A Survey on User Positioning in mmWave MIMO System*

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Abstract

Accurate user positioning plays a key role in millimeter wave massive multiple-input multiple-output (mmWave-MIMO) systems by improving beamforming and ensuring reliable connectivity. This paper presents a structured review of positioning techniques with a focus on high-mobility scenarios and challenging non-line-of-sight (NLoS) environments. We first review recent positioning methods that enhance communication speed, reliability, and efficiency in mmWave MIMO systems. It covers angle-based, time-based, and learning-based techniques that help overcome signal blockage, user mobility, and complex environments. We also review real-time positioning methods that support accurate beam alignment, reduce training time, and improve spectral efficiency. Finally, we discuss significant challenges, including beam misalignment, limited positioning accuracy, and high system complexity and present solution strategies that aim to improve system performance.

Keywords

Positioning, Beamforming, Millimeter Wave, MIMO, Cell free

1. Introduction

The ability to accurately determine a user's location has become a key component of modern communication systems. This feature supports various applications, including navigation, logistics, emergency response, and a wide range of location-based services (LBS) [1]. Early positioning systems primarily relied on satellite technologies, which delivered reliable performance in open outdoor environments. However, as wireless communication networks have spread into urban, indoor, and densely populated settings, the limitations of satellite-based positioning have become increasingly evident. To overcome these challenges, alternative positioning methods based on Wi-Fi, Bluetooth, and cellular networks have been adopted, offering better resilience in complex environments [2].

As wireless networks move toward sixth generation (6G), the need for accurate and fast positioning is becoming more important. Many researchers have already studied how positioning works in fifth generation (5G) networks, especially using technologies like millimeter-wave (mmWave), massive multiple-input multiple-output (mMIMO), and cooperative localization methods [3]. Some of these studies discussed improvements in positioning across different network generations and suggested new ways to include location features directly in 5G systems. Other studies explored the use of mmWave and MIMO to support precise tracking in urban and indoor environments. However, a significant part of this research was conducted before 5G was widely deployed, so there is still a gap in understanding the practical performance of these systems [4]. This gap brings new opportunities for 6G, where positioning will likely become a built-in part of the network design. Recent studies on integrated localization and communication (ILAC), along with current discussions about 6G development, show that future systems aim to provide less than one meter level accuracy, very low delay, and affordable solutions [5].

To support the growing need for accurate positioning, researchers and industry experts are focusing

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on advanced technologies such as mmWave and distributed MIMO (D-MIMO). mmWave communication works in the 30–300 GHz frequency range and offers high time and spatial resolution for accurate location tracking. It uses features such as angle of arrival (AOA) and time of flight (TOF) to improve positioning, especially in places where traditional systems, including global positioning system (GPS) do not work well [6]. When combined with large antenna arrays, mmWave systems have shown the ability to achieve centimeter-level accuracy. This level of precision is important for many real-time applications, such as self-driving vehicles, tracking of industrial equipment, and augmented reality systems. Recent research also shows that using mmWave with multiple antennas can further improve the accuracy of position estimates, especially in high-density settings.

However, achieving accurate and reliable positioning in high-mobility environments brings several technical challenges. Although mmWave signals offer high precision, objects like buildings, vehicles, and people can easily block them. In high mobility, including trains and autonomous cars, the signal path changes quickly and often without a clear line-of-sight (LoS). This makes it harder to maintain a stable connection. The users moving at high speeds also face problems like doppler shift and beam squint. Doppler shift happens when movement changes the signal frequency at low mmWave frequencies beam squint affects the direction of the signal across different frequencies. Both issues can reduce the quality of communication and reduce positioning accuracy. To deal with these problems, systems need to track user movement in real time. This involves quickly estimating the position and direction of moving users using fast feedback and smart algorithms. One commonly used method is the extended kalman filter (EKF), which combines different signal measurements such as time-difference-of-arrival (TDOA) to track the user's location and speed [7]. These tracking techniques help the network adjust signal directions as the user moves so that both communication and positioning stay accurate.

