and RF chain, which is modeled more simply as a uniform linear array (ULA). A more general model in the 3D scenario is shown in Fig. 11, where the transmitter and receiver are denoted as Tx and Rx, respectively. Considering the Rician channel model for each path, the Tx-Rx, Tx-RIS, and RIS-Rx channels can be respectively represented by

$$\mathbf{H} = \alpha_0\left[\sqrt{\frac{\kappa_0}{\kappa_0+1}}\mathbf{a}_{\mathrm{Rx}}(\varphi_0,\theta_0)\mathbf{a}_{\mathrm{Tx}}^{\mathrm{H}}(\varphi_0,\theta_0) + \sqrt{\frac{1}{\kappa_0+1}}\tilde{\mathbf{H}}\right], \tag{20}$$

$$\mathbf{F} = \alpha_1\left[\sqrt{\frac{\kappa_1}{\kappa_1+1}}\mathbf{a}_{\mathrm{RIS}}(\varphi_1,\theta_1)\mathbf{a}_{\mathrm{Tx}}^{\mathrm{H}}(\varphi_1,\theta_1) + \sqrt{\frac{1}{\kappa_1+1}}\tilde{\mathbf{F}}\right], \tag{21}$$

and

$$\mathbf{G} = \alpha_2\left[\sqrt{\frac{\kappa_2}{\kappa_2+1}}\mathbf{a}_{\mathrm{Rx}}(\varphi_2,\theta_2)\mathbf{a}_{\mathrm{RIS}}^{\mathrm{H}}(\varphi_2,\theta_2) + \sqrt{\frac{1}{\kappa_2+1}}\tilde{\mathbf{G}}\right], \tag{22}$$

where α_i, κ_i, φ_i, and $\theta_i (i = 0, 1, 2)$ are the pathloss, Rician factor, azimuth, and elevation, respectively, $\mathbf{a}_{\mathrm{Tx}}$, $\mathbf{a}_{\mathrm{Rx}}$, and $\mathbf{a}_{\mathrm{RIS}}$ are the steering vectors, and each entry in $\tilde{\mathbf{H}}$, $\tilde{\mathbf{F}}$ and $\tilde{\mathbf{G}}$ are independently and identically distributed to $\mathcal{CN}(0, 1)$.

Therefore, the received noiseless signal can be expressed as

$$\mathbf{r}(t) = \mathbf{H}\mathbf{s}(t-\tau_0) + \mathbf{G}\Phi\mathbf{F}\mathbf{s}(t-\tau_1-\tau_2), \tag{23}$$

which gives the received signal as

$$\mathbf{y}(t) = \mathbf{r}(t) + \mathbf{n}(t), \tag{24}$$

where τ_i denotes the corresponding time delay and $\mathbf{n}(t) \sim \mathcal{CN}(\mathbf{0}, N_0\mathbf{I})$ is the Gaussian noise. Then, the FIM of $\mathbf{p}$ can be obtained by

$$[\mathbf{F}_{\mathbf{p}}]_{ij} = \frac{2}{N_0}\int_t \Re\frac{\partial \mathbf{r}^{\mathrm{H}}}{\partial p_j}\frac{\partial \mathbf{r}}{\partial p_i}\mathrm{d}t. \tag{25}$$

In fact, $\mathbf{F}_{\mathbf{p}}$ is often hard to obtain directly, which is usually calculated by the chain rule instead, i.e.,

$$\mathbf{F}_{\mathbf{p}} = \mathbf{J}\mathbf{F}_{\boldsymbol{\xi}}\mathbf{J}^{\mathrm{T}}, \tag{26}$$

where

$$\mathbf{J} = \frac{\partial \boldsymbol{\xi}^{\mathrm{T}}}{\partial \mathbf{p}} \tag{27}$$

is the Jacobian mapping matrix from $\boldsymbol{\xi}$ to $\mathbf{p}$, with $\boldsymbol{\xi}$ denoting available measurements, such as delays and angles. It can be inferred from (25)–(27) that the Fisher information will be impacted by the asynchronicity effect of the direct and RIS-reflected links. Fig. 12 provides an example of the positioning accuracy when RIS acts as a reflector. It is shown that RIS is helpful for improving positioning accuracy when the UE-BS link is obstructed. Meanwhile, increasing the number of RISs also benefits positioning. Moreover, it is also seen that both the configuration and position of RISs also have an impact on localization precision.

In [10], the authors provided a detailed derivation of the CRLB, and better positioning accuracy was viewed through both theoretical analysis and numerical results, compared with the system without the assistance of RIS.

In [11], the authors took into account multiple RISs along a flat wall, each modeled as a ULA; OFDM signals were also considered, but both the BS and UE were assumed to be equipped with a single antenna. Compared with a passive reflector/scatterer, RIS is demonstrated to achieve better performance through both theoretical and simulation results.

Instead of OFDM, the authors of [12] combined RIS-assisted indoor positioning with the UWB technique, and investigated the CRLB for ToA and/or AoA-based positioning. Compared with virtual anchor approaches in single-AP positioning, the superiority of RIS lies in that it does not require the assumption of perfect flat walls.

For the RSS-based mmWave ranging scheme in a dense blockage environment, the authors of [13] derived the blockage probability and the CRLB for ranging errors. The RIS-assisted links are shown to considerably improve the localization performance.

In [61], taking into consideration a more practical 3D MIMO scenario, the authors focused on the positioning when the BS-UE link is obstructed. The RIS was modeled as a uniform planar array, and the Fisher information matrix and the CRLB for the estimate of the mobile station position were derived.

