electronics

Review

Intelligent Reflecting Surface Assisted Localization: Opportunities and Challenges

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Abstract: Future generation communication systems are aiming to provide a tremendous high data rate with low-latency high reliable and three-dimensional coverage. To achieve such a challenging goal, it is required to have very precise location information related to the mobile terminal. The advancement of signal processing techniques and communication technologies enables the path for improving localization performance. Recently, intelligent reflecting surface (IRS) has been widely considered as the key element for the future generation of wireless communication. Over the past few years, the performance of IRS-assisted networks is extensively investigated from the point of view of communication purposes and its improvement. However, by virtue of its potential, IRS finds its application for wireless localization. In this paper, we discuss and summarize the works that have already been carried out targeting localization performance improvement. In addition, we figured out the associated challenges and the opportunities to scale up the localization accuracy. Particularly in this paper, the authors have discussed the challenging issues such as channel modeling, channel estimation, system architecture, hardware impairment, IRS deployment strategies, phase optimization, mobility management, and near-field environments. Although these challenges are associated with opportunities to make the IRS-assisted system more effective and efficient.

Keywords: IRS; localization; MIMO; microwave; mmWave; TeraHertz (THz)

Citation: Sur, S.N.; Singh, A.K.; Kandar, D.; Silva, A.; Nguyen, N.D. Intelligent Reflecting Surface Assisted Localization: Opportunities and Challenges. *Electronics* **2022**, *11*, 1411. https://doi.org/10.3390/electronics11091411

Academic Editor: Alina Caddemi

Received: 29 March 2022
Accepted: 25 April 2022
Published: 28 April 2022

1. Introduction

IRS represents a breakthrough technology to fulfill the goals of the future generation communication and localization system by exploiting its capability to actively modify the incident electromagnetic wave [1]. The IRS is basically a collection of IRS units and these units/elements are responsible for changing the behavior of the incident signals by independently controlling the amplitude, phase frequency, and polarization of the incident signals [2–5]. A pictorial representation of such a system is represented in Figure 1. Through numerous research works it has been already demonstrated that a very directive and high gained beam-formation can significantly improve the signal quality or can be utilized for interference nulling. These benefits can be utilized to extract the wireless localization information with minimum errors. In addition, the IRS provides resounding benefits, such as that it is very cost-effective and low in energy consumption.

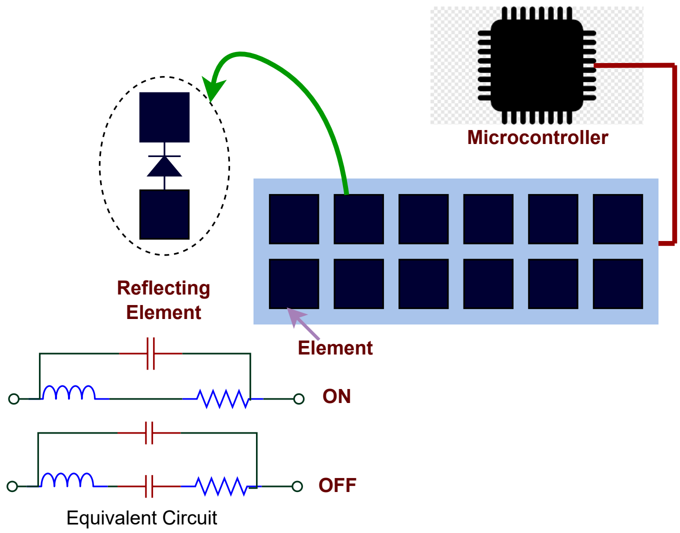

Figure 1. Basic architecture of IRS [6].

The localization of devices is an important aspect to ensure seamless connectivity in a network. Particularly, in sensor networks, localization information is of utmost importance to ensure reliable multi-hop connectivity. Similarly, location information is very important for efficient network planning and dynamic resource allocation in order to enhance link quality. With the growing demand and the advancement in society, its find lots of applications such as the industrial Internet of Things (IIoT), the intelligent transportation system (ITS), simultaneous wireless information and power transfer (SWIPT), location-aware communication system, radar, robot localization and extended reality, etc. [7]. Over the past few years, lots of works have been carried out and several approaches have been proposed to improve the localization accuracy. In this regard, IRS provides an extra degree of freedom to improve the localization information. Such a platform can be used in indoors and outdoors. This motivates the researchers to explore the possibilities of IRS for localization. In [8] the authors have demonstrated that the position error bounds (PEB) and orientation error bounds (OEB) can be significantly improved by utilizing IRS. It also improved the multi-user location by improving the signal strength with the help of IRS [9]. Apart from signal strength-based measurement, time-delay can be exploited as the same is presented in [10]. Here, the authors have optimized the PEB by optimizing the phase distribution for the IRS elements and their selection. Furthermore, the IRS can be utilized as a reflector or lens for sensing and localization purpose. The same is reported, in [11] IRS for assisting sensing applications and in [12–14] IRS lens for the localization. The impact of the IRS size, IRS deployment strategies, and related impairments are discussed in [12]. The impact of IRS quantization on the localization performance is reported in [13]. In [14], the authors have demonstrated the possibilities of utilizing IRS for 3D localization. Therefore, the IRS has the great potential to significantly improve the localization performance, and this motivates the authors of this paper to explore the research works carried out in this field and summarized the possible challenges and opportunities.

The major outlines of this paper are presented as follows:

- a brief discussion of the wireless localization system;
- an extensive review on the IRS-assisted localization systems;
- brief mathematical model related to the IRS-assisted communication and localization system;
- an extensive discussion on the relevant challenges and opportunities.

The remainder of this paper is as follows. A brief overview on the wireless localization system is presented in Section 2. Section 3 discusses the works carried out on IRS-assisted localization. This section particularly highlights the IRS-assisted microwave, millimeter-wave, THz, and airborne mobile network localization. This is followed by the discussion on the relevant challenges and opportunities in Section 4. Finally, the conclusion is in Section 5.

2. Overview on the Wireless Localization

Wireless Localization System is a system to locate the desired object. This can be achieved using the local area networks such as Wi-fi, cellular area networks, or using GNSS. The nomenclature given to the target object is AgN(AgN) or mobile user whose location is completely unknown and the reference nodes whose locations are known are referred to as anchor nodes (ANs) or landmarks. The wireless localization is used to estimate the position of the AgNs with reference to the ANs and it locates the estimated position on a coordinate of a map where several ANs are placed.

Generally, a localization system build with two major ingredients: (i) a set of ANs [whose location details are known]; (ii) an estimation unit (EU) that can be deployed on the AgN/AN or at some other remote location.

The localization process can be broadly summarized as:

1. A reference signal is transmitted from the AN or the AgN and the same is measured at the other end of the link to have certain location-based information such as RSS, AoA/AoD, ToA, and TDoA, etc.
2. All the information received at step (1) is used by the local estimation unit (LEU) to approximate the location of the AgN/AN.

Localization systems can be grouped on the basis of location-based algorithms [15] or location infrastructures [16]. However, self-localization and remote localization systems are considered the most popular ones.

Self-localization: Referring to Figure 2, the AgN which is embedded with LEU receives reference signals from different ANs. The AgN is efficient enough to perform signal measurement based on which its own location is determined.

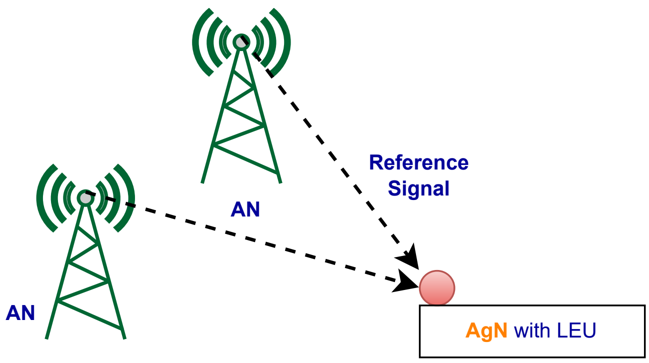

Figure 2. Self-Localization.

Self localization has several advantages. Some of them are mentioned below:

- Since all the localization algorithm depends only on the AgN, the computational efficiency of the AgN will determine the speed of operation. Hence, a small change or update of hardware/software at the AgN may increase the system's overall performance. No need to change the entire network infrastructure.
- Since all the localization algorithm is implanted at the AgN, the possibility of leaking the information reduces as ANs act as only a transmitter with all authorization access limited to the AgN only.
- Dynamic localization scenarios can be further implanted on the AgNs to provide some motion information so that the accuracy can be improved further [17].

