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A Survey on 5G Massive MIMO Localization

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Abstract

Massive antenna arrays can be used to meet the requirements of 5G, by exploiting different spatial signatures of users. This same property can also be harnessed to determine the locations of those users. In order to perform massive MIMO localization, refined channel estimation routines and localization methods have been developed. This paper provides a brief overview of this emerging field.

Keywords: Massive MIMO, Localization, Millimeter Wave, 5G, Distributed Sources

1. Introduction

Passive source localization based on measurements from spatially separated sensors has been an important problem in radar, sonar, mobile communications and wireless sensor networks. Localization from radio signals has a long history, with the most prominent example being the global positioning system (GPS), cellular localization, and Wi-Fi localization. In these systems, the commonly used measurements are received-signal-strength (RSS), time-of-arrival (TOA),

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time-difference-of-arrival (TDOA) and angle-of-arrival (AOA) of the emitted signal [1, 2].

Localization is a highly desirable feature of future wireless networks [3]. It generally involves a two-step procedure, where measurements are first processed to obtain distance and/or angle information, followed by triangulation to determine the user positions. The performance of these methods is greatly degraded in the presence of multipath, due to the inability to correctly identify and/or estimate the measurements of the line-of-sight (LOS) paths [4, 5]. Recent work in radio-based positioning exploits multipath propagation using geometrical channel models [6]. The above two-step procedure leads to performance loss, as information present in the physical waveform is condensed to a point estimate. This is especially detrimental when the measurement is ambiguous (e.g., two AOA values are roughly equally likely). In such a case, direct localization may be applied, converting directly from waveform to location estimate, though at a severe cost in complexity.

As new cellular communication standards are rolled out, they are often available to reuse for localization [3]. Such localization is based on dedicated reference signals (positioning reference signals) and involve minimal changes to a receiver chain (leading to a preference for two-phase localization). Currently, with the introduction of 5G, the use of massive mulitple-input multiple-output (MIMO) and millimeter wave (mmWave) systems are attracting interest from the localization community. Indeed, large-scale antenna system does not only offer advantages in communications by assigning the same time-frequency resources to multiple users, it also has the potential for localization, due to its high angular resolution [7, 8, 9]. When combined with short wavelenghts in mmWave, hundreds of antennas can also be packed at the user side, providing opportunities not available in previous generations of cellular communications. Due to these benefits, localization is considered in various study item in 3GPP and we can expect to see new dedicated signals, localization algorithms, and use cases in the coming years.

In this paper, we consider the radio localization problem from a massive

MIMO point of view, with a substantial focus on the mmWave regime. We provide an overview of different methods for estimating angles and delays with respect to sources in multipath channels and demonstrate how such estimates can be used for localization.

The rest of the paper is organized as follows. In Section 2, we first introduce the channel model for distributed sources. The widely used channel parameter estimation algorithms for point and distributed sources, such as subspace and compressed sensing (CS) methods are discussed in Section 3. The-state-of-the-art localization techniques are introduced in Section 4. Challenges and opportunities are discussed in Section 5. Conclusions are drawn in Section 6.

2. Channel Models

From a localization point of view, it is desirable to parameterize the channel as a function of location-related parameters (distances and angles). Hence, geometric channel models are widely used in the localization literature.

2.1. From Centimeter to Millimeter Wave Channels

In the centimeter wave (cm-wave) regime, channels are often divided into two categories: LOS and non-line-of-sight (NLOS). In NLOS the channel on a given subcarrier is generally modeled as independent Rayleigh fading, with no direct connection to the relative position of transmitter and receiver. In the most LOS case, the channel is often determined by a single path, with delay and angle parameters related to the user location. A model to unify LOS and NLOS uplink channels for a given subcarrier n is [10]:

$$\mathbf{h}_n = \sqrt{\frac{\beta}{L}} \sum_{l=0}^{L-1} e^{-2\pi n \tau_l / T} \mathbf{a}(\theta_l), \tag{1}$$

in which L is the total number of paths, β is the deterministic path loss, τ_l is a delay due to path l (T is an OFDM symbol duration), and $\mathbf{a}(\theta_l)$ is the antenna steering vector for AOA θ_l. Considering $L \to \infty$ the law of large numbers tell us, under a common AOA density, that $\mathbf{h}$ will tend to a zero-mean normal random variable with covariance

$$\mathbf{R}_n = \beta \int p(\theta)\mathbf{a}(\theta)\mathbf{a}^{\mathrm{H}}(\theta)\mathrm{d}\theta. \tag{2}$$

where $p(\theta)$ is the angular power density of the source [11].