On the contrary, the BS-UE link was considered in [62], where the model is valid for the 3D SISO OFDM localization and synchronization scheme. Theoretical and numerical results exhibited that all the ToA, AoD, and clock bias of the user can be estimated with the aid of RIS even for single-input single-output (SISO) systems.

Standing on another similar point where RIS acts as a lens, the authors of [63] performed a Fisher information analysis and investigated the CRLB of the 3D SISO scheme, and the impact of different lens configurations was evaluated, where the near field was taken into account.

In [64], the authors investigated the CRLB of the universal 3D MIMO OFDM scheme, which is suitable for near-field propagation conditions, and is valid also for both synchronous and asynchronous scenarios.

For a conventional multi-carrier system, the authors of [65] analyzed the theoretical positioning performance of near-field SISO localization in both LoS and NLoS conditions.

In [66], the authors presented the general signal model of wideband localization with RIS, and then performed Fisher information analysis to determine the theoretical limits. Two special scenarios including complete coupling scenarios and complete decoupling scenarios were discussed and evaluated, where the former depicted better performance.

Considering the RIS hardware impairments, [67] investigated the near-field localization system by introducing a practical phase-dependent RIS amplitude variations model. The misspecified CRLB was derived to assess the loss of localization performance under model mismatch, and the lower bound of the true parameter as well as the mismatched maximum likelihood estimator was also given.

Similarly, the authors of [68] also considered the effect of hardware impairments, but for non-ideal transceivers rather than the RIS. A detailed derivation of the mean squared error of the user's position through an ML estimator was given, which was further verified by the derived CRLB.

Coincidentally, [69] also considered the effect of hardware impairments on the transceivers and investigated the theoretical bounds of the joint localization and synchronization processes in an RIS-assisted mmWave multiple-input single-output (MISO) OFDM system.

To illustrate the influence of RIS coefficients, the authors of [70] focused on distributed RISs-assisted indoor positioning under the developed quasi-static and dynamic modes. Specifically, in the quasi-static mode, for reducing the implementation cost, the reflection coefficients of each RIS are preset and remain constant. In the dynamic mode, the reflection coefficients can be updated with a two-step positioning approach toward more accurate positioning performance. Simulation results demonstrated that RIS has the potential to realize accurate positioning even with a single AP, and the accuracy can be further enhanced when there is some prior information on the user's position.

Most recently, [71] envisioned the integration of continuous RIS into the mmWave localization system in the near-field propagation regime, and the CRLB was derived to investigate the fundamental limits of localization accuracy of the proposed system.

In general, when operating in the reflector mode, RIS is well compatible with existing wireless networks as an additional anchor to provide extra channel DoFs. For example, when the LoS link is obstructed, which may occur indoors or in crowded buildings, the two-hop RIS-reflected path will help to construct a VLoS link, thus maintaining robust localization services. On the other hand, the use of RIS to form multiple RSS fingerprinting maps will also play an important role in single-AP indoor positioning schemes.

According to the above results, we summarize the characteristics of RISL in different RIS modes in Table 2 to provide readers with more concise guidance. No matter which mode RIS works in, the received signal contains the information of distance, angle, delay, and signal strength, establishing the connection between the positions of anchors (transmitter or RIS) and the interested target. However, in different scenarios, the signal and channel models have some difference, and the direct expression for the CRLB may not be available; by contrast, the angle, delay, and signal strength are much easier to acquire. Therefore, practical localization algorithms using different measurements in various RIS-assisted localization systems are an issue worth studying. Meanwhile, when the RIS acts as a reflector, the positioning accuracy bound, i.e., CRLB, not only is a function with respect to the target position $\mathbf{p}$, but also is influenced by RIS coefficient Φ and RIS position $\mathbf{p}_{RIS}$. Hence, the optimization of Φ and $\mathbf{p}_{RIS}$ for the

TABLE 2. Characteristics of RISL in different RIS modes.

Modes	Principles	Superiorities	Limitations	Applications
Receiver	beyond massive array	high precision	high hardware cost	indoor positioning, moving nodes
Reflector	controllable VLoS path reconfigurable coefficients	flexible deployment	high pathloss	eliminating blind spots high-precision RSS fingerprint maps
Lens	coherent addition	simple hardware structure	installed on transceivers	rada-communication BSs

TABLE 3. Overview of RISL on localization algorithms.