However as mentioned above, the AgN requires high computational efficiency and thus can be deployed only on devices enriched with powerful computational capability.

Remote Localization: As shown in Figure 3, the reference signal is transmitted from the AgN to the ANs. Once all the ANs receive the signal, it forwards the same to the central station for location estimation.

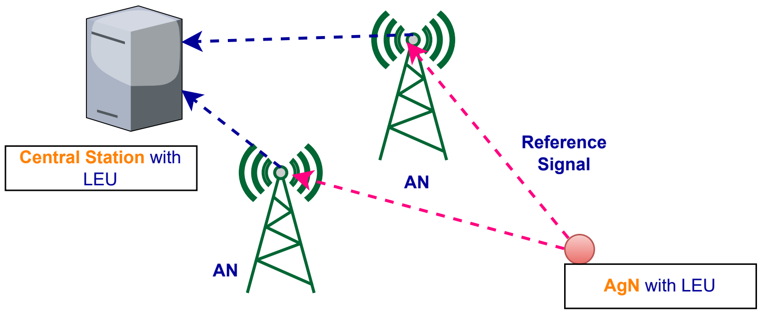

Figure 3. Remote Localization.

The advantage of this system over self-localization is, the pressure on the AgN is reduced and thus all the computational work is done at the central station sometimes referred to as base stations (BS). Therefore, this kind of mechanism is considered more useful for resource-limited devices such as IoT, and sensor nodes.

Unlike self-localization where all the location-based information is stored only at the AgN, in this method the central station stores the location information of several AgNs. The security becomes a major concern as a single central station is processing and storing the location information of several AgNs.

The basic *localization technique* is broadly classified into direct localization [18] and two-step localization [19]. In direct localization, the received signal is processed for the location estimation of the AgN, whereas the information from, e.g., RSS, ToA, AoA, and TDoA, is extracted at first in case of two-step localization. These information is utilized for the location estimation of the AgN. In terms of efficiency, the direct localization technique is proved better over the two-step localization; however, if system complexity and implantation constraints are considered, then two-step localization is preferred in most of the practical applications. Going further, The two-step localization is categorized as (1) geometric based localization, (2) scene analysis, and (3) proximity approach.

Geometric based localization(GBL): As the name suggests, it uses geometric properties such as trilateration and triangulation of a triangle to estimate the location of the AgN. Trilateration, also called as ranging uses the distance-related information from different ANs to estimate the location of the AgN [20–22]. On the contrary, triangulation measures the AoAs of the received signal from different ANs and the AgNs and estimates the location at the intersection of the angle direction lines [23].

Scene Analysis/Fingerprinting-based Localization: The efficiency of GBL reduces to a lower extent in complex environments. Thus, an alternative approach has to be looked out based on scene analysis or fingerprint [24–27]. Such methods are used to collect data from different sensors such as cameras, wireless apps, etc., and extract specific information such as geotagged signatures (fingerprints), and then estimates the location of the AgNs.

Proximity-Based Localization: This technique works on proximity constraints [28]. It depends on the location of the actual ANs, thus the efficiency relies on the density of the ANs. The efficiency of the technique is directly proportional to the number of ANs. This method is simple to implement, however, as the performance depends on the density of ANs; therefore, it finds its application where the location accuracy can be compromised.

3. IRS-Assisted Radio Localization and Mapping (RLM)

Improved RLM of mobile units (MUs) and other Internet of Things (IoT) devices using IRS is a key ingredient of 6G systems. The coexistence and cooperation between sensing, localization, and communication aims to boost security and trust in 6G connectivity in indoor and outdoor scenarios.

3.1. IRS Asisted Microwave/Millimeter-Wave Localization

As the world is moving towards the 5G and beyond (5GB) communication system, it is evident to have better localization accuracy due to its higher frequencies of operation. At a higher frequency, it is very much likely to have a blockage in the line-of-sight (LoS) path between the transmitter and the receiver. Under such circumstances, it is required to explore the multipath-aided localization. Therefore, at a higher frequency, IRS comes out as a potential solution by providing a guaranteed coverage when the LoS is blocked as presented in Figure 4.

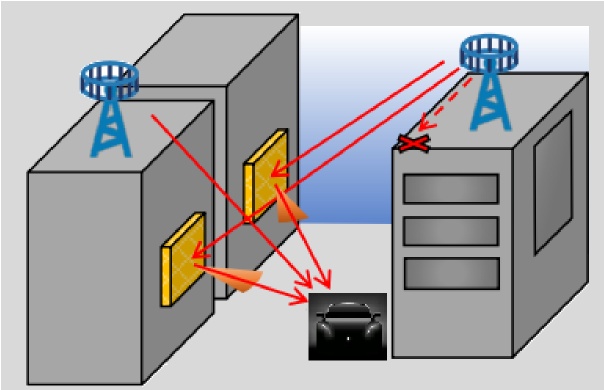

Figure 4. Localization in absences of LoS path [29].

The intelligent controlling capability of the propagation environment makes IRS an attractive research topic for localization and mapping.

Figure 5 represents the required components for developing an efficient localization and mapping system.

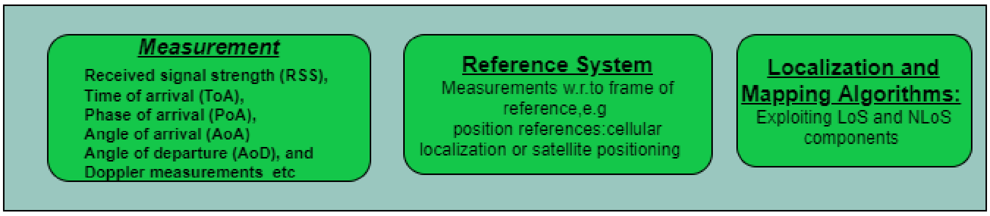

Figure 5. Components of a localization and the mapping system.

The introduction and advancement of the IRS improve the system performance significantly. This is because of the measurement accuracy of the RSS, ToA, AoD, PoA, AoA, and the Doppler shift defense of the nature of the wave and the channel. The inclusion of the IRS provides an additional degree of freedom. In the case of an IRS-assisted RLM system, the measurement accuracy can be increased significantly by optimizing the power allocation, beam formation etc. [12,30]. As in [31], the authors proposed an alternative optimization method and a GDM-based algorithm to optimize the reflect beamforming in order to estimate the mobile station position more accurately. Along with the passive element reflecting surface, active large intelligent surfaces (LISs) are also exploited to enhance localization. As in [12,32], authors investigated the distributed and centralized LIS systems in terms of Cramer–Rao lower bounds (CRLB) of all the dimensions. The proposed scheme aims to increase the robustness by subdividing the reflecting surface area into smaller units and to increase the coverage to have improved positioning. From the point of view of positioning, RSS plays an important role. With the of improving the RSS for the mobile users, authors in [33], have proposed Spherical LIS systems, which have Lower CRLB compared to planar LIS.

A large amount of works have been imparted towards the enhancement of the wireless localization using IRS-assisted network and the same is summarized in the Tables 1 and 2.

Table 1. Summary of works: IRS-assisted Localization (Part-I).