In recent years, several studies have explored the role of positioning in supporting beamforming in mmWave and MIMO-based systems. These studies highlight its potential to reduce beam training overhead and improve link reliability. Many of these works focus on either mmWave localization or beamforming separately, often under simplified conditions. However, research that combines high-accuracy user positioning with mmWave-distributed MIMO beamforming in a unified framework remains limited. While some initial efforts have introduced context-aware beamforming strategies using location data, a detailed survey specifically targeting user positioning in mmWave MIMO systems is still lacking. Additionally, few studies address practical concerns such as implementation complexity, error sensitivity, and the impact of user mobility on system performance. This survey aims to fill that gap by reviewing existing positioning techniques in the context of the mmWave MIMO system and analyzing their impact on beamforming performance across various deployment scenarios. Figure 1 shows the positioning scenarios in the mmWave MIMO system. In this paper, we provide a detailed review of the current positioning techniques used in mmWave MIMO systems and examines their role in improving beamforming performance. The review categorizes these techniques into two main groups: those that rely on traditional positioning methods and those that integrate machine learning to enhance accuracy and adaptability. Additionally, the paper discusses the challenges in mmWave positioning, including issues related to positioning errors, orientation inaccuracies, obstacles in the environment, and storage requirements for positioning data. This study also explores the impact of these challenges on the beamforming process and focuses on their effect on the overall performance and efficiency of the system.

The rest of the paper is organized as follows. Section 2 provides a literature review covering key areas such as positioning in mmWave systems, location-aware beamforming, high-accuracy positioning in high-mobility scenarios, and techniques to reduce complexity in non-line-of-sight (NLoS) environments. Section 3 discusses the main challenges in mmWave positioning. Section 4 concludes the paper.

2. Literature Review

In recent years, various positioning techniques for mmWave MIMO systems have been proposed to address the challenges of accurate localization. This section provides a summary of the different

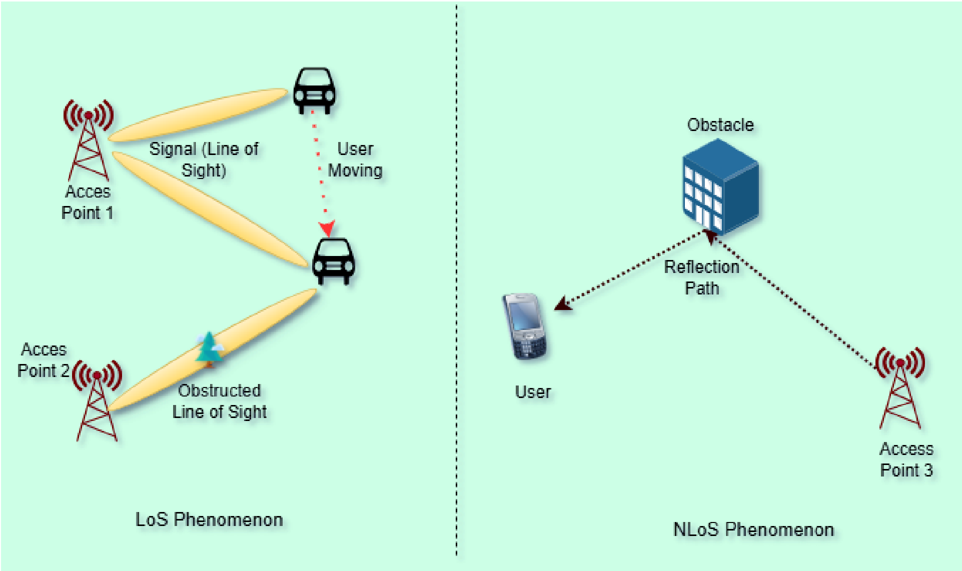

Figure 1: Positioning Scenarios in mmWave MIMO with User Mobility

approaches, categorizing them into angle-based, time-based, and signal-strength-based methods, and discusses the improvements made in positioning accuracy and system performance in these challenging environments. The table 1 shows the comparison of paradigm with different criteria.

Table 1
Comparison of Positioning Paradigms in mmWave MIMO Systems

Criteria	Paradigm	Qualitative metrics
Communication Speed	Angle-Based	Medium
	Time-Based	Low to Medium
	Learning-Based	High
Reliability	Angle-Based	Medium
	Time-Based	Medium
	Learning-Based	Medium to High
Positioning Accuracy	Angle-Based	High (in LoS, challenging in NLoS)
	Time-Based	Medium to High (depends on bandwidth)
	Learning-Based	Medium to High (depends on training and data quality)
Complexity	Angle-Based	Medium to High (needs antenna arrays and signal processing)
	Time-Based	Medium (needs synchronization and timing estimation)
	Learning-Based	High (needs training, data collection, model tuning)
Efficiency	Angle-Based	Medium
	Time-Based	Low to Medium
	Learning-Based	Medium to High