References	Measurements	Signal Types	Dimensions	Transceiving Types	Involved Approaches
[62]	AoD&ToA	OFDM	3D	SISO	IFFT, 2D-IFFT, gradient descent
[63]	AoA	\	3D	SISO	Jacobi-Anger expansion and linearization
[72]	AoA&ToA	\	2D	SIMO	correlation detection
[73]	AoD&ToA	OFDM	2D	MISO	relaxed ML
[74]	ToA	\	3D	SISO	coplanar ML
[75]	AoD	\	2D	MIMO	ON/OFF, Taylor series
[76]	TDoA	\	3D	SISO	IFFT, gradient descent
[77]	AoA&ToA	OFDM	3D	SIMO	neural networks
[78], [79]	TDoA	OFDM	3D	SISO	correlation, FFT, ML, LS
[80]	AoA	\	3D	MISO	FFT
[81]	AoA	\	2D	SISO	atomic norm, SDP, gradient descent
[82]	RSS	\	2D	SISO	WLS, Nesterov accelerated gradient
[83]	AoA&ToA	\	2D	MIMO	compressive sensing
[84]	AoA	\	3D	MIMO	MUSIC
[85]	AoA&ToA	\	3D	MIMO	relative entropy
[86]	AoA	\	3D	SIMO	FFT, centralized ML
[87], [88]	AoA	\	3D	MIMO	Bayesian estimation
[89]	RSS	\	2D	SISO	formulative solution
[90]	ToA	\	2D	SISO	reinforcement learning, iterative LS
[91]	TDoA	\	2D	SISO	extended Kalman filter
[92]	AoA&RSS	mmWave	3D	MIMO	extended Kalman filter
[93]	TDoA&AoA	OFDM	2D	SISO	generalized trust region
[94]	ToA	OFDM	3D	SISO	codebook, IFFT, ML
[95]	ToA&AoA	OFDM	3D	MIMO	LS, direct, subspace, tensor
[96], [97]	AoA	mmWave	3D	SISO	ESPRIT
[98]	AoA&RSS	\	2D	SIMO	edges, accumulation, sliding window
[99]	AoA&ToA&Doppler	OFDM	3D	SISO	quasi-Newton
[100]	ToA&AoA&RSS	\	2D	SISO/SIMO	ML, focal scanning

sack of improving positioning accuracy is also an interesting problem.

C. ON LOCALIZATION ALGORITHMS

Thanks to the above theoretical studies that laid a solid foundation for the application of RIS in localization, a number of practical positioning algorithms emerged accordingly. One straightforward way is using the ML estimator. Specifically, for RIS in receiver and reflector modes, we respectively have

$$\hat{\mathbf{p}} = \arg\max_{\mathbf{p}} f_{y|\mathbf{p}} = \arg\min_{\mathbf{p}} \iiint_{x,y,t} (y - r|\mathbf{p})^2 \mathrm{d}x\mathrm{d}y\mathrm{d}t, \quad (28)$$

and

$$\hat{\mathbf{p}} = \arg\max_{\mathbf{p}} f_{\mathbf{y}|\mathbf{p}} = \arg\min_{\mathbf{p}} \int_t (\mathbf{y} - \mathbf{r}|\mathbf{p})^2 \mathrm{d}t. \quad (29)$$

In fact, ML estimators exist only in theory and UE's position is estimated indirectly in practice by gathering the positioning-related measurements, i.e., ToA/TDoA, AoA/AoD, and RSS.

The first attempt at practical positioning algorithms in RIS-based localization was made in [72], where the authors considered a dual-RIS and single-input multiple-output (SIMO) uplink positioning scheme, and adopted correlation detection to estimate time delays.

On the other hand, besides the theoretical derivations, the authors of [62] and [63] also developed localization approaches suitable for their conceived systems. Specifically, a low-complexity estimation algorithm that decouples the relationship between AoDs and ToAs by inverse fast Fourier transform (IFFT) and 2D IFFT was proposed in [62], while [63] developed a low-complexity three-stage localization algorithm through Jacobi-Anger expansion and linearization.

In line with the purpose of decoupling the relationship between AoDs and ToAs in [62], the authors of [73] developed a relaxed maximum likelihood estimation approach for the downlink mmWave MISO OFDM system, obtaining a reduced-complexity yet near-optimal estimator.

In [74], an efficient coplanar maximum likelihood-based (CML) localization approach for RIS-assisted 3D mmWave SISO system was proposed, for achieving a low-complexity channel estimation via the geometric information contained in the channels.

For the scenario of multiple RISs, the authors of [75] investigated the interplay between beam training and positioning. In more details, AoD and AoA estimates of the reliant links yield the terminal position, which, associated with anchor positions and directions, can assist in beam training thus improving the precision of AoD and AoA estimation in turn. For the above considerations, [75] carried out beam training designs through an ON/OFF mode, namely, activating RIS one by one to estimate the corresponding AoD and AoA, and then an iterative positioning algorithm based on Taylor Series was developed with the aid of estimated AoDs and AoAs.

As an extension of [62], the authors further investigated the 3D passive localization problem for multiple RIS-enabled users under multi-static and asynchronous setup in [76], each user equipped with an RIS. In this design, a low-complexity positioning algorithm that utilizes orthogonal sequences for RIS configurations was proposed to resolve multipath interference, thus further enabling localization of terminals with the aid of TDoA measurements.

Following the model in [9] where RIS acts as a receiver, the authors of [77] proposed a method to perform positioning based on estimated channel state information (CSI) in an RIS. Specifically, the RIS is divided into a number of panels, each of which has signal processing capabilities. Once CSI is available locally at a panel, a machine learning algorithm based on neural networks produces a probabilistic description of the user position. All probability functions from different panels are then used to obtain a point estimate of the user location.

The authors of [78] and [79] investigated the scheme of LoS/NLoS near-field localization with a large RIS, where a discrete Fourier transformation (DFT)-based signal extraction approach was proposed, together with a practical two-step positioning algorithm.

In [80], the authors developed a 3D AoA-positioning strategy based on discrete Fourier transformation, where multiple RISs are deployed in the air to assist in locating the user.

For the UAV swarm system, the authors of [81] investigated using multiple lifted RISs for estimating the target DoA. In this paper, a new atomic norm-based DoA estimation was proposed, further solved by a customized semi-definite programming (SDP) method, and a gradient descent method was also applied to refine the estimated DoA and the position perturbation.

In [82], the authors applied RIS to construct VLoS paths between the anchor target for near-field localization, where an RSS-based localization algorithm was developed, and a far-field or near-field discrimination scheme was derived to further improve the localization accuracy.