Ref.	Year	Environment	IRS-Assisted System Configuration	Performance Matrix	Significant Observations
[12]	2018	With perfect LoS component	Large intelligent surface (LIS)-mMIMO	Fisher-information matrix (FIM) and CRLB	It compare the centralized and distributed deployments of the LIS and established that the distributed deployments extend the coverage of terminal-positioning and improved the average CRLBs for all dimensions.
[30]	2020	mmWave channel with obstructed LoS path.	mmWavw MIMO-OFDM system.	Positioning accuracy and data rate.	It highlights the importance of proper phase design and proposed an adaptive phase shifter design based on hierarchical codebooks and feedback from the mobile station (MS).
[31]	2020	mmWave channel with obstructed LoS.	mmWave MIMO system.	CRLB (MS position estimate)	It proposed the gradient decent method (GDM) based Reflect Beamforming with Alternative Optimization Method at the IRS to reduce the localization error. It also demonstrates that by utilizing the IRS, decimeter-level or even centimeter-level positioning can be achieved with a large number of reflecting elements.
[10]	2020	mmWave channel with LoS component.	OFDM system with IRS-assisted network.	FIM, Position Error Bound (PEB)	It proposed a two-step optimization technique to select the best phase shift combination of the IRS to improve the wireless localization performance.
[34]	2020	mmWave channel with LoS component.	mmWave MIMO-OFDM system.	Impact of phases on CRB.	It provides the theoretical CRBL for positioning, and analyzed the impact of the number of LIS elements and the value of phase shifters on the position estimation accuracy.
[35]	2020	Indoor(office)/outdoor (Street Canyon)channel with LoS and NLoS components.	mmWave MIMO system.	Data Rate	It highlights the importance of the deployment of IRS and provide useful analysis regarding efficient positioning of the IRS-assisted communication systems.
[8]	2020	Near field/far field propagation environment with 3D scattering channel model.	MIMO-OFDM system.	CRLB, geometric dilution of precision (GDOP), PEB and orientation error bound (OEB).	It highlights the impact of the deployment geomertric of IRS and optimal phase design on the positioning information. The positioning performation is evaluated in terms of PEB and OEB, considering both near- and far-field propagation conditinon.
[36]	2020	Indoor environment	Access point (AP)-IRS combined system	Localization error	It proposed a heuristic state selection (HSS) algorithm for selecting the optimal IRS configuration subset and a machine learning feature selections (ML-FS) algorithm for enhancing localization accuracy and position acquisition time with reduced complexity.
[9]	2020	mmWave indoor environment.	MetaRadar based localization system.	Localization error and map	IRS aided multi-user localization protocol was proposed, based on signal strength measurements. As demontrated the proposed system with a 0.48 m^2 metasurface can achieve a centimeter localization accuracy with up to 2 m localization range for single user and multiple users without obstruction.
[37]	2021	Indoor environment	UWB	CRLB of the position estimates.	The combination of IRS and UWB signals can be used to aquair accurate indoor positioning with a single access point.
[14]	2021	mmWave with Near Field propagation environment	mmWave positioning system with IRS based lens	Position Error Bounds (PEBs)	It demontrated the location estimation performance by exploiting the wavefron curvature of the IRS lens.
[38]	2021	mmWave channel with LoS and NLoS components.	mmWave MISO OFDM system	Root mean squared error (RMSE) on the estimation and CRLB of the estimation error.	It proposed direct ML estimator for the position and clock offset. Furthermore, it also proposed a low complex relaxed ML-based estimator (RML) that can obtain suboptimal performance in absence of optimized beamforming and IRS control matrix.
[39]	2021	mmWave channel with LoS blockage.	mmWave MIMO system.	RMSE of the estimated position.	It proposed a parallel adaptive multi-target localization algorithm based on the hierarchical codebook concept.
[40]	2021	Multipath-channel both LoS and NLoS components under near and far field condition.	SISO multi-carrier system.	PEB	It demonstrate the impact of the wavefront curvature under near field conditions.
[41]	2021	Outdoor environment with LoS component.	SISO OFDM system.	Estimation error and PEB	It proposed a low-complex 3D localization and synchronization method. It also demonstrated that the localization is possible by AoD estimation from the IRS.
[42]	2022	Indoor environment	Multi-IRS-assisted Sensing system.	PEB	It demonstrated a ML-based localization method with multiple IRSs having single RF chain. The proposed scheme depends on the beamspace OMP technique for AoA estimation and LS-based line intersection.

Table 2. Summary: IRS-assisted Indoor/Outdoor Localization (Part-II).

Ref.	Year	Area	Number of IRS	IRS Deployment Strategies	Outcome	Localization Accuracy	Limitation
[12]	2018	Indoor/ Outdoor	Single/ multi(4)-IRSs	Centralized/ Distributed deployment	Extend the coverage of terminal-positioning.	-	The proposed analysis is based on the assumption of perfect LoS environment.
[30]	2020	Outdoor	Single	Fixed single IRS between BS and UE.	Improved accuracy and Data rate	-	There is perfect knowledge of IRS position to the BS.
[31]	2020	Outdoor	Single	Fixed large IRS	Improved accuracy	decimeter-level/centimeter-level with IRS with a large number of reflecting elements.	The large no of IRS elements leads to the increase in the complexity in estimation.
[10]	2020	Outdoor	Multiple IRSs	Fixed linear array of multiple IRSs on wall.	Improved coverage and accuracy	For single IRS,PEB is less than 5 m whereas with 5 IRSs PEB is less than 2.5 m.	The uncertainty of UE location should also be considered.
[35]	2020	Indoor/ Outdoor	Single	Indoor:mounted on side wall. Outdoor: facade of a building.	Improved rate		Accurate modeling of the composite channel.
[8]	2020	Indoor	Single	Mounted on wall	Improved PEB,OEB	The localization accuracy strongly depends on the geometry and the orientation of the UE.	Performance limits in presence of multiple IRSs.
[36]	2020	Indoor	Single	Mounted on wall	Improved accuracy	Oder of meter with 22 elements in IRS.	Analysis with mixed environment (LoS and NLoS) and multiple IRSs.
[9]	2020	Indoor	Single	Mounted on wall	Improved accuracy	A centimeter scale accuracy with up to 2 m range for single user and multiple users without obstruction.	Analysis on the impact of interference in case of multi-user scenario.
[37]	2021	Indoor	Single	Mounted on wall	Improved accuracy	The positioning accuracy can be improved significantly by adopting ToA in comparison to AoA.	Analysis under multi-user scenario.
[14]	2021	Indoor	Single	Single receiver comprising of IRS lens.	Improved accuracy.	A decimeter-level accuracy achieved within 3 m to the lens.	Analysis in presence of multi-path and multi-user scenario.
[40]	2021	Indoor	Multiple	Mounted on wall	Improved accuracy	Under near field condition number of elements in IRS significantly improve the accuracy.	Analysis of multi-user environment and with uncertainty in UE location.
[42]	2022	Indoor	Multiple	Mounted on side wall	Improved accuracy	Accuracy upto 0.07 m can be possible with 4-IRSs (64 elements each).	Impact of multi-user on the localization accuracy.

3.2. IRS Asisted THz Localization

For future generation communication systems, Terahertz (THz) communications are the key players for converged localization. It enjoys more precise localization and high angular resolution [29]. As in [43], the authors demonstrated that with identical total transmission power and time, THz-based localization is approximately 5 (20) times more accurate than the mmWave-based localization without (with) prior position information. Although the severe path losses in THz band make the localization and the mapping more difficult. Due to the strong directionality, the THz waves hardly cover the blind areas, and therefore, with the blocked LoS path, the localization problem becomes more challenging.

Lots of works have been carried out in this field but mostly in the microwave and mmWave frequency bands. A thorough analysis of THz localization, related challenges, and possible approaches are discussed in [44–46]. As discussed the biggest problems in THz localization are path/penetration losses and lower scattering profile. To get rid of such a problem, the use of coherent array processing and relay networks seems to be not useful. Under such a situation, IRS provides the breakthrough by converting the channel into a favorable environment [44,45]. Particularly, the IRS deployments can thus solve these issues as depicted in Figure 6.

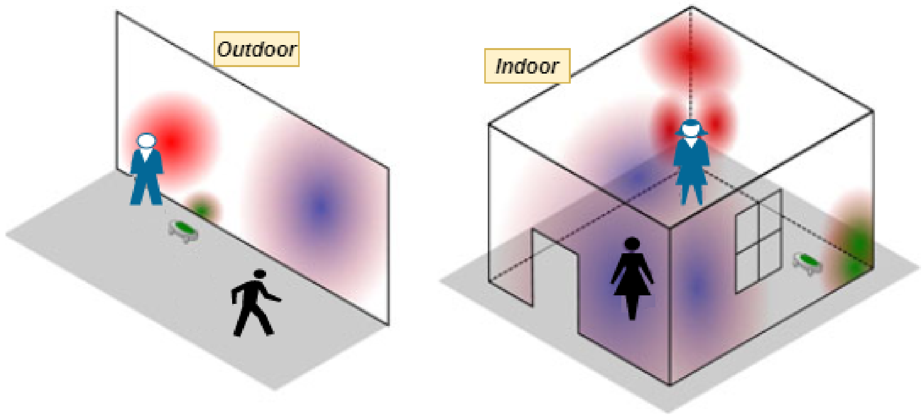

Figure 6. IRS-assisted THz localization.

The size of the IRSs at THz bands and its controlled scattering feature make it the most feasible and effective solution. Moreover, IRSs could enable tracking/surveillance applications in NLoS communications and autonomous localization. As discussed in [46], the localization performance of the SLAM system can be improved by utilizing the high-resolution THz images but at the cost of a complex model. However, the THz localization system enables us not only to have the fine-grained location information but also to enrich us with electromagnetic properties and material types in the target objects.