In the mmWave regime, the channel is characterized with only very few one-bound paths (L is less than 10) and antennas installed at both the transmitter and receiver, leading to a model

$$\mathbf{H}_n = \sqrt{\frac{1}{L}} \sum_{l=0}^{L-1} \beta_l e^{-2\pi n \tau_l / T} \mathbf{a}_r(\theta_l)\mathbf{a}_t^{\mathrm{H}}(\phi_l), \tag{3}$$

in which the subscripts r and t are used to denote receiver and transmitter respectively. The angle-of-departure (AOD) is denoted by ϕ_l and β_l denotes the path loss. The statistics of the channel further depend on how each path is modeled: either coming from a point source or a distributed source.

2.2. From Point to Distributed Source Models

As shown in Fig.1, there are different types of reflection. The massive

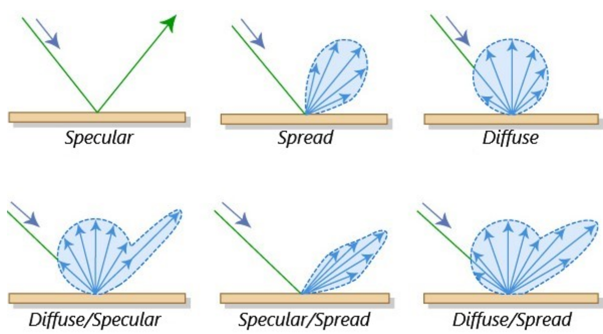

Figure 1: Different types of reflection.

MIMO channel estimation problem has been studied in [12, 13, 14], where their algorithm developments are based on specular reflection models and $p(\theta_l) = \delta(\theta_l^* - \theta_l)$. In the mmWave bands, building and terrain surface height variations are significant compared to the wavelength. Therefore, several works have shown the significance of considering the diffuse scattering phenomena to obtain an accurate channel model [15, 16, 17].

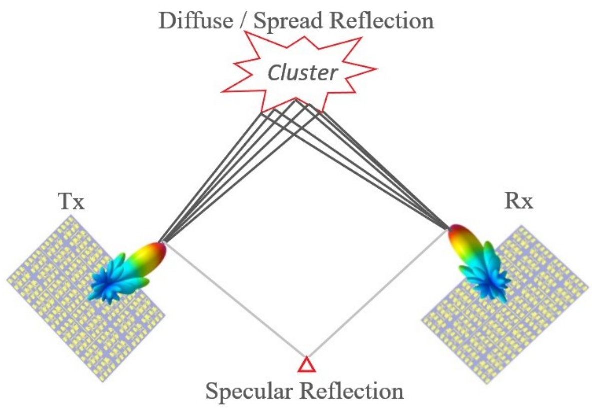

Figure 2: Illustration of mmWave point and distributed sources.

Distributed sources can be classified as coherently distributed (CD) and incoherently distributed (ID) sources by comparing the channel coherency time and observation period [11]. For CD sources, they are slow time varying. Whereas in the ID case, it is rapidly time-varying [18].

Angular signal density and angular power density are two widely used models to describe the properties of the distributed sources [19]. Two types of distribution (Gaussian and uniform) for random angular deviation have been extensively studied [20]. It is interesting to note that the choice of density function is not critical for small angular spreading [21]. Many parameter estimation techniques have been proposed for distributed source models. However, most of them are limited to the simplified scenarios, such as azimuth and/or elevation angles and delay [22, 18]. In the context of localization, proper and realistic stochastic models of dense multipath are required [23]. Let us introduce the following channel model, there are L clusters and each cluster has K_l rays. The parameters for the k-th ray from the lth cluster are azimuth and elevation angles (ϕ_{lk}, ψ_{lk}) at the transmitter, their azimuth and elevation angles $(\theta_{lk}, \varphi_{lk})$ at the receiver, as well as the corresponding propagation delays τ_{lk}, leading to a 5-D channel model,

$$\mathbf{H}_n = \frac{1}{\sqrt{L\sum_l K_l}} \sum_{l=0}^{L-1} \sum_{k=1}^{K_l} \beta_{lk} e^{-2\pi n \tau_{lk}/T} \mathbf{a}_r(\theta_{lk}, \varphi_{lk}) \mathbf{a}_t^{\mathrm{H}}(\phi_{lk}, \psi_{lk}), \tag{4}$$