The authors of [83] proposed a framework to locate a UE in a multipath near-field RIS-aided environment, where a compressive sensing technique was introduced for positioning, and the optimal RIS phase design was investigated to enhance positioning by maximizing the SNR.

In [84], a self-sensing RIS architecture was presented, where the RIS was composed of a controller that can transmit probing signals, and dedicated sensors for receiving echo signals. A customized MUSIC algorithm was developed for angle estimation, and the optimal solution of the RIS reflection coefficients was investigated to maximize the average power of echo signals at RIS sensors.

The authors of [85] considered using RIS to improve the multi-target detection accuracy of radar systems, where the detection problem was formulated based on the criterion of relative entropy.

The authors of [86] presented a user localization method with multiple RISs, each incorporating a single receive RF chain for measurement collection. Specifically, the proposed method includes a DFT-based initial step for direction estimation at each RIS, followed by a centralized ML approach for position estimation.

In [87], the authors studied the user localization and tracking problem in the multiple RISs-aided mmWave MIMO system, where a message-passing algorithm, termed the Bayesian user localization and tracking (BULT) algorithm, was developed to estimate the user position and the AoAs at the user in an online fashion.

As a promotion of [87], the authors in [88] further provided a more detailed description of the probability transition model for user mobility and more in-depth elaboration of the developed BULT algorithm.

The authors of [89] introduced a practical positioning approach with the assistance of two or three RISs by estimating the distances via specifically designed RIS coefficients. Simulation results demonstrated the effectiveness of the developed approach under both the LoS and Rayleigh fading scenarios.

In [90], the positioning of the target was performed by one BS and three RISs selected from a set of available RISs. Different reinforcement learning algorithms based on the gradient ascent and the log-linear learning models were introduced to enable the target to autonomously and dynamically select the optimal RIS subset for the best accuracy, and an iterative LS algorithm was then realized to determine the position of the target.

Considering the UE tracking problem, the authors of [91] investigated the scenario with one BS and one RIS to localize and track a mobile station. An extended Kalman filter was proposed, which showed a comparable performance to the conventional two-BS case.

Reference [92] also studied the UE tracking problem, but combined communication and localization in presence of multiple RISs. Specifically, the extended Kalman filter was adopted to track the user trajectory by processing the positioning information gathered by the signals backscattered from the RISs, whereas the RISs were in turn optimized accounting for the outcomes of the estimator. Meanwhile, the impact of positioning onto communication performance in terms of achievable rate was also analyzed.

The use of RIS to improve the performance of sensor network-based TDoA systems was presented in [93], where each RIS made a directional beam shaping to scan the area of interest and ensured coverage of the surveillance area. Additionally, in order to improve the reception of the reflected signal from each RIS, a cooperative sensor

TABLE 4. Characteristics of RISL based on different measurements.

Measurements	Accuracy	Algorithms	Hardware Cost	Software Cost	Application Range
ToA	high	correlation, IFFT	wideband signal processing precise synchronization	low	narrow(OFDM or UWB positioning)
TDoA	high	IFFT, Taylor series	anchors' synchronization	middle	wide
AoA/AoD	middle	FFT, spatial spectrum compressive sensing	massive antenna/RIS arrays	high	wide
RSS	low	fingerprint matching	low	high	narrow(indoor positioning)
Hybrid	high	hybrid algorithms	high	high	wide

equipped with a directional antenna next to the reference sensor was considered, thus providing extra angle information.

Reference [94] presented a use-case for RIS-enabled localization, where an RIS is used to reflect the signal transmitted from the UE back to the UE itself. A specific RIS profile was designed to remove the undesired multipath from the surrounding environment, and the user position was estimated by first obtaining a coarse estimate and then refining it to maximize the likelihood function. The proposed estimator was shown to attain the derived CRLB at high SNRs.

Reference [95] considered the channel estimation and environment mapping problems in RIS-MIMO-OFDM systems. Given specific conditions on the allocated temporal-frequency training resources, four channel estimation approaches, i.e., LS, direct, wideband direct, and wideband subspace methods, were developed by leveraging tensor techniques and nonlinear system solvers. By fully exploiting the characteristics of conformal RISs, two decoupling modes to precisely recover the multipath parameters without ambiguities were proposed, which further yielded the scatterer map and user position.

The authors of [96] and [97] proposed an RIS-enabled multi-user integrated sensing and communication (ISAC) framework, where the RIS was composed of one passive sub-RIS and two semi-passive sub-RISs that were capable of sensing. During the ISAC period, the passive sub-RIS assisted the uplink transmission, and meanwhile, the semi-passive sub-RIS conducted multi-user location sensing by AoA estimation and paring.

In [98], a low-overhead joint localization and channel reconstruction scheme was proposed for extra-large RIS-assisted multi-user SIMO systems. Three approaches, i.e., a rising and falling edges-based method, an accumulation function-based one, and a sliding window-based one were developed to obtain an accurate channel estimate, which further yielded the users' locations.

Reference [99] devised a low-complexity estimator that attains the CRLB at high SNRs by taking into account the mobility of the user and spatial-wideband effects. The channel gain, delay, and Doppler of the LoS path were estimated firstly whose effect was further subtracted from the received signal. Then, the parameters of the NLoS path, involving the delay, Doppler, and AoD from the RIS to UE were estimated.