3.3. IRS-Assisted Airborne Mobile Networks Localization

Unmanned Aerial Vehicles (UAVs) have gained lots of attention from the research community due to their mobility and easily deployment. UAV-assisted communication networks to gain significant importance in scenarios where LoS links are obstructed due to the presence of physical structures. The main motivation behind the UAV-assisted airborne mobile networks is to extend the coverage by avoiding the coverage blind spot.

From the point of view of the key performance matrix energy efficiency (EE) and as influencing fact, the trajectory of the UAVs have a direct impact on the reliability and seamless connectivity of the airborne network [47,48]. Considering the opportunities created with the advancement of IRS, its deployment in airborne platforms is gaining significant attention from researchers around the world. By exploiting the potential of IRS, a combination of IRS with UAV-assisted [49] communication networks can improve the overall network performance in terms of high precision localization, extended coverage, high energy efficiency, security, and low-cost network densification. The potential uses of IRS-assisted airborne platforms can be types as presented in Figure 7.

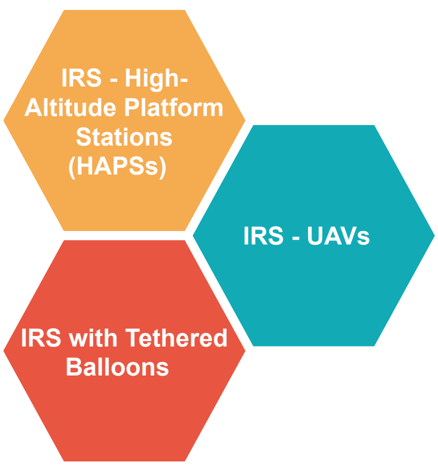

Figure 7. IRS-Assisted Airborne Mobile Networks.

4. Mathematical Model

This section represents the mathematical model for IRS with single user and multi user system. In addition, also it highlights the IRS-assisted localization system.

4.1. System Model

4.1.1. Single-IRS Single User

Figure 8 shows an IRS-assisted simple (downlink) communication system with single IRS supporting a user. Here, the IRS is with N_r discrete elements, the user terminal is with N_u antennas and BS with N_{bs} antennas. As depicted, there exist a line of sight (LoS) and a reflected path (NLoS). In the above figure, $h_{BU} \in \mathbb{C}^{N_{bs} \times N_u}$ represents the channel matrix corresponding to the user to BS. In addition, $h_{RU} \in \mathbb{C}^{N_{bs} \times N_r}$ denotes the channel matrix between the user and IRS. Similarly, $h_{BR} \in \mathbb{C}^{N_r \times N_u}$ is the channel matrix related to the path between the IRS and BS. The received signal at the user corresponding to the transmitted signal $\mathbf{s}$ can be expressed as

$$\mathbf{y} = (\mathbf{h}_{BU} + \mathbf{h}_{RU}\boldsymbol{\psi}\mathbf{h}_{BR})\mathbf{ps} + \mathbf{n} \tag{1}$$

$$\mathbf{y} = \underbrace{(\mathbf{h}_{BU}\mathbf{ps})}_{Uncontrollable} + \underbrace{(\mathbf{h}_{RU}\boldsymbol{\psi}\mathbf{h}_{BR})\mathbf{ps}}_{Controllable} + \mathbf{n} \tag{2}$$

where, $\mathbf{n}$ denotes the complex valued AWGN and $\mathbf{p}$ represents the precoding matrix corresponding user employed by BS. As in the figure, the path (h_{BU}) is uncontrollable whereas the reflected path can be controlled by exploiting the reconfigurable ($\boldsymbol{\psi}$).

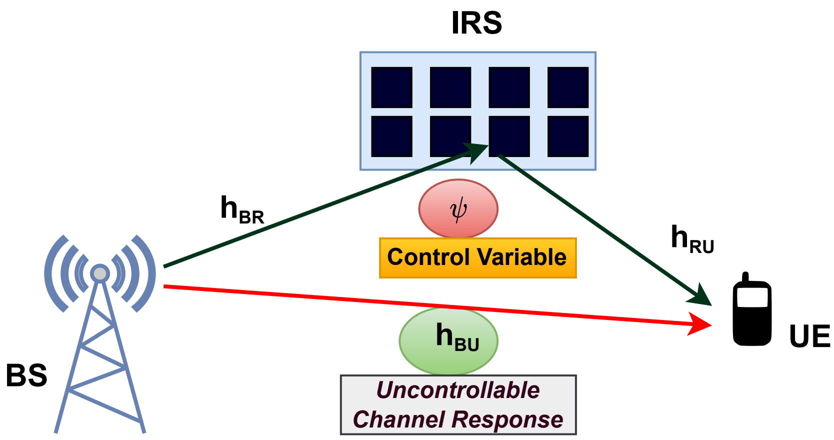

Figure 8. IRS-assisted Communication System: Single IRS and Single User.

4.1.2. Multi-IRS Multi User

Figures 9 and 10 represent the IRS-assisted uplink/downlink communication system with multiple IRSs and under multiuser scenario. As in figure, it consists of M IRSs with N_r discrete elements, K users with N_u antennas and BS with N_{bs} antennas. It is assumed that there is a direct link between the users and the BS. In addition, there is a cascaded channel via the reflection at the IRS.

In Figure 9, $h_{UB_k} \in \mathbb{C}^{N_{bs} \times N_u}$ represents the channel matrix corresponding to kth user to BS. In addition, $h^m_{UR_k} \in \mathbb{C}^{N_r \times N_u}$ denotes the channel matrix between the kth user and mth IRS. Similarly, $h^m_{RB} \in \mathbb{C}^{N_{bs} \times N_r}$ is the channel matrix related to the path between the mth IRS and BS. Therefore, the channels $h^m_{UR_k}$ and h^m_{RB} formed cascaded channel model. The benefits of IRS can be exploited by proper design of the phase matrix and the phase shift matrix $\boldsymbol{\psi} = \rho\, diag(e^{j\phi_1}, ., e^{j\phi_{N_r}})$, where $\phi_i \in [0, 2\pi]$, $i = 1, ., N_r$, is the phase-shift corresponding to the ith elements of IRS and $\rho \in [0, 1]$ is the reflection coefficient. The phase matrix corresponding to the lth IRS is denoted by $\boldsymbol{\psi}^m$. Considering the system as in Figure 6 the received signal at BS corresponding to the transmitted signal $\mathbf{s}_k$ from the kth user is

$$\mathbf{y} = \sum_{k=1}^{K} \left(\mathbf{h}_{UB_k} + \sum_{l=1}^{M} \mathbf{h}_{RB}^{m} \boldsymbol{\psi}^{m} \mathbf{h}_{UR_k}^{m} \right) \mathbf{p}_k \mathbf{s}_k + \mathbf{n} \tag{3}$$

where, $\mathbf{n}$ denotes the complex valued additive white Gaussian noise and $\mathbf{p}_k$ represents the precoding matrix corresponding to the kth user. The signal can be estimated ($\hat{\mathbf{s}}$) at the BS by utilizing appropriate filter ($\mathbf{W}$), i.e., $\hat{\mathbf{s}} = \mathbf{W}^H \mathbf{y}$.

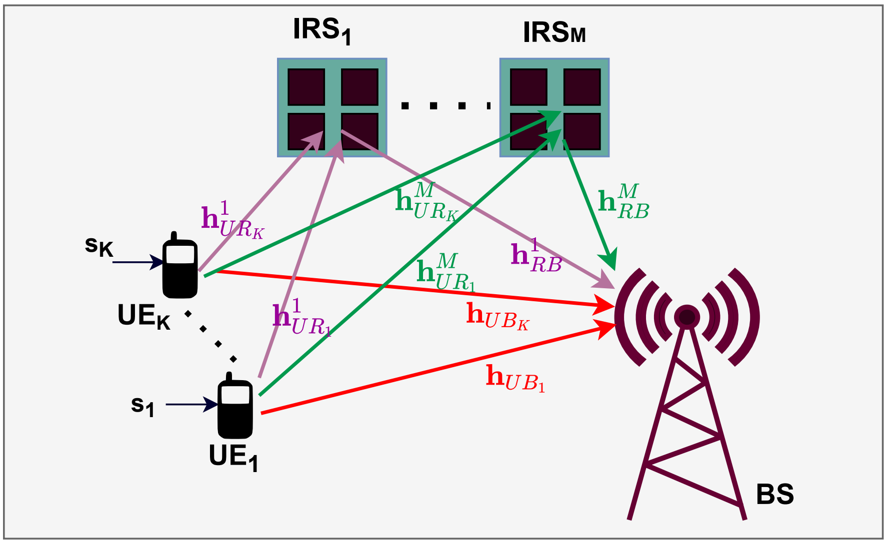

Figure 9. IRS-assisted Uplink Communication System: Multi-IRS and Multi-User.

