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Review:

An overview of beam-tracking techniques for mmWave wireless communications[#]

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Abstract: Millimeter-wave (mmWave) communication is the key to increasing the demand for high data rates and low latency resulting from the rapid evolution of wireless communications, especially in the fifth generation (5G) of wireless communication systems and beyond. The mmWave band suffers from high path loss and obstacle blockage, significantly reducing the transmission range. Note that high-directional beams are required to perform well in the mmWave band. Hence, beam alignment is crucial for high-data-rate transmission between the transmitter (Tx) and the receiver (Rx). One of the drawbacks is getting an accurate beam alignment when the transceiver (Tx, Rx, or both) is mobile. Beam tracking plays a considerable role in 5G communications, especially in vehicular communications, due to the repeated change of the transceiver (Tx, Rx, or both) position. This work presents an overview of the different beam-tracking methods used in mmWave communications, focusing on hybrid beamforming techniques. We also compare the various tracking techniques in a recommendation table. This overview suggests that some tracking methods used in the sub-6-GHz band, such as least mean squares (LMS), recursive least squares (RLS), and Kalman filter, are unsuitable for the mmWave band (due to higher frequency and shorter coherence time), and it recommends faster tracking strategies.

Key words: Beam tracking; Millimeter wave (mmWave); Vehicle communication; 5G communication
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1 Introduction

Millimeter-wave (mmWave) communication technology is viable for fifth-generation (5G) wireless communication systems and beyond because of the growing demand for data speeds and the restricted spectrum available for the sub-6-GHz band (Samimi et al., 2016). These frequencies have an available spectrum up to 200 times larger than current cellular spectrums (Barati et al., 2015; Kokshoorn et al., 2016) and frequency bands ranging from 30 GHz to 300 GHz (Wang P et al., 2015; Wang CX et al., 2020).

mmWave frequencies suffer from high path loss and keen shadowing compared to traditional sub-6-GHz frequencies (Haghighatshoar and Caire, 2016) because they have a much smaller wavelength of about 1–10 mm (Wu S et al., 2021). This makes them susceptible to precipitation and oxygen absorption (Hur et al., 2013). Therefore, the receiver (Rx) and the transmitter (Tx) use directional beamforming (BF) to get around the channel attenuation problem (Va, 2018) and reduce interference in mmWave networks (Hashemi et al., 2018; Liu Q et al., 2022). They use large antenna arrays to obtain high gain

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with narrow beams (Wu W et al., 2019).

mmWave communications use different BF techniques, such as analog BF (ABF), digital BF (DBF), and hybrid BF (HBF), to beat the rise in power consumption and the enormous hardware cost that results from using a large array of antennas (Han C et al., 2019). As seen in Fig. S1, ABF uses only one radio frequency (RF) chain with phase shifters to form the beams. To compensate for the large amount of channel attenuation, ABF uses directivity gains and spatial division to send the signal to different areas. DBF allows enormous flexibility in molding the transmitted beams. Because many antennas operate in a considerable bandwidth, DBF requires one RF chain for each antenna element, raising the cost and complexity. Using the channel state information (CSI) of an active channel with a tiny dimension, DBF lowers the intrasector interference and provides a gain (El Ayach et al., 2014). As seen in Fig. S2, the HBF technology combines ABF and DBF into a single structure. ABF is produced in HBF by connecting a series of phase shifters for every RF chain (Perfecto et al., 2017). HBF gives a reasonable solution for both hardware complexity and performance gain (Mavromatis et al., 2017). For the mmWave, the channels' sparseness reduces the design's HBF complexity. The capacity to create beam patterns from the sum of two or more RF chain BF vectors is the primary benefit of HBF structures (Tagliaferri et al., 2021). The BF and precoding steps improve the mmWave spectral efficiency (Ciaramitaro et al., 2023). This paper focuses on HBF due to its flexibility and low complexity. Subsequently, BF with precoding (multiple data streams) improves the mmWave spectral efficiency (Ali et al., 2020). Beam alignment is necessary for fast-moving states because the angular spread of each path is very small. There are other works of literature illustrating the beam alignment problem in different scenarios (Wang Y et al., 2019; Satyanarayana et al., 2019), sensor-assisted beam alignment (Mizmizi et al., 2022; Shokri-Ghadikolaei et al., 2015), radar-assisted beam alignment (Wang J et al., 2009), machine learning (ML) beam alignment (Jog et al., 2019), and map-based beam alignment (Torkzaban et al., 2022). Still, mmWave communication that uses ABF and HBF has sampling subspace limits because only a limited number of RF chains are available for use by the many antennas present in the network. Because of frequent outages brought on by mobility and blockage, mmWave networks are notorious for their low dependability (Palacios et al., 2017). However, the primary obstacle in channel estimation and tracking for highly mobile mmWave applications is the extensive training overhead time needed due to the use of several antennas at the Tx and Rx ends (Mollel et al., 2021). When the Tx and Rx beams are perfectly aligned, communication with narrow beams can be possible. Beam alignment, also known as beam training and beam search (Heath et al., 2016), is needed to form narrow, aligned beams between the Tx and Rx, and set up a reliable communication link in mmWave systems. It is a process to identify the optimal beam for the Tx and Rx that gains the maximum received signal strength (RSS). In other words, beam tracking involves locating the necessary beam to link the transceiver equipment and minimizing the first access latency. During the BF alignment, the Tx transmits training packets in predefined beam directions (beams). Beam misalignment can reduce the throughput from multiple megabits per second (Mbps) to a few hundred gigabits per second (Gbps) (Hassan et al., 2020). If both the Tx and Rx are mobile, you can use beam tracking at the Tx or Rx ends.

mmWaves are the key to 5G communications and beyond because of their wide bandwidth, which makes them a viable solution for high-data-rate demands in wireless communications. In conventional beam-training methods, there is a trade-off between the achievable data rate and the beam training overhead. 5G and future 6G systems can achieve data throughput requirements while minimizing beam-training overhead using artificial intelligence (AI)/ML in the beam-training approach (Narengerile et al., 2022). This section reviews and analyzes recent work on beam-tracking techniques for mmWave wireless communications.

1.1 Ray tracing

This method includes a beam approach for beam tracking. We transmit a beam from the Tx in all directions to acquire the channel response, allowing us to accurately capture a whole 2D or 3D picture. This method uses various techniques. In a previous work (Han C et al., 2019), an approach for tracking the dynamic beam direction of a single path using angular velocity-based recursive beam tracking (AVRBT) was presented. This algorithm could improve the recursive beam and channel tracking (RBCT) algorithm. This is due to the unsuitability of estimating the angle of arrival (