Reference [100] considered two types of receivers in the radiating near field of the RIS: 1) for a ULA-equipped receiver, RIS coefficients were designed to convert planar waves into cylindrical waves; 2) for a single-antenna receiver, RIS coefficients were designed to convert planar waves into spherical waves. Based on the derived RIS reflection coefficients, the ML and focal scanning methods were proposed to sense the location of the receiver.

Table 4 summarizes the characteristics of RISL based on different measurements. From the authors' point of view, TDoA or/and AoA-based schemes might be more promising for high-precision positioning, while RSS-based solutions may be more useful for indoor positioning, after weighing the advantages and weaknesses of different measurements and the characteristics of RIS.

D. ON RIS OPTIMIZATION ALGORITHMS

Besides the guidance of practical positioning algorithms, theoretical works also help to direct the optimization problem for RIS-assisted positioning. From the derivation of CRLB we note that the positioning accuracy depends on the configuration coefficients and the deployment of RIS. Therefore, there must be an optimal solution that maximizes the positioning accuracy within an area of interest. Specifically, such optimization problem can be modeled as

$$\begin{aligned} \min \quad & \epsilon(\Phi, \mathbf{p}_{RIS}) \triangleq \int_{\mathbf{p}\in\mathcal{P}} \mathrm{tr}\mathbf{F}_{\mathbf{p}} d\mathbf{p} \\ \text{s.t.} \quad & |\phi_{ii}| \le 1, \forall i \in \{1, 2, \ldots, N_R\}, \\ & |\phi_{ij}| = 0, \forall i \ne j \in \{1, 2, \ldots, N_R\}, \end{aligned} \tag{30}$$

where $\mathcal{P}$ denotes the localization area of interest. For example, the optimal RIS deployment to minimize the blockage probability or CRLB was also investigated in [13], a gradient decent method-based alternative optimization algorithm was provided in [61] to minimize the CRLB, and a suboptimal phase design for RIS was obtained in a closed-form in [64] to enhance localization performance by maximizing the SNR. In [71], the RIS optimization problem to minimize the worst-case CRLB with respect to an uncertainty set of UE positions was formulated, which was further solved by an iterative entropy regularization-based method.

Meanwhile, a two-stage positioning method was also adopted in [72] to improve positioning accuracy. More specifically, the angle information is estimated in the first stage, which is further utilized to select the more suitable RIS to optimize in the second stage, thus better accuracy could be achieved. In [85], an AO-SDR-based approach was

TABLE 5. Overview of RISL on optimization algorithms.

References	Signal Types	Dimensions	Transceiving Types	Optimization Methods
[13]	\	2D	SISO	Formulative solution
[61]	\	3D	MIMO	Gradient decent, AO
[64]	OFDM	3D	MIMO	AO, Cauchy-Schwartz inequality
[71]	\	3D	MISO	Iterative entropy regularization
[72]	\	2D	SIMO	Formulative solution
[85]	\	3D	MIMO	AO, SDR
[88]	\	3D	MIMO	BCD
[96], [97]	mmWave	3D	SISO	Estimation of distribution
[101]	OFDM	2D	MIMO	Hierarchical codebooks
[102]–[104]	\	3D	SISO	Iterative searching, global descent
[105]	\	2D	SISO	Supervised learning, heuristic state selection
[106]	\	3D	SISO	Bisection search, SCA
[107]	\	2D	MIMO	Atomic norm minimization, root finding
[108]	OFDM	3D	MIMO	Tensor signal processing, atomic norm denoising,
[109]	\	3D	MIMO	Hierarchical codebook
[110]	\	3D	SISO	Particle filtering
[111]	\	3D	SIMO	Genetic algorithm, particle filtering
[112]	\	3D	SIMO	Monte Carlo sampling, SDR
[113]	\	2D	MISO	Time-reversal resonating, AO
[114]	\	2D	SISO	Iterative entropy regularization
[115]	mmWave OFDM	2D	MIMO	Difference of convex
[116]	mmWave	3D	SISO	BCD
[117]	\	3D	SISO	Gradient projection
[118]	OFDM	2D	SISO	Lagrange duality, penalty-based optimization
[119]	mmWave	2D	MIMO	Manifold optimization, formulative solution
[120]	\	3D	SIMO	SDR, ZF, BCD
[121]	OFDM	2D	MISO	Codebook, ML
[122]	\	3D	SISO	Iterative searching
[123]	OFDM	3D	SISO	BCD, deep reinforcement learning

further presented to optimize the waveform and RIS phase shifts to improve the detection performance. In [88], the Bayesian CRLB was derived to characterize the fundamental performance limit of the considered tracking problem. To improve the tracking performance, the block coordinate descent (BCD) algorithm was adopted to optimize the BS beamforming vector and the RIS coefficients so as to minimize the derived Bayesian CRLB. Moreover, the estimated location information was also exploited for joint active and passive beamforming to maximize received signal power at the BS in [96] and to maximize the sum rate with discrete RIS phase shifts in [97], respectively.

Toward both accurate positioning and high data-rate communication, the authors of [10] also developed an adaptive beamforming and RIS configuration design based on hierarchical codebooks and feedback from the mobile station in [101].

In [102] and [103], the authors proposed a practical RSS fingerprinting-based positioning protocol for the multi-user outdoor localization scheme. Specifically, RIS was utilized to create different RSS values at the same location, thus acquiring multiple RSS maps. In this design, an iterative searching algorithm was developed to minimize the expectation of localization errors.

As an extension of [102] and [103], the authors further formulated the RSS fingerprinting-based and RIS-aided multi-user localization in more details in [104], where the weighted probabilities of false localization were minimized. Meanwhile, the convergence, complexity, and optimality of the developed RIS configuration optimization algorithm were also analyzed.