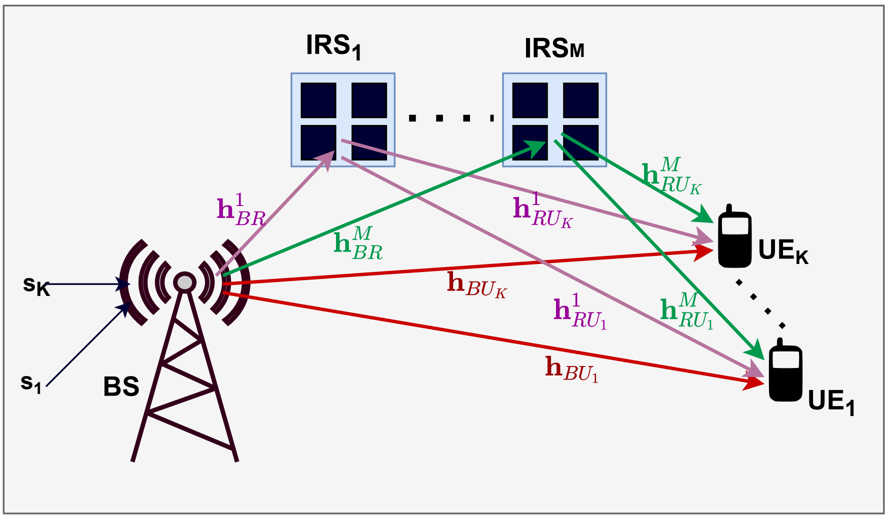

Figure 10. IRS-assisted Downlink Communication System: Multi-IRS and Multi-User.

Here, BS allocate $N_{s,k}$ streams for each users and $\mathbf{s}_k$ is the signal transmitted towards the kth user. In above figure, $h_{BU_k} \in \mathbb{C}^{N_{bs} \times N_u}$ represents the channel matrix corresponding to kth user to BS. In addition, $h_{RU_k}^{m} \in \mathbb{C}^{N_{bs} \times N_r}$ denotes the channel matrix between the kth user and lth IRS. Similarly, $h_{BR}^{m} \in \mathbb{C}^{N_r \times N_u}$ is the channel matrix related to the path between the mth IRS and BS. Similarly, considering the system as in Figure 10 the received signal at the kth user corresponding to the transmitted signal $\mathbf{s}_u$ can be expressed as

$$\mathbf{y}_k = \left(\mathbf{h}_{BU_k} + \sum_{m=1}^{L} \mathbf{h}_{RU_k}^{m} \boldsymbol{\psi}^{m} \mathbf{h}_{BR}^{l} \right) \sum_{k=1}^{K} \mathbf{p}_k \mathbf{s}_k + \mathbf{n}_k \tag{4}$$

where $\mathbf{n}$ denotes the complex valued AWGN and $\mathbf{p}_k$ represents the precoding matrix corresponding to the kth user employed by BS. The signal corresponding to each user can be estimated ($\hat{\mathbf{s}_k}$) by utilizing appropriate filter ($\mathbf{W}_k$), i.e., $\hat{\mathbf{s}_k} = \mathbf{W}_k^H \mathbf{y}_k$.

Section 4.1 represents a basic signal processing model for IRS assisted system. Considering its application for communication and localization, there are opportunities to develop new signal processing algorithms addressing the scaling laws, near-field propagation challenges, channel modeling considering the sparsity, mutual coupling, IRS mobility, etc. Overall the signal processing research challenges include system modeling, algorithmic design, and optimization to achieve maximum gain.

4.2. Localization Estimation: Near-Field

The target localization becomes more challenging under near-field conditions. The far-field methods are not applicable as in the near-field region the signal wavefront is spherical. The localization estimation techniques are broadly classified [50] into maximum likelihood (ML)-based methods [51,52] and the subspace-based methods [53,54]. All these methods provide high performance but from the application of view, these methods are limited for their typical hardware requirements [50]. In addition, these methods also assume that there exists a LoS link for the localization. However, in the practical scenario that may not be always true and that gives rise to the requirement of new technology. In this context, IRS has been considered to be a promising technology to enhance localization performance. In [50], the authors proposed IRS-assisted methods for the localization services for all targets in an area of interest (AOI) by avoiding the problems associated with traditional methods.

A simplestic model for IRS-assisted localization system (RALS) is presented in Figure 11. Here, IRS consists of N_r passive elements, which are distributed in an uniform linear array (ULA) and same times of consideration can be found in liturature [55,56]. As in Figure 11, there is no direct link between the anchor node (S) and the target node (T) due to the existance of blockage in between. The location information is extracted by utilizing th ereflected signal from the IRS. Let $\mathbf{p}_a = [p_{a,x}, p_{a,y}]^T$, $\mathbf{p}_r = [p_{r,x}, p_{r,y}]^T$ and $\mathbf{p}_t = [p_{t,x}, p_{t,y}]^T$ represents the position of the S, IRS and T within the AOI respectively.

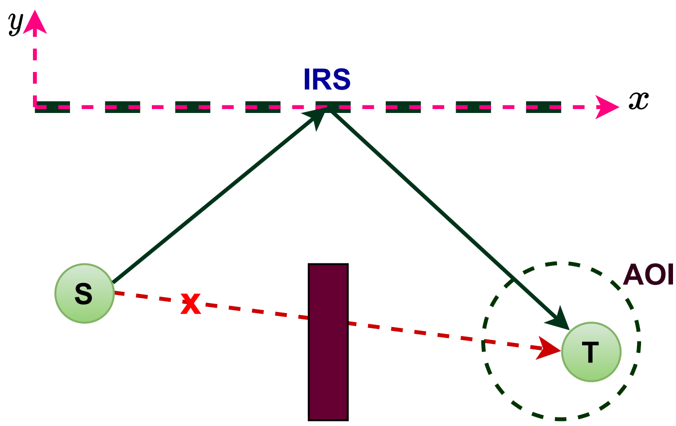

Figure 11. IRS-assisted Localization System.

The localization information is extracted by processing the received signal ($\mathbf{y}$) corresponding to the transmitted ($\mathbf{x}$) positioning reference signal (PRS). As in [50], for a perfectly synchronous system the position information of the target node can be extracted from the time of arrival (τ_{rt}), angle of departure (φ_{rt}), and path loss coefficient (ρ).

The goal of the RALS is to maximize the localization accuracy by constructing a reflection-coefficients vector $\mathbf{\Gamma}$ by virtue of proper phase design. The performance evaluation of the localization accuracy can be obtained by exploiting squared position error bound (SPEB) and it can be defined as

$$\xi(\mathbf{p}_t;\boldsymbol{\Gamma}) \triangleq tr\left\{\mathbf{J}^{-1}(\mathbf{p}_t;\boldsymbol{\Gamma})\right\} \tag{5}$$

where $\mathbf{J}^{-1}(\mathbf{p}_t;\boldsymbol{\Gamma})$ denotes the Fisher information matrix (FIM) associated with the reflection-coefficients vector $\boldsymbol{\Gamma}$ and the position parameters. Now the position parameters (ToA, AoD and path loss) can be extracted using the ML criteria and the estimation problem can be defined as

$$(\hat{\varphi}_{rt}, \hat{\tau}_{rt}) = \arg\min_{\varphi_{rt},\tau_{rt}} L(\varphi_{rt}, \tau_{rt}) \tag{6}$$

where $L(\varphi_{rt}, \tau_{rt}) \triangleq \left\|\mathbf{y} - \sqrt{\rho}\sqrt{P_t}\mathbf{h}^T\mathbf{x}\right\|^2$ is the compressed form of the log-likelihood function. Here, P_t is the power corresponding to RRS and $\mathbf{h}$ denotes the channel vector. More detailed analysis cab be found in [50]. The generalized approch can be summarized as follows,

- Detrmination of the channel parameters (τ_{rt}, φ_{rt} and ρ) and finding out the FIM of the said parameters.
- Determination of position parameters corresponding the Jacobian $\mathbf{J}$ and extract the FIM of the position parameters.
- After the extraction of the position parameters, finally the PEB is to be computed to evaluate the location estimation accurecy.