2.1. Positioning in mmWave Systems

Positioning methods in mmWave systems typically fall into three categories: angle-based, time-based, and signal strength-based. Techniques like AoA and angle-of-departure (AoD) achieve high angular resolution using narrow beams and large antenna arrays, but their performance drops in multipath-dense environments. To overcome this, recent work explores advanced models that leverage diffuse scattering and tensor decomposition to extract positional information even under NLoS conditions. To improve positioning in high-speed railway scenarios, the authors [8] proposed a hybrid beamforming method for mmWave communication that tackles beam misalignment caused by rapid movement. The system uses a non-uniform analog beamforming codebook that adjusts beamwidth based on the distance between the base station and mobile relays to improve alignment along the train's path. In the digital domain, zero-forcing precoding is used to suppress inter-relay interference. Together, these techniques form a beamforming framework that stabilizes connections during cell crossings. Although it doesn't directly estimate user location, this method improves spatial consistency and makes positioning more reliable in high-mobility environments.

In [9], they discussed two-stage beam training algorithm to enhance beam alignment in multi-user millimeter-wave systems. To improve efficiency, the algorithm first removes low-quality beams with coarse signal measurements and then performs a more detailed search within the remaining candidate set. Unlike previous methods that align beams for users one at a time, this approach enables parallel beam alignment and reduces training overhead and inter-user interference. The authors [10] provide a foundational analysis of the positioning capabilities of mmWave systems, examining how wide bandwidths and highly directional antennas can support accurate localization. The paper explores key techniques such as time-of-arrival (ToA), time-difference-of-arrival (TDoA), and angle-of-arrival (AoA), comparing their effectiveness at mmWave frequencies like 28 GHz and 73 GHz. Narrower beams and larger arrays yield finer AoA estimates, which are essential for high-precision positioning. The paper also emphasizes the potential of hybrid localization methods combining angular and time-based measurements to improve robustness in real-world environments.

In [11], an angle-based positioning method was proposed that uniquely leverages diffuse scattering paths in mmWave MIMO systems to improve localization under NLoS conditions. While many existing systems discard scattered multipath components as interference, this work treats them as useful information. The authors develop a tensor decomposition algorithm based on a spherical wavefront model to estimate angular parameters from both direct and scattered paths. The method improves angular diversity and robustness in complex urban or indoor scenarios by extracting multiple incident angles from the environment. The authors [12] investigated the theoretical and practical feasibility of achieving millimeter-level positioning accuracy using mmWave systems equipped with large antenna arrays. The paper calculates the cramér-rao bounds (CRB) to establish the lower limits of error in range and position estimation across different system configurations. It considers both LoS and NLoS environments that examine the effects of prior channel knowledge and analysis about the antenna array geometry and time synchronization affect positioning accuracy. It also introduces the concept of position dilution of precision (PDOP) as a metric to evaluate the spatial configuration of anchors in relation to localization accuracy. A recent advancement in Direct Position Determination (DPD) methods is the Passive Synthetic Aperture (PSA)-DPD technique, which directly estimates the position of a signal emitter by coherently combining received pulse signals from multiple moving receivers [13]. Unlike traditional two-step methods that first estimate parameters like time delay or doppler shift before calculating position, PSA-DPD maximizes a cost function based on the combined signals, improving localization accuracy. Inspired by synthetic aperture radar, this approach uses the motion of receivers to create a virtual large antenna aperture, enhancing spatial resolution without increasing hardware complexity.

2.2. Location-Aware Beamforming

In mmWave MIMO systems, beamforming is used to reduce signal loss and keep connections focused in the right direction. Traditional beam training methods can be slow and resource-heavy, especially when users are moving or there are many users in the area. Location-aware beamforming uses information about the user's position from GPS, motion sensors, or radio signals to select and adjust the best beam direction. This makes it easier and faster to find the right beam, improving connection speed and reducing delay. In [14], the authors proposed a method to enhance indoor positioning accuracy by combining the observed time difference of arrival (OTDOA) with beamforming. OTDOA estimate the user position based on the time difference in receiving reference signals from multiple base stations. However, its accuracy is limited by quantization errors, particularly in environments where many user devices are closely spaced leading to overlapping estimated positions. To address this, the authors used beamforming techniques that rely on measuring the reference signal received power (RSRP) from the two strongest beams. These RSRP values are used to estimate the angle between the user and the serving base station. The system updates the initial OTDOA-estimated position by projecting it along this angle, which gives more accurate location.