Also considering RSS fingerprinting-based localization, the authors of [105] considered a supervised learning-based feature selection, where two heuristic state selection algorithms were developed to select RIS configurations that generate desired radio maps for use.

Standing on another point of robot navigation, the authors of [106] minimized the traveling time/distance of the mobile robotic user from a given starting point to a predefined final location, while satisfying constraints on the communication quality. Specifically, radio map-based approaches were proposed for both single-user and multiple-user scenarios with the assistance of graph theory, where the robot path and RIS configurations were jointly optimized by invoking the bisection search and the successive convex approximation (SCA) method.

Regarding the influence of position information on communication performance, the authors of [107] proposed a position information-based beam training method, where an atomic norm minimization-based channel estimation algorithm was resorted to obtaining a refinement of the channel parameters.

For the joint channel estimation and user localization problem, the authors of [108] proposed a tensor-based approach for the RIS-assisted MIMO OFDM system, presenting four designs of RIS training coefficients, i.e., random, structured, grouping, and sparse patterns. Specifically, the cascaded channel parameters were extracted by leveraging array signal processing and atomic norm denoising techniques, multipath parameters were recovered by a nonlinear equation system with two efficient decoupling modes, while the environment mapping and user localization were achieved based on the estimated channel parameters.

On the other hand, the authors of [109] utilized the RIS to enhance the radar sensing and communication capabilities for the mmWave dual-function radar communication system, where the RIS was adaptively partitioned by reserving separate RIS elements to simultaneously localize the target and to serve the user. A multi-stage hierarchical codebook to localize the target while ensuring a strong communication link to the user was designed, and a method to choose the number of times to transmit the same beam in each stage to achieve a desired target localization probability of error was present.

In [110], an RIS-assisted simultaneous indoor localization and mapping protocol to coordinate RIS and the mobile agent was developed, and an optimization problem aiming at minimizing the agent positioning error was formulated, where a particle filter-based localization and mapping algorithm was designed to solve the optimization problem.

As a promotion of [110], [111] further investigated the multi-RIS case, where the channel model was modified while a genetic algorithm and a particle filter one were developed to optimize the RIS phase shifts, the localization and mapping estimation function, respectively.

In [112], considering the prior statistical information on the possible position of the UE, the authors devised a practical localization system, where ToA and AoA-based measurements were utilized. Moreover, a two-stage solution was designed that aims at obtaining the optimal RIS configuration that is robust against the uncertainty in the UE position.

The authors of [113] considered RIS-aided privacy-aware localization enhancement. Specifically, the RIS is required to optimize the mutual information of the channel and the received signal for a legitimate user locating itself, thus obtaining a fine-grained localization accuracy, while maintaining coarse positioning performance for adversarial devices overhearing the transmitted signals.

Reference [114] explored the target regional localization problem in the near field. By defining the average localization accuracy (ALA) of the area of interest, a discretization method to design the RIS phase was presented to minimize the ALA; meanwhile, a robust phase design based on iterative entropy regularization was further developed.

Similarly, the authors of [115] considered RIS-enabled area positioning which aims at providing good localization services for potential users within a region. A joint array gain and path loss search algorithm was proposed to find the worst-case location with fixed beamforming and RIS coefficient, and a difference of convex was adopted to optimize beamforming and RIS coefficient in turn when fixing the location.

In [116], the authors studied the cooperative localization problem in an RIS-aided mmWave system, where the RIS is deployed to assist the localization of two users who further cooperate to improve their localization performance. An efficient BCD-based reflect beamforming design algorithm was proposed to minimize the CRLB.

Reference [117] investigated the optimal RIS phase design to minimize the position error bound (PEB) of NLoS near-field localization. the closed-form expressions of the corresponding FIM and CRLB were derived, and the optimal solution for RIS phases was then obtained assuming prior knowledge of the user equipment location was available.

Reference [118] considered the RIS-aided simultaneous localization and communication system, where the sum squared PEB was derived as the localization accuracy metric. The joint problem of RIS discrete phase shifts design and subcarrier assignment was formulated to minimize the sum squared PEB while guaranteeing each user's achievable data rate requirement, which was solved by utilizing the Lagrange duality as well as penalty-based optimization methods.

Reference [119] studied the potential of RIS for cooperative localization performance in mmWave MIMO systems, where an optimal RIS optimization algorithm based on manifold optimization was proposed to minimize the CRLB. Moreover, under some mild conditions, the CRLB minimization was cast as the joint channel gain maximization problem, which enables a low-complexity closed-form passive beamforming design at RIS.

Reference [120] investigated the RIS-assisted multiuser wireless positioning scheme with the goal of minimizing the total transmission power, where the BS combining vectors and the RIS phase shifts were jointly optimized. For the orthogonal signal case, the optimization problem was recast into a convex problem via the semidefinite relaxation, while for the nonorthogonal signal case, the zero-forcing combining vectors were adopted to eliminate the interference among users and the block coordinate descent algorithm was used to decouple the combining vectors and RIS phases.

In [121], a low-complexity method for joint localization and synchronization based on an optimized design of the BS active precoding and RIS passive phase profiles was proposed for the challenging case of a single-antenna receiver. By exploiting the low-dimensional structure of the solution, a codebook-based robust design strategy with optimized beam power allocation was then proposed, which provides low complexity while taking into account the uncertainty of the user position. Finally, a reduced-complexity ML-based estimation procedure was devised to jointly recover the user position and the synchronization offset.