5. Relevant Challenges and Opportunities

This section highlights the relevant challenges and opportunities for researchers for designing an effective IRS-assisted network for future generation localization systems (see Figure 12).

Lots of efforts have been imparted and research is continuously going on but several challenges exist towards the realization of a highly accurate localization system. These involve understanding the physical design, dealing with the hardware impairment, the number of IRS elements and their segmentation and deployment strategies, etc. From the perspective of the UAV/Drone assisted airborne network the analysis of mobility and effective estimation and design of motion trajectory is a hot research topic.

Figure 12. Challenges.

5.1. IRS and Channel Modeling/Channel Estimation

In terms of IRS physical structure modeling, coupling between the IRS elements, impedance matching, reflection, and refraction losses plays a significant role in the system performance. Therefore, the IRS model should be designed considering the accurate model for the meta-surfaces and its interaction with the EM waves. In addition to the IRS geometry, its element segmentation [57], and periodicity need to be taken into account. Having knowledge about the channel is always beneficial for any communication localization system [45,46]. Efforts are imparted toward this direction, but still, there are some limitations such as experimental validation of the channel model and fading characteristic [58,59]. Therefore, the channel modeling and the estimation protocol are important and immediate challenges to hit on. Particularly under highly dynamic channel conditions, channel state information plays a significant role. Therefore, exploration of multiple-antenna nodes, spatial scattering modulation, beam index modulation, resource allocation, understanding and analysis of correlated channels, and system performance analysis under different fading environments, etc., appears to be interesting research topics.

With the increase in frequency, the wireless environment becomes sparse and becomes dependent on the geometric configuration (related to BS, UE, and IRS). In addition to prior location information corresponding to UE and IRS, location and orientation significantly influence the localization accuracy. However, the uncertainty of UE location makes the estimation more challenging and it brings an opportunity to develop a proper model for RLM.

5.2. System Architecture and Mitigation of Hardware Impairment

The localization information can be extracted from the uplink, downlink, or sidelink signal by exploiting the corresponding architecture [29,60]. The uplink localization can exploits the processing power at the base station, whereas downlink localization can make use of the high-power downlink pilots to gather the information. It also requires less UE power. The sidelink signals can be utilized to have the relative localization and for the same bistatic and monostatic architecture can be utilized. However, for successful realization of the IRS-assisted localization, hardware impairment-related problems need to be addressed. Certainly, the quantized phase in IRS is the main limiting factor. Thus more robust physical layer architecture is required along with its in-depth analysis in the presence of hardware impairment [61,62].

Although the hardware impairment has a significant impact on the system performance but higher number of the elements in an IRS can be exploited to suppress. Therefore, researchers can exploit the judicious segmentation of the IRS elements, optimized beamforming to overcome such problem.

5.3. Deployment Strategies

As discussed, IRSs have the ability to create virtual LoS link and proved to be beneficial for improving the system performance. From the point of view of localization, the deployment strategy of IRSs is also a significant point of concern. Available research works suggest that, as part of the strategy, researchers are looking for cooperative deployment [63,64], centralized/distributed deployment [65,66], stochastic geometry-based deployment [67,68], and machine learning-based deployment [69]. Considering the importance of the deployment, one can explore the deep learning, reinforcement learning-based soft computing approach for the development of low complex optimized deployment strategies to improve wireless localization.

5.4. Waveform Design/Optimized Beamforming/Phase Shift

The beam formation algorithm [12] should be robust to account for location estimation errors, which include both position and orientation [70]. In order to optimize beam formation, the channel state information and locational information can be exploited. Moreover, beam formation algorithm with practical discrete phase-level constraints at the IRS is another research area, and it is required to address the critical problem of joint optimization to minimize the localization error. The hierarchical codebook-based design can be explored in this regard. As further extension joint designs of both waveforms at the BS and codebooks at the IRS should be flexible enough to support accurate estimation of angle or delay.

5.5. IRS Control/Mobility Management

IRS control is the most significant and critical factor as it is fundamentally responsible to change the impedance of the surface to change the beam orientation [29]. However, the material and hardware properties put a limitation on the accuracy and the speed of the operation. Therefore, it is very much evident that it has a significant role in localization accuracy, continuity. In addition, the IRS control allows an incident signal to be reflected towards multiple directions simultaneously, providing multiuser localization support. In the case of localization, mobility management is also a point of concern and it needs to be addressed. In the highly dynamic condition, particularly for vehicular localization, UAV- based localization, maintaining the connection between the BS, IRS, and users becomes very challenging. The issue can be resolved with the help of an agile mobility management scheme.

5.6. Near-Field Propagation

The near field propagation aspect is particularly important as it is proportional to the surface area of the IRS. In addition, it accounts for wavefront curvature [14]. This should be taken into account during IRS, channel modeling, and estimation. Particularly PoA can be exploited directly in terms of spherical wave localization. Therefore, dedicated signal processing approaches should be explored for near-field localization and mapping.

6. Conclusions

In this article, the authors have first provided an overview on the basics of wireless localization then an extensive overview of IRS-assisted wireless localization. It also highlights the inherent challenges and also pointed out the opportunities. The localization accuracy can be improved significantly with the help of the IRS. However, before exploiting the true potential, we have to overcome many challenges and we have summarized them in this paper. The concept of IRS can be a revolutionary idea for localization applications.

Author Contributions: S.N.S., A.K.S., D.K., A.S. and N.D.N. have designed the study, developed the structure, performed the analysis, and written the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the FCT/MCTES through National Funds and when applicable co-funded European Union (EU) funds under Project UIDB/50008/2020-UIDP/50008/2020. The work of Nhan Duc Nguyen was financially supported by Van Lang University under Project 1000.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

IRS	Intelligent Reflecting Surface
THz	TeraHertz
IIoT	Industrial Internet of Thing
ITS	Intelligent Transportation System
SWIPT	Simultaneous Wireless Information and Power Transfer
PEB	Position Error Bounds
OEB	Orientation Error Bounds
SPEB	Squared Position Error Bound
RLM	Radio Localization and Mapping
MU	Mobile Units
LoS	Line-of-Sight
NLoS	Non-Line-of-Sight
LISs	large intelligent surfaces

CRLB	Cramer–Rao lower bounds
RSS	Received Signal Strength
AoA	Angle of Arrival
ToA	Time of Arrival
PoA	Phase of Arrival
TDoA	Time Difference of Arrival
AoD	Angle-of-Departure
GMD	Geometric Mean Decomposition
MIMO	Multi Input and Multi Output
SISO	Single Input and Single Output
mmWave	Millimeter Wave
UWB	Ultra Wide Band
OFDM	Orthogonal Frequency Division Multiplexing
UAV	Unmanned Aerial Vehicle
EE	Energy Efficiency
SE	Spectral Efficiency
AWGN	Additive White Gaussian Noise
ML	Maximum Likelihood
AOI	Area of Interest
ULA	Uniform Linear Array
FIM	Fisher Information Matrix
UE	User Equipment
EM	Electromagnetic