where β_{lk} denotes path loss. For each ray, the parameters can be further represented as nominal parameter plus deviation, where $\tau_{lk} = \tau_l + \delta_{\tau_{lk}}$, $\theta_{lk} = \theta_l + \delta_{\theta_{lk}}$, $\varphi_{lk} = \varphi_l + \delta_{\varphi_{lk}}$, $\phi_{lk} = \phi_l + \delta_{\phi_{lk}}$ and $\psi_{lk} = \psi_l + \delta_{\psi_{lk}}$. That is, the first term denotes the nominal parameter and the second term is deviation from the nominal parameter [24]. It becomes quite complicated and challenging, if both the nominal parameter and deviation are parameters of interest. Attempts have been made for a stochastic description of the dense multipaths [25, 26].

A classification of distributed source models in terms of source property and parameter dimension is given in Table 1. The 2-D angles correspond to the azimuth and elevation AODs (ϕ, ψ) or the azimuth and elevation AOAs (θ, φ), and 1-D angles corresponds to the azimuth or elevation angle.

Table 1: Classification of distributed source models

Source Property	Parameter Dimension
CD sources	1-D angles (AOD and/or AOA)
ID sources	2-D angles (AOD and/or AOA)
Hybrid sources [27]	1-D/2-D angles (AOD and/or AOA) and delay

3. Channel Parameter Estimation

In this section, we review popular location-related channel parameter estimation techniques for point and distributed sources. Subspace methods and compressed sampling are presented.

3.1. Point Sources

3.1.1. Subspace Methods

Modern subspace based algorithm achieves a good balance between estimation accuracy and computational complexity [28]. In the traditional approaches to subspace-based parameter estimation, the R-dimensional (R-D) signals are stored in matrices. Obviously, it does not account for the multidimensional grid structure inherent in the data. Therefore, tensors become a natural approach to store and manipulate multi-dimensional data [29].

The R-D tensor ($R \geq 3$) is denoted by $\boldsymbol{\mathcal{X}} \in \mathbb{C}^{M_1 \times M_2 \times \cdots \times M_R}$, where M_r is the size of the rth dimension of the tensor and the $(m_1, m_2, \cdots, m_R)$-th entry of $\boldsymbol{\mathcal{X}}$ is denoted as $x_{m_1, m_2, \cdots, m_R}$. Tensor decomposition is an efficient way for dimensionality reduction and eliciting the intrinsic structure of the R-D data [30]. The Tucker decomposition of a tensor $\boldsymbol{\mathcal{X}}$ is given by:

$$\boldsymbol{\mathcal{X}} = \boldsymbol{\mathcal{S}} \times_1 \mathbf{U}_1 \times_2 \mathbf{U}_2 \times \cdots \times_R \mathbf{U}_R, \tag{5}$$

where $\boldsymbol{\mathcal{S}} \in \mathbb{C}^{M_1 \times M_2 \times \cdots \times M_R}$ is the core tensor and $\mathbf{U}_r \in \mathbb{C}^{M_r \times M_r}$, $r = 1, 2, \cdots, R$, is the unitary matrix containing the r-th mode singular vectors, and operator $\times_r$ denotes the product of a tensor and matrix along the rth dimension. While CANDECOMP/PARAFAC decomposes a tensor into a sum of rank-one tensors [31].

Subspace methods have been extended from matrix to tensor framework to estimate the R-D parameters of the dominant multipath components from MIMO channel measurements [29]. Numerous tensor decomposition based techniques have been developed, such as tensor-estimation of signal parameters via rotational invariance technique (tensor-ESPRIT) [32], multidimensional ESPRIT [33, 34], tensor-principal-singular-vector utilization for modal analysis (tensor-PUMA) [35], tensor-method of direction estimation (tensor-MODE) [36], multi-dimensional folding (MDF) [37], R-D rank reduction estimator (RARE) [38] and tensor eigenvector (TEV) [39], and an overview can be found in [40]. Recently, CP decomposition-based channel parameter estimation for mmWave MIMO-OFDM systems is proposed in [41]. Furthermore, developing efficient tensor completion and decomposition methods from incomplete measurements are also desirable [42, 43, 44, 45, 46, 47].