Reference [122] studied the RIS-assisted multi-user localization system where the users derived position information through signals not only from the reflected links via the RIS but also from the cooperative links among users. The joint design of power allocation and RIS phase shifts was investigated with the goal of minimizing the CRLB, assuming that the system has limited power resources, which was solved by an iterative searching algorithm.

Reference [123] proposed the UAV-mounted RIS-aided communication and localization integration system for ground vehicles. A unified joint UAV trajectory planning and RIS phase-shifts configuration problem was formulated to strike a balance between localization and communication, which was solved by a BCD-based phase shifts optimizer and a deep reinforcement learning (DRL) based real-time trajectory generator.

E. A BRIEF SUMMARY

As presented above, RIS is proven to have the potential to provide high-precision and wide-coverage localization services in future wireless networks. In terms of the role that RIS plays, RIS could not only be integrated into the transceiving structure as a new type of massive antenna array, but also provide additional channel DoFs as a reflector, or converge multipath signals as a lens. However, the second one receives more attention due to its quasi-passive features. Meanwhile, characterised by its 2D structure, RIS could be easily deployed on the surface of both stationary buildings and moving vehicles. Therefore, RIS is well-compatible with existing wireless communication and localization systems. In particular, when the LoS link is obstructed, the two-hop RIS-reflected path will help to construct a VLoS link, which is especially beneficial in heavily crowded building groups and in single-AP positioning schemes such as indoors. Moreover, it is also noted that both time and angle-based techniques are welcome in the design of practical positioning algorithms, while using RIS to construct different RSS maps is easier to implement. Furthermore, current works on RISL also demonstrate that the coefficient and position of RIS can be optimized to further improve the positioning accuracy. However, the non-convex optimization problem is hard to solve, which is often handled by AO, SDR, SCA, etc.

V. CHALLENGES AND ROAD AHEAD

A. CHANNEL ESTIMATION

In principle, the channel response is associated with the geometric relationships of the BS, UE, and environment that includes RIS, which is more evident at high frequencies. On the other hand, the extraction for position-related parameters, i.e., ToA, TDoA, AoA, AoD, and RSS of each path, is also required for localization, which reflects a measure of geometric relationships. Therefore, the position-related information can be converted to partial or statistical CSI, which, in turn, assists the optimization of RIS to enhance communication or positioning. Meanwhile, the full potential of RIS is achieved when CSI is perfectly known, thus putting forward high demand for accurate CSI for the purpose of RIS optimization. However, due to the fact that RIS may be limited in signal reception and processing when operating in reflection mode, or enslaved to the number of RF chains when acting as a transceiver, channel estimation may become the most challenging issue for its practical use.

In fact, there have been several strategies to tackle channel estimation for RIS-based mobile communication systems. A straightforward method is to estimate the RIS channels element-by-element, namely, an ON/OFF mode, as embodied in [124]. However, the large aperture of RIS is not fully utilized, which degrades the channel estimation accuracy, since only one of the elements is switched on every time. To overcome this problem, a protocol was proposed in [125] to separately estimate the LoS and RIS channels by activating an RIS with different phase patterns while sending pilots. Moreover, a three-phase pilot-based channel estimation framework was developed for RIS-assisted uplink multiuser communications in [126]. In particular, the user-BS direct channels and the user-RIS-BS reflected channels of a typical user are estimated in Phase I and Phase II, respectively; meanwhile, in Phase III, the user-RIS-BS reflected channels of the other users are estimated with low overhead, utilizing the channel correlation properties with the typical user. Furthermore, for discrete phase shifts of RIS, the authors of [127] conceived a hierarchical training reflection design to progressively estimate RIS channels over multiple time blocks by exploiting the RIS-elements grouping and partition. Most recently, some sophisticated algorithms based on matrix factorization [128], tensor processing [129], compressive sensing [130], and so on, have sprung up, in order to tackle the channel estimation issue in more complex scenarios such as MIMO OFDM.

However, current methods generally require large training overhead or computation complexity, especially when the RIS is physically very large. Therefore, low-complexity and near-optimal channel estimation approaches are crucial issues in the domain of RIS-assisted positioning. Meanwhile, the theoretical analysis on the influence of channel estimation errors on positioning accuracy is also an interesting problem worth studying.

B. ACQUISITION OF POSITION-RELATED PARAMETERS

Despite that some recent works have made attempts to overcome channel estimation, the issue of acquisition of position-related parameters remains further studied. In fact, this issue is of considerable difference compared with the aforementioned channel estimation. To be more specific, conventional channel estimation algorithms can only give the numerical value of position-related parameters such as the ToA and AoA; the indices are, however, ambiguous. In other words, we do not know whether a certain ToA/AoA corresponds to the base station or a certain RIS. Recently, the authors of [131] combined RIS-assisted mobile communication with code-division multiple access (CDMA), where each RIS is assigned with a fast time-varying coefficient; hence, the receiver can identify the time delays from different RISs by sliding correlation. However, the estimation accuracy of this approach is highly dependent on the auto-correlation and cross-correlation properties of spread spectrum sequences. Meanwhile, for angle-based positioning, the matching of angles and anchors is still an open issue. Moreover, as future mobile communications tend to exploit mmWave, THz, and even higher frequency bands, the channel response will become sparse in the angle domain that depends mainly on the geometric relationship between devices and environments. Hence, the process of channel estimation and the acquisition of position-related parameters are likely to be linked more closely, which could be solved by resorting to compressive sensing methods.