References

1. Renzo, M.D.; Debbah, M.; Phan-Huy, D.T.; Zappone, A.; Alouini, M.S.; Yuen, C.; Sciancalepore, V.; Alexandropoulos, G.C.; Hoydis, J.; Gacanin, H.; et al. Smart radio environments empowered by reconfigurable AI meta-surfaces: An idea whose time has come. *EURASIP J. Wirel. Commun. Netw.* **2019**, *2019*, 129. [CrossRef]
2. Yang, H.; Cao, X.; Yang, F.; Gao, J.; Xu, S.; Li, M.; Chen, X.; Zhao, Y.; Zheng, Y.; Li, S. A programmable metasurface with dynamic polarization, scattering and focusing control. *Sci. Rep.* **2016**, *6*, 35692. [CrossRef] [PubMed]
3. Wan, X.; Qi, M.Q.; Chen, T.Y.; Cui, T.J. Field-programmable beam reconfiguring based on digitally-controlled coding metasurface. *Sci. Rep.* **2016**, *6*, 20663. [CrossRef]
4. Ozdogan, O.; Bjornson, E.; Larsson, E.G. Using Intelligent Reflecting Surfaces for Rank Improvement in MIMO Communications. In Proceedings of the ICASSP 2020—2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 4–8 May 2020. [CrossRef]
5. Sur, S.N.; Bera, R. Intelligent reflecting surface assisted MIMO communication system: A review. *Phys. Commun.* **2021**, *47*, 101386. [CrossRef]
6. Wu, Q.; Zhang, R. Towards Smart and Reconfigurable Environment: Intelligent Reflecting Surface Aided Wireless Network. *IEEE Commun. Mag.* **2020**, *58*, 106–112. [CrossRef]
7. Elzanaty, A.; Guerra, A.; Guidi, F.; Dardari, D.; Alouini, M.S. Towards 6G Holographic Localization: Enabling Technologies and Perspectives. *arXiv* **2021**, arXiv:2103.12415.
8. Elzanaty, A.; Guerra, A.; Guidi, F.; Alouini, M.S. Reconfigurable Intelligent Surfaces for Localization: Position and Orientation Error Bounds. *arXiv* **2020**, arXiv:2009.02818.
9. Zhang, H.; Hu, J.; Zhang, H.; Di, B.; Bian, K.; Han, Z.; Song, L. MetaRadar: Indoor Localization by Reconfigurable Metamaterials. *arXiv* **2020**, arXiv:2008.02459.
10. Wymeersch, H.; Denis, B. Beyond 5G Wireless Localization with Reconfigurable Intelligent Surfaces. In Proceedings of the ICC 2020—2020 IEEE International Conference on Communications (ICC), Dublin, Ireland, 7–11 June 2020. [CrossRef]
11. Hu, J.; Zhang, H.; Di, B.; Li, L.; Bian, K.; Song, L.; Li, Y.; Han, Z.; Poor, H.V. Reconfigurable Intelligent Surface Based RF Sensing: Design, Optimization, and Implementation. *IEEE J. Sel. Areas Commun.* **2020**, *38*, 2700–2716. [CrossRef]
12. Hu, S.; Rusek, F.; Edfors, O. Beyond Massive MIMO: The Potential of Positioning With Large Intelligent Surfaces. *IEEE Trans. Signal Process.* **2018**, *66*, 1761–1774. [CrossRef]
13. Alegria, J.V.; Rusek, F. Cramér-Rao Lower Bounds for Positioning with Large Intelligent Surfaces using Quantized Amplitude and Phase. In Proceedings of the 2019 53rd Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, 3–6 November 2019. [CrossRef]
14. Abu-Shaban, Z.; Keykhosravi, K.; Keskin, M.F.; Alexandropoulos, G.C.; Seco-Granados, G.; Wymeersch, H. Near-field Localization with a Reconfigurable Intelligent Surface Acting as Lens. In Proceedings of the ICC 2021—IEEE International Conference on Communications, Montreal, QC, Canada, 14–23 June 2021; pp. 1–6. [CrossRef]
15. Laoudias, C.; Moreira, A.; Kim, S.; Lee, S.; Wirola, L.; Fischione, C. A Survey of Enabling Technologies for Network Localization, Tracking, and Navigation. *IEEE Commun. Surv. Tutor.* **2018**, *20*, 3607–3644. [CrossRef]

16. Yassin, A.; Nasser, Y.; Awad, M.; Al-Dubai, A.; Liu, R.; Yuen, C.; Raulefs, R.; Aboutanios, E. Recent Advances in Indoor Localization: A Survey on Theoretical Approaches and Applications. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 1327–1346. [CrossRef]
17. Gustafsson, F.; Gunnarsson, F. Mobile positioning using wireless networks: Possibilities and fundamental limitations based on available wireless network measurements. *IEEE Signal Process. Mag.* **2005**, *22*, 41–53. [CrossRef]
18. Weiss, A. Direct position determination of narrowband radio transmitters. In Proceedings of the 2004 IEEE International Conference on Acoustics, Speech, and Signal Processing, Montreal, QC, Canada, 17–21 May 2004. [CrossRef]
19. Wang, T.; Hua, W.; Ke, W. A two-step sequential method for device-free localization using wireless sensor networks. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 155014771983281. [CrossRef]
20. Guvenc, I.; Chong, C.C. A Survey on TOA Based Wireless Localization and NLOS Mitigation Techniques. *IEEE Commun. Surv. Tutor.* **2009**, *11*, 107–124. [CrossRef]
21. Wahab, A.A.; Khattab, A.; Fahmy, Y.A. Two-way TOA with limited dead reckoning for GPS-free vehicle localization using single RSU. In Proceedings of the 2013 13th International Conference on ITS Telecommunications (ITST), Tampere, Finland, 5–7 November 2013. [CrossRef]
22. Jung, S.Y.; Hann, S.; Park, C.S. TDOA-based optical wireless indoor localization using LED ceiling lamps. *IEEE Trans. Consum. Electron.* **2011**, *57*, 1592–1597. [CrossRef]
23. Kumar, S.; Gil, S.; Katabi, D.; Rus, D. Accurate indoor localization with zero start-up cost. In Proceedings of the 20th Annual International Conference on Mobile Computing and Networking, Maui, HI, USA, 7–11 September 2014; ACM: New York, NY, USA, 2014. [CrossRef]
24. Feng, C.; Au, W.S.A.; Valaee, S.; Tan, Z. Received-Signal-Strength-Based Indoor Positioning Using Compressive Sensing. *IEEE Trans. Mob. Comput.* **2012**, *11*, 1983–1993. [CrossRef]
25. Vo, Q.D.; De, P. A Survey of Fingerprint-Based Outdoor Localization. *IEEE Commun. Surv. Tutor.* **2016**, *18*, 491–506. [CrossRef]
26. He, S.; Chan, S.H.G. Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons. *IEEE Commun. Surv. Tutor.* **2016**, *18*, 466–490. [CrossRef]
27. Khalajmehrabadi, A.; Gatsis, N.; Akopian, D. Modern WLAN Fingerprinting Indoor Positioning Methods and Deployment Challenges. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 1974–2002. [CrossRef]
28. Li, M.; Liu, Y. Rendered Path: Range-Free Localization in Anisotropic Sensor Networks With Holes. *IEEE/ACM Trans. Netw.* **2010**, *18*, 320–332. [CrossRef]
29. Wymeersch, H.; He, J.; Denis, B.; Clemente, A.; Juntti, M. Radio Localization and Mapping With Reconfigurable Intelligent Surfaces: Challenges, Opportunities, and Research Directions. *IEEE Veh. Technol. Mag.* **2020**, *15*, 52–61. [CrossRef]
30. He, J.; Wymeersch, H.; Sanguanpuak, T.; Silven, O.; Juntti, M. Adaptive Beamforming Design for mmWave RIS-Aided Joint Localization and Communication. In Proceedings of the 2020 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), Seoul, Korea, 6–9 April 2020. [CrossRef]
31. Liu, Y.; Liu, E.; Wang, R. Reconfigurable Intelligent Surface Aided Wireless Localization. *arXiv* **2020**, arXiv:2009.07459.
32. Alghamdi, R.; Alhadrami, R.; Alhothali, D.; Almorad, H.; Faisal, A.; Helal, S.; Shalabi, R.; Asfour, R.; Hammad, N.; Shams, A.; et al. Intelligent Surfaces for 6G Wireless Networks: A Survey of Optimization and Performance Analysis Techniques. *arXiv* **2020**, arXiv:2006.06541.
33. Hu, S.; Rusek, F. Spherical Large Intelligent Surfaces. In Proceedings of the ICASSP 2020—2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 4–8 May 2020. [CrossRef]
34. He, J.; Wymeersch, H.; Kong, L.; Silven, O.; Juntti, M. Large Intelligent Surface for Positioning in Millimeter Wave MIMO Systems. In Proceedings of the 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), Antwerp, Belgium, 25–28 May 2020. [CrossRef]
35. Basar, E.; Yildirim, I.; Kilinc, F. Indoor and Outdoor Physical Channel Modeling and Efficient Positioning for Reconfigurable Intelligent Surfaces in mmWave Bands. *arXiv* **2020**, arXiv:2006.02240.
36. Nguyen, C.L.; Georgiou, O.; Gradoni, G. Reconfigurable Intelligent Surfaces and Machine Learning for Wireless Fingerprinting Localization. *arXiv* **2020**, arXiv:2010.03251.
37. Ma, T.; Xiao, Y.; Lei, X.; Xiong, W.; Ding, Y. Indoor Localization With Reconfigurable Intelligent Surface. *IEEE Commun. Lett.* **2021**, *25*, 161–165. [CrossRef]
38. Fascista, A.; Coluccia, A.; Wymeersch, H.; Seco-Granados, G. RIS-Aided Joint Localization and Synchronization with a Single-Antenna Mmwave Receiver. In Proceedings of the ICASSP 2021—2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Toronto, ON, Canada, 6–11 June 2021. [CrossRef]
39. Cisija, E.; Ahmed, A.M.; Sezgin, A.; Wymeersch, H. Ris-Aided mmWave MIMO Radar System for Adaptive Multi-Target Localization. In Proceedings of the 2021 IEEE Statistical Signal Processing Workshop (SSP), Rio de Janeiro, Brazil, 11–14 July 2021. [CrossRef]
40. Rahal, M.; Denis, B.; Keykhosravi, K.; Uguen, B.; Wymeersch, H. RIS-Enabled Localization Continuity Under Near-Field Conditions. In Proceedings of the 2021 IEEE 22nd International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Lucca, Italy, 27–30 September 2021. [CrossRef]
41. Keykhosravi, K.; Keskin, M.F.; Seco-Granados, G.; Wymeersch, H. SISO RIS-Enabled Joint 3D Downlink Localization and Synchronization. In Proceedings of the ICC 2021—IEEE International Conference on Communications, Montreal, QC, Canada, 14–23 June 2021. [CrossRef]