Table 2: Summary of the CS algorithms

Measurements	Grid Type	Recovery Algorithms
Single	On-grid	Optimization
Multiple	Off-grid	Greedy Iterative
	Grid-less	Bayesian Inference

3.1.2. Compressed Sensing

As a paradigm to recover the sparse signals, CS has stimulated a great deal of interest [48, 49]. It has spread rapidly in different disciplines such as machine learning, wireless communication, signal processing and computer science. In massive MIMO [50] or mmWave systems, due to the limited number of scattering clusters and the increased spatial resolvablity, the channel can be sparsely represented in the angular and delay domain. Furthermore, experiments performed on mmWave channels show the limited number of the scattering clusters in angular domain [51]. CS-based techniques offer significant performance gain over the conventional approaches for sparse channels.

Major CS approaches include convex optimization approach [52, 53], greedy algorithm [54, 55, 56], iterative algorithm [57] and statistical sparse recovery [58, 59]. Sparse vector recovery from multiple observations has received much attention due to its superior performance compared to the single measurement scenario. A brief summary of the CS algorithms is given in Table 2, and more details can be found in [60, 61]. The opportunities and challenges of applying the CS techniques to 5G are investigated in [49, 62, 63, 64, 65, 66, 67].

3.2. Distributed Sources

As shown in Table 3, channel parameter estimation techniques for distributed sources can be divided into different categories, in terms of the source property, parameter dimension and estimation scheme. The R-D parameters could be azimuth and elevation angles of departure and arrival, delay and Doppler shift, as well as the spread of these parameters that may exist. CD sources have been well addressed in the past decades [68, 69, 70, 71]. While the estimation

Table 3: Classification for channel parameter estimation techniques

Source Property	Parameter Dimension	Estimation Scheme
CD sources	1-D	Exhaustive search
ID sources	2-D	Search-free
Hybrid sources	R-D	Others

problem for ID sources are complicated and challenging, the typical techniques include pseudo-subspace [11, 69], maximum likelihood [72], covariance matching [73] and generalized beamforming [19].

Although the above methods are designed for 1-D ID source localization, some of them are still applicable for 2-D scenarios. Moreover, more efficient techniques, such as distributed signal parameter estimator (DISPARE) [73] and subspace-based [74] can be generalized for 2-D localization. While multi-dimensional optimization or search is still required for these extensions. A low-complexity 1-D spectral search 2-D ID source localization algorithm is proposed in [75]. However, this method imposes strict requirements on array geometry.

In [76], an ESPRIT-based approach has been proposed for 2-D ID source localization. It reduces the computational burden significantly and spectral search is not required. But it still involves the high-dimensional matrix operations such as inversion and eigen-decomposition. Recently, an efficient beamspace 1-D spectral search-based approach is proposed for special cylindrical array. To further reduce computational burden, a beamspace-based approach for 2-D AOA estimation of ID sources is proposed in [18].

One set of numerical results is shown in Figure 3 to evaluate the hybrid point and distributed source estimation performance. The simulation setup is as follows. Both transmitter and receiver are uniform linear arrays with 32 elements. There are five well separated sources, two of which are point sources and three are distributed sources, each distributed source consists of 20 rays and the maximum angle spread is 4 degrees. Tensor-ESPRIT algorithm is utilized to estimate AOAs and AODs.

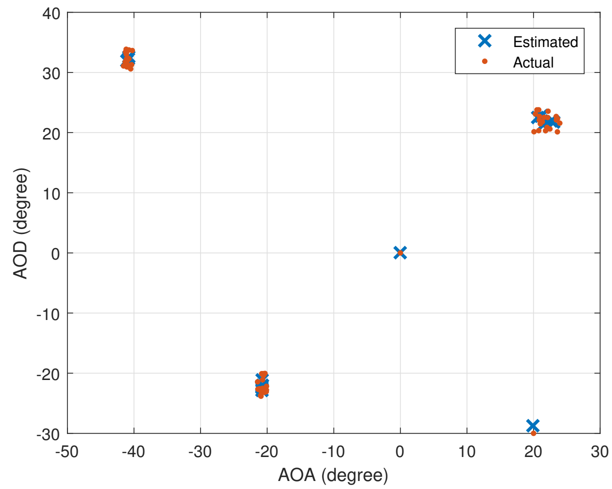

Figure 3: AOA and AOD estimation for hybrid point and distributed sources.