C. PRACTICAL RIS OPTIMIZATION ALGORITHMS

Conventional RIS optimization approaches tended to minimize the CRLB so as to improve the positioning accuracy, which, however, is a chicken-or-egg question. Concretely speaking, the purpose of localization is to estimate the position of the interested target, i.e., the target position is an unknown parameter. However, to minimize the CRLB, we have to possess the knowledge of the target position, since the CRLB is indeed a function of all position-related parameters, including the coordinates of the target. In this sense, the method adopted by the authors of [102], [103], [104], [105] that utilizes RIS to create multiple RSS maps is a practical way worth trying. Unfortunately, the accuracy of RSS-based positioning tends to be coarse-grained. Thus, other practical RIS optimization algorithms that have low requirements on the target position remain further investigated. In especial, feedback and iterative algorithms could be an interesting area, i.e., the RIS can be optimized by utilizing current low-precision positioning results, thus obtaining a new position estimate of increased accuracy.

D. MULTI-DEVICE POSITIONING

The future 6G networks will witness massive connections, such as the industrial IoT and smart cities, where the RIS may become an essential infrastructure therein. In the development of multiple access technologies, conventional orthogonal multiple access (OMA) approaches such as time-division multiple access (TDMA), frequency-division multiple access (FDMA), and CDMA, allow the transmission of different users in an orthogonal way. In such cases, the multi-device positioning may have little difference from the single-device one. However, during the research progress of 5G and B5G networks, the non-orthogonal multiple access (NOMA) schemes that bring additional DoFs in the power domain have already been paid growing attention to. Meanwhile, the introduction of RIS may bring extra DoFs to the spatial domain. Against this backdrop, the positioning for multiple and even massive devices in the future 6G systems would put forward novel demand in terms of localization protocols, RIS scheduling approaches, and more advanced positioning algorithms.

E. INTEGRATED SENSING AND COMMUNICATION

With the commercialization of the 5G mobile communications, new application scenarios with both communication and sensing requirements such as smart homes, industrial IoT, IoV, and UAV networks, are emerging due to the great improvement of communication capabilities. Therefore, the fusion of communication and sensing is a consensus in future wireless networks. In fact, the IMT-2020 promotion group has been promoting the research on ISAC scenes, requirements, standards, and technologies in 5G-Advanced systems, and ISAC is also considered as an important trend in 6G networks. In the long term, ISAC not only requires the provision of sensing services such as localization and imaging based on the acquired sensing information that can also be utilized in turn to enhance communication performance, but also demands a deeper integration of architectures and waveforms. In this sense, RIS, characterized by its unique ability to artificially adjust the reflected electromagnetic waves, naturally has the potential in ISAC. However, how to apply RIS to serve both communication and positioning has not been widely studied and some key issues are still open, including but not limited to the resource allocation of data packets and positioning signals, the mutual-interfere, signal processing technologies, network architectures, transmission protocols, and the optimization of RIS coefficients.

F. NEAR-FIELD LOCALIZATION

Due to the multiplicative pathloss existing in the RIS-reflected channel, RIS has to be deployed near the transmitter or receiver for higher SNR. Meanwhile, it is also a common option to enlarge the size of RIS to increase the power of the RIS-reflected signal. Unfortunately, according to the definition of Fraunhofer distance, i.e., $\rho = 2D^2/\lambda$, where D is the maximum linear size of the RIS, the range of the near-field area is proportional to the RIS size and carrier frequency. For example, For a 1-m^2 RIS working at 3 GHz, the Fraunhofer distance is about 20 m, which is comparable to the size of the indoor environment. Therefore, most of the existing works that take the assumption of far-field and plane waves may not fit the realistic propagation environment well, which needs to be modified to a spherical+plane wave model. In particular, transceivers are more likely to be located in the near field as the carrier frequency and the RIS size increase, which may become a common problem in indoor localization and IoT positioning schemes.

G. MOVING NODES

Characterized by its 2D structure, RIS could be mounted on the surface of almost all macroscopic objects, not restricted to stationary buildings, ground, ceilings, walls, and caves, but also including moving vehicles, trains, ships, aircrafts, and UAVs. For example, in autonomous driving, the aperture of vehicle-mounted radar can be increased by using the new RIS-based antenna architecture, thus improving the positioning accuracy. Meanwhile, RIS-equipped UAVs can more easily collect radio signals from the equipment on the ground and the water as a complement to the current way of monitoring by optical cameras alone. However, current papers on RISL have little consideration for moving nodes, where more dynamic channel modeling, the Doppler effects from node velocity, the impact of channel fluctuations on localization precision, and the planning of trajectories are all issues worth discussing.

VI. CONCLUSION

In this paper, we introduced the emerging concept of RIS and its application domains, along with a generic system model of RIS-based mobile communication system. Then, we gave a brief summary of classic localization principles and clarified the potential of employing RIS in localization. Next, a comprehensive survey of the current state of research on RIS-assisted localization was provided, where the researches were classified into i) investigation of theoretical bound derivations, ii) localization algorithms, and iii) optimization approaches, depending on the focus of these studies. Finally, this article discussed the most significant research issues and challenges to tackle.

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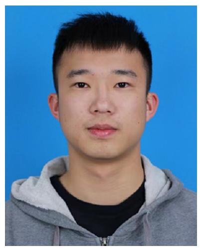

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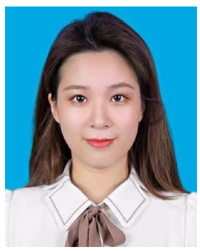

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