42. Alexandropoulos, G.C.; Vinieratou, I.; Wymeersch, H. Localization via Multiple Reconfigurable Intelligent Surfaces Equipped with Single Receive RF Chains. *arXiv* **2022**, arXiv:2202.13939.
43. Chen, H.; Sarieddeen, H.; Ballal, T.; Wymeersch, H.; Alouini, M.S.; Al-Naffouri, T.Y. A Tutorial on Terahertz-Band Localization for 6G Communication Systems. *arXiv* **2021**, arXiv:2110.08581.
44. Chen, Z.; Ma, X.; Han, C.; Wen, Q. Towards intelligent reflecting surface empowered 6G terahertz communications: A survey. *China Commun.* **2021**, *18*, 93–119. [CrossRef]
45. Bourdoux, A.; Barreto, A.N.; van Liempd, B.; de Lima, C.; Dardari, D.; Belot, D.; Lohan, E.S.; Seco-Granados, G.; Sarieddeen, H.; Wymeersch, H.; et al. 6G White Paper on Localization and Sensing. *arXiv* **2020**, arXiv:2006.01779.
46. Sarieddeen, H.; Saeed, N.; Al-Naffouri, T.Y.; Alouini, M.S. Next Generation Terahertz Communications: A Rendezvous of Sensing, Imaging, and Localization. *IEEE Commun. Mag.* **2020**, *58*, 69–75. [CrossRef]
47. Zhang, S.; Zhang, H.; Di, B.; Song, L. Cellular UAV-to-X Communications: Design and Optimization for Multi-UAV Networks. *IEEE Trans. Wirel. Commun.* **2019**, *18*, 1346–1359. [CrossRef]
48. Popoola, O.; Ansari, S.; Ansari, R.I.; Mohjazi, L.; Hassan, S.A.; Aslam, N.; Abbasi, Q.H.; Imran, M.A. *IRS*-Assisted Localization for Airborne Mobile Networks. *Auton. Airborne Wirel. Netw.* **2021**, 141–156. [CrossRef]
49. Alfattani, S.; Jaafar, W.; Hmamouche, Y.; Yanikomeroglu, H.; Yongaçoglu, A.; Đào, N.D.; Zhu, P. Aerial Platforms with Reconfigurable Smart Surfaces for 5G and Beyond. *arXiv* **2020**, arXiv:2006.09328.
50. Luan, M.; Wang, B.; Zhao, Y.; Feng, Z.; Hu, F. Phase Design and Near-Field Target Localization for RIS-Assisted Regional Localization System. *IEEE Trans. Veh. Technol.* **2022**, *71*, 1766–1777. [CrossRef]
51. Sheng, X.; Hu, Y.H. Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks. *IEEE Trans. Signal Process.* **2005**, *53*, 44–53. [CrossRef]
52. Zhang, X.; Wang, F.; Li, H.; Himed, B. Maximum Likelihood and IRLS Based Moving Source Localization with Distributed Sensors. *IEEE Trans. Aerosp. Electron. Syst.* **2020**, *57*, 448–461. [CrossRef]
53. Zuo, W.; Xin, J.; Zheng, N.; Sano, A. Subspace-Based Localization of Far-Field and Near-Field Signals Without Eigendecomposition. *IEEE Trans. Signal Process.* **2018**, *66*, 4461–4476. [CrossRef]
54. Zhou, N.; Luo, L.; Sheng, G.; Jiang, X. Power Distribution Network Dynamic Topology Awareness and Localization Based on Subspace Perturbation Model. *IEEE Trans. Power Syst.* **2020**, *35*, 1479–1488. [CrossRef]
55. Han, H.; Liu, Y.; Zhang, L. On Half-Power Beamwidth of Intelligent Reflecting Surface. *IEEE Commun. Lett.* **2021**, *25*, 1333–1337. [CrossRef]
56. Tian, G.; Song, R. Cooperative beamforming for a double-IRS-assisted wireless communication system. *EURASIP J. Adv. Signal Process.* **2021**, *2021*, 67. [CrossRef]
57. Mao, Z.; Wang, W.; Xia, Q.; Zhong, C.; Pan, X.; Ye, Z. Element-Grouping Intelligent Reflecting Surface: Electromagnetic-Compliant Model and Geometry-Based Optimization. *IEEE Trans. Wirel. Commun.* **2022**, 1–15. [CrossRef]
58. Wang, Z.; Liu, L.; Cui, S. Channel Estimation for Intelligent Reflecting Surface Assisted Multiuser Communications: Framework, Algorithms, and Analysis. *IEEE Trans. Wirel. Commun.* **2020**, *19*, 6607–6620. [CrossRef]
59. Zhang, W. Introduction. In *Dynamics of Coupled Systems in High-Speed Railways*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 1–54. [CrossRef]
60. Alexandropoulos, G.C.; Lerosey, G.; Debbah, M.; Fink, M. Reconfigurable Intelligent Surfaces and Metamaterials: The Potential of Wave Propagation Control for 6G Wireless Communications. *arXiv* **2020**, arXiv:2006.11136.
61. Xing, Z.; Wang, R.; Wu, J.; Liu, E. Achievable Rate Analysis and Phase Shift Optimization on Intelligent Reflecting Surface With Hardware Impairments. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 5514–5530. [CrossRef]
62. Nguyen, N.D.; Le, A.T.; Munochiveyi, M.; Afghah, F.; Pallis, E. Intelligent Reflecting Surface Aided Wireless Systems with Imperfect Hardware. *Electronics* **2022**, *11*, 900. [CrossRef]
63. Han, Y.; Zhang, S.; Duan, L.; Zhang, R. Cooperative Double-IRS Aided Communication: Beamforming Design and Power Scaling. *IEEE Wirel. Commun. Lett.* **2020**, *9*, 1206–1210. [CrossRef]
64. Li, Z.; Hua, M.; Wang, Q.; Song, Q. Weighted Sum-Rate Maximization for Multi-IRS Aided Cooperative Transmission. *IEEE Wirel. Commun. Lett.* **2020**, *9*, 1620–1624. [CrossRef]
65. Zhang, S.; Zhang, R. Intelligent Reflecting Surface Aided Multiple Access: Capacity Region and Deployment Strategy. *arXiv* **2020**, arXiv:2002.07091.
66. He, J.; Yu, K.; Shi, Y. Coordinated Passive Beamforming for Distributed Intelligent Reflecting Surfaces Network. In Proceedings of the 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), Antwerp, Belgium, 25–28 May 2020. [CrossRef]
67. Zhang, C.; Yi, W.; Liu, Y.; Qin, Z.; Chai, K.K. Downlink Analysis for Reconfigurable Intelligent Surfaces Aided NOMA Networks. *arXiv* **2020**, arXiv:2006.13260.
68. Kishk, M.A.; Alouini, M.S. Exploiting Randomly Located Blockages for Large-Scale Deployment of Intelligent Surfaces. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 1043–1056. [CrossRef]
69. Liu, X.; Liu, Y.; Chen, Y.; Poor, H.V. RIS Enhanced Massive Non-Orthogonal Multiple Access Networks: Deployment and Passive Beamforming Design. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 1057–1071. [CrossRef]
70. Wang, W.; Zhang, W. Joint Beam Training and Positioning for Intelligent Reflecting Surfaces Assisted Millimeter Wave Communications. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 6282–6297. [CrossRef]