In [15], a positioning-assisted three-dimensional (3D) beamforming system was designed to improve the reliability and efficiency of millimeter-wave communication. Traditional beamforming based on channel state information (CSI) requires high training overhead and power consumption, which becomes impractical with large antenna arrays. To address this, the authors used user positioning data to steer beams toward the estimated receiver location and reduce the need for complex channel estimation. The paper develops a closed-form expression for outage probability that considers factors such as positioning errors, transmission power link distance, and beamwidth. The paper [16] introduced a method to improve positioning accuracy in cellular MIMO systems by using Hybrid Analog and Digital Beamforming (HBF). With the growing need for high-accuracy positioning, the authors focus on a novel technique called sensing beamforming, which enhances positioning while maintaining efficient communication. This approach optimizes fisher information to adjust beam alignment and allocate power across multiple resources, including the time frequency and beam dimensions. The method starts by estimating sensing elements such as the AoA, AoD, and time of arrival (ToA) from multiple signal paths. A newton-based algorithm then refines these estimates to filter out multiple path clutters caused by NLoS conditions, making the positioning more robust.

The authors [17] proposed a method to optimize intelligent reflecting surface-assisted multiple-input single-output (IRS-assisted MISO) systems by jointly designing beamforming and IRS positioning in multi-access point environments. They introduced algorithms based on generalized benders decomposition (GBD) for beamforming, mixed-integer semidefinite programming (MISDP) for access point (AP) user pairing, and a heuristic iterative link removal (GBD-ILR) to reduce computational complexity. The paper also explores aerial IRS positioning using a successive convex approximation (SCA) method to improve performance. Finally, [18] proposed a machine learning-based fingerprint positioning method for massive MIMO systems in NLoS environments. It is considered a spatially refined beam-based channel model to improve angle resolution and extract a beam domain channel amplitude matrix as a location-related fingerprint, which includes multi-path information including amplitude, AoA, and DoA. This work introduced two machine learning models. The first is a classification-based model that categorizes user terminal (UT) fingerprints to reduce search space. The second is a regression-based model that directly estimates position coordinates and eliminates the need for similarity searches.

2.3. High accuracy positioning under high mobility

Achieving high positioning accuracy in high-mobility scenarios is a critical challenge for modern wireless systems, especially in applications such as autonomous vehicles and high-speed trains. Rapid movement, frequent handovers, and changing signal conditions require robust and responsive positioning techniques. The integration of high-accuracy positioning services with high-speed vehicles in mmWave communications was discussed in [19]. It focuses on simultaneous localization and communication (SLAC) techniques that use CSI to track vehicles in dynamic environments. While Doppler and spatial wideband effects challenge positioning accuracy, the paper shows how these effects can be used to improve vehicle tracking. By using parameters such as ToA, AoA, and Doppler shifts, the study demonstrates that high-accuracy positioning can be achieved with low-complexity algorithms that approach the cramér-rao lower bound (CRLB) performance. The work in [20] explores high-accuracy positioning for urban road traffic using 5G mmWave technology. It evaluates various positioning techniques, such as multilateration (based on time-of-arrival and signal strength) and triangulation (using angle-of-arrival), as well as hybrid methods combining both. The authors used ray-tracing simulations to evaluate performance in real-world conditions taking into account errors and network synchronization. This paper [21] focused on positioning high-speed trains (HSTs) using 5G new radio (NR) synchronization signals. The authors explore how time-of-arrival (TOA) and angle-of-departure

(AOD) measurements from 5G synchronization signals can be used to track the train's position, velocity, and acceleration in real time. Using an extended kalman filter (EKF), the train's position is estimated even at high speeds (up to 500 km/h). The results show that combining both TOA and AOD measurements provides sub-meter accuracy for over 75% of the tracking time, which is essential for mission-critical applications like autonomous trains.

In [22], they presented a real-time fusion positioning system for urban rail transit that combines ultra-wideband (UWB) and inertial measurement unit (IMU) data using an error-state kalman filter (ESKF) algorithm. The system aims to improve the accuracy of the train position in tunnels where satellite-based positioning is ineffective. The authors proposed a UWB ranging error model based on both static and dynamic measurements and validated the fusion algorithm through simulations and real-world tests. The results showed that the ESKF-based fusion system greatly improves positioning accuracy compared to standalone UWB that achieves an error of less than 0.4 meters under normal conditions. High-accuracy positioning method that combines carrier phase measurements and Bayesian estimation to enhance mobile features for positioning was presented in [23]. The authors propose a system that estimates the mobile feature using time-differential carrier phase measurements and utilizes this information along with distance and carrier phase measurements to enhance positioning accuracy. The method applies bayesian estimation to calculate the posterior probability, which is then solved using a factor graph and sum-product algorithm.