4. Localization Techniques

There are various types of classification for localization techniques [77]. In this section, we first review and compare some typical localization algorithms in terms of LOS or NLOS environments, and non-cooperative or cooperative processing, followed by recent research on 5G localization.

4.1. LOS or NLOS

In cluttered urban areas with dense residential and office buildings or indoor environments, signals may experience reflection and diffraction, and LOS measurements from the signal sources may not be readily available. NLOS error mitigation techniques in localization have been extensively investigated [78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88].

One common approach to model NLOS measurements is to treat the effect of reflection and diffraction on range measurements as a positive stochastic bias [78, 79, 80, 81, 82, 83, 84, 85]. Another approach is based on ray tracing, where the geometry of signal propagation paths is analyzed [86, 87, 88, 89, 90]. Under the assumption that individual propagation paths can be resolved, relationships between range and AOA measurements can be derived, which produces a more accurate model than simply treating NLOS effects as positive biases.

4.2. Non-cooperative or Cooperative

In a cooperative localization scheme, the localization of all sources or sensors in the network is treated as a joint estimation problem. Unlike non-cooperative schemes, where localization errors propagate from one sensor to another, a cooperative localization procedure typically attempts to estimate all sensor locations by minimizing a global error function, and in general performs better than non-cooperative methods. The joint estimation can be done using either a centralized optimization procedure where information from all sensors is sent to a central processor, or a distributed procedure where sensors perform local processing and message exchanges with neighboring nodes. Compared to centralized methods, distributed procedures are more robust, flexible, and scalable, and are more suitable for *ad hoc* sensor networks.

Distributed localization methods that assume LOS measurements include [91, 92, 93, 94, 95]. In [91], a distributed second-order cone programming method is developed, while [93] imposes convex hull constraints to achieve better accuracy. [94] develops a belief propagation framework to perform simultaneous localization and synchronization using TOA measurements. Distributed localization algorithms under NLOS environments are proposed in [84, 85, 89, 90, 96, 95]. In [89], the cooperative localization of multiple sensors in a network is achieved using belief propagation, while [90] considers the localization of an uncooperative source in a NLOS environment using a distributed expectation maximization (EM) approach that estimates the source location through TDOA and AOA measurements. [96] develops a semidefinite programming method to mitigate NLOS errors and to track mobile source nodes, while [95] proposes a posterior linearization belief propagation approach to deal with nonlinear measurement models in NLOS scenarios.

4.3. 5G Localization

High carrier frequencies, large bandwidths, large-scale antenna systems, device-to-device (D2D) communication and ultra-dense networking are five properties of 5G networks. These properties are favorable for accurate localization [97]. Positioning and location awareness not only enable various location-based applications, but also contribute to significant performance improvement of 5G communication systems.

4.3.1. Indirect Localization

The principle of indirect localization is that the channel parameters (AOD, AOA, TOA) grouped together in $\boldsymbol{\eta}$, are a function of the location parameters (user location, orientation, denoted by $\mathbf{s}$ as well as the incidence points of NLOS paths, denoted by $\boldsymbol{\nu}$). There exists a straightforward geometric mapping $\boldsymbol{\eta} = f(\mathbf{s}, \boldsymbol{\nu})$. Now, given an estimate of $\boldsymbol{\eta}$, the localization algorithm aims to recover an estimate of $\mathbf{s}$ (localization [25, 98]) and/or $\boldsymbol{\nu}$ (mapping).

The authors in [99] presents a method for localization and mapping from multiple access points, exploiting the geometric relationship $f(\cdot)$ through angle-difference-of-arrival. A method for localization based on the LOS path, solving a low-dimensional least squares problem is proposed in [25]. The performance was shown to approximate fundamental performance bounds. In contrast to the above point estimators, Bayesian methods are investigated in [100]. Using a Gibbs sampler, the high-dimensional states $\mathbf{s}, \boldsymbol{\nu}$ are determined in a piece-wise manner, leading to a low-complexity localization and mapping algorithm, even when the LOS path is not identified. In [101] a method using factor graphs is investigated, which is applicable even when the LOS path is not present. In [102], downlink mmWave signals from a single base station is used to jointly estimate the vehicle position, orientation, environment, and vehicles clock bias.

4.3.2. Direct Localization

An alternative way for indirect localization is estimating the source location directly from the measurements, while intermediate parameters such as the

AOAs of the LOS paths are not required [103]. The direct localization concept was introduced in [104], and later applied to AOA-based [105] and hybrid AOA-TOA localization [106]. However, all these methods are developed for LOS paths. In the literature, some direct localization techniques [107] targeted to multipath scenarios, but they are not tailored to AOA information and large-scale antenna systems.

Large-scale antenna systems make it possible to accurately estimate the AOAs of multipath components [76]. Recently, Direct Source Localization (DiSouL) technique is proposed in [108], and the measurements acquired at each base station are jointly processed [108]. The possibility of directly inferring the transmitter position for mmWave has been investigated in [109]. It shows the advantage of using lens-embedded antenna array to reduce the antenna size or improve the localization performance.

5. Challenges and Opportunities

5.1. Accurate mmWave Propagation Modeling

Massive MIMO is one of the most important 5G technologies [110]. The antenna pattern is changed from sector-level wide beams to user-centric dynamic narrow beams. Therefore, accurate mmWave propagation models are required. Due to the importance of mmWave channel modeling and the novelty of using higher frequencies for mobile communications, many groups around the world have embarked on mmWave channel models [17]. Compared with the radio propagation features of low frequency bands, the signals in mmWave bands are more susceptible to issues such as architecture materials and vegetation [111].

5.2. Efficient Channel Parameter Estimation Techniques

Complicated Propagation Models. Accurate channel parameter information is critical for both mmWave wireless communications and localization [112]. Most of the existing distributed source parameter estimation techniques are limited to 1-D or 2-D scenarios, extension to R-D scenarios with hybrid specular and diffuse reflection is not straightforward. Computational efficient channel parameter estimation techniques are needed [113].

System Constraints. Furthermore, large antenna arrays are used at both the base station and the user equipment (UE) sides, combined with hybrid analog/digital processing and low-resolution analog-to-digital converters [12]. Therefore, algorithms to handle the hardware constraints and channel characteristics are required. In [18], beamspace-based algorithm is proposed for 2-D AOA estimation of ID sources in massive multiple-input multiple-output (massive MIMO) systems. Another interesting research direction is compressed sensing based distributed source parameter estimation [114].

5.3. Cooperative Localization in 5G Networks

5G networks will allow connecting large number of stationary and mobile devices, sensors, machines, and supporting Internet of Things (IoT) [115, 116]. Dense networks and D2D communications enable implementing cooperative localization [117]. Furthermore, cooperative positioning is very demanding for 5G-enabled IoT environments, where direct access to anchor nodes is not required to localize mobile nodes with low power devices and limited communication capabilities. It can be expected that localization, especially collaborative localization, will be an important feature in 5G networks.

Intelligent transportation systems (ITS) and intelligent and connected vehicles (ICV) [118] are two commercial applications of IoT, which can be driven by 5G localization and vehicle-to-everything (V2X) communications with cooperative operations, such as vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N) and vehicle-to-pedestrian (V2P) [119].

5.4. Artificial Intelligence Meets 5G Localization

Artificial intelligence (AI) has gained much attention in various research fields in recent years due to its promising performance on complicated problems, if there may not be a closed-form solution. Different from the traditional analytic methods, it first uses massive data to train a model and then apply for localization. AI based localization algorithms can be classified into two categories: the algorithm can either use the channel measurements to directly determine the UE location, or to estimate the channel parameters (e.g. channel gain, delay and angle information), which can be applied for localization in a straightforward way.

For the first category, the fingerprint of the channel contains the position information, which can be exploited using neural network (NN) [120], convolutional neural network (CNN) [121] and weighted k-nearest neighbor (kNN) [122]. For the second category, NN can be applied to estimate parameters of static MIMO channel [123, 124, 125] and dynamic MIMO channel [126]. A data-driven deep neural network (DNN) approach is proposed in [127] to localize mobile nodes using lower frequency spectrum, and 5G indoor sub-meter accuracy is achieved. Recently, a supervised machine learning approach based on Gaussian process regression is proposed in [128] for distributed localization in massive MIMO systems.

6. Conclusion

In this paper, we have provided an overview on 5G massive MIMO localization, describing the common channel models and propagation effects, constrasting different channel estimation methods as well as localization techniques. We have presented recent research progress and outlined four promising research directions that involve (i) accurate mmWave propagation modeling, (ii) efficient channel parameter estimation techniques to handle the complicated propagation models and system constraints, (iii) cooperative localization and (iv) artificial intelligence in 5G networks.

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