2.4. Reduce Complexity in NLoS Environment

Accurate positioning in mmWave systems with low hardware requirements requires reducing system complexity in NLoS or partially blocked scenarios without sacrificing performance. In [24], the low-complexity method was presented for positioning single-antenna users in mmWave systems using downlink (DL) signals. Unlike traditional uplink (UL) methods that rely on AoA and require more power from user devices, this approach uses AOD and adaptive beamforming from the base station. A two-step process is proposed: first, the base station sends uniform signals, and the user estimates its rough direction and feeds it back and second, the base station steers focused beams toward that direction, improving accuracy. The authors [25] proposed a low-complexity position estimation method for beyond 5G and 6G networks using angle-based localization. It combines downlink AoD and uplink AoA measurements in a massive MIMO-OFDM system. Instead of relying on complex iterative methods like gradient descent, it uses a simplified least squares (LS) approach to estimate user location with reduced computation.

Machine learning methods to improve radio positioning in NLoS environments within beamforming networks were discussed in [26]. This work compares three techniques: k-nearest neighbors (k-NN), deep neural networks (DNN), and long short-term memory networks (LSTM) for estimating user positions using signal features from beamforming transmissions. This paper [27] presents a practical approach for tracking vehicles in multipath NLoS environments using mmWave MIMO systems. The method relies on a two-stage Kalman filter. In the first stage, the system estimates a rough position by tracking signal directions from the base station. In the second stage, it improves the estimate by using motion data from the vehicle. By treating both the wireless channel and the vehicle's movement as evolving patterns over time, the system adapts well to sudden changes in the environment.

3. Research challenges in mmWave Positioning

The mmWave technologies offer significant promise in improving user positioning accuracy but face several challenges in real-world environments. This section explores the main research challenges associated with mmWave positioning systems, focusing on their impact on performance and potential solutions.

3.1. Beam Misalignment in High Mobility Environments

One of the major challenges in positioning beamforming is maintaining accurate beam alignment in high-mobility environments. When users or vehicles move rapidly, frequent changes in location cause the AoA and AoD to shift quickly. This dynamic behavior leads to beam misalignment, which degrades both communication quality and positioning accuracy. Additionally, high mobility introduces Doppler shifts that distort the received signals and complicate channel estimation. The situation is made worse in wideband systems where beam squint causes different subcarriers to experience different spatial characteristics, making it difficult to maintain consistent beamforming across the bandwidth. These factors combined make real-time low-latency beam tracking very challenging when limited by computational resources and the lack of precise real-time location information. To address beam misalignment in high-mobility environments, techniques like low-complexity direct position determination (DPD) algorithms and fisher information-based hybrid beamforming optimization can improve positioning accuracy by leveraging doppler shifts and beam squint effects. Machine learning models can further optimize beam alignment by dynamically adapting to movement patterns.

3.2. Positioning Accuracy in NLoS Scenario

Positioning accuracy in NLoS scenarios is significantly impacted by both static and mobile obstacles. In mmWave networks, static obstacles like buildings and walls block the LoS between the transmitter and receiver, leading to signal degradation. Mobile obstacles, such as moving people, are especially problematic in indoor environments. These obstructions generate multipath signals that complicate the localization process and reduce accuracy. GPS becomes unreliable in urban and indoor areas due to poor signal strength, while technologies like Li-Fi, which depend on LoS communication, are highly sensitive to any obstructions. The constant movement of users in environments like vehicles further increases the likelihood of signal blockage, making it more challenging to maintain accurate positioning. To solve positioning accuracy issues in NLoS scenarios, techniques like crowdsensing, machine learning models (k-NN, DNN, LSTM), and sensor fusion can be used to improve accuracy. Kalman filters, dynamic channel estimation, and autoregressive models help track and predict channel changes.

3.3. Positioning Overhead

Positioning overhead is also one of the major challenges in beamforming systems that rely on positioning-based beamforming schemes that use large databases for location information. These systems require significant computational resources and storage to manage large amounts of positioning data. Storing current and historical positioning information in databases consumes a lot of memory in dynamic environments with many users. Beam training setup times increase as the system needs to update beam pairs during each beacon frame. This leads to higher power consumption. Additionally, maintaining accurate positioning in environments with mobility and obstacles such as vehicles or urban areas increases the difficulty. Traditional offline learning methods struggle to adapt to environmental changes, while machine learning methods require careful management of feature selection and network complexity.

4. Conclusions

In this paper, we presented a systematic review of user positioning methods in mmWave MIMO systems and explained their role in improving beamforming in high mobility and NLoS scenarios. This paper covers angle-based, time-based, and learning-based approaches that improve beamforming accuracy, reduce overhead, and enable real-time communication. It also presented major challenges, including beam misalignment, positioning errors, and system complexity, along with solution techniques from recent research.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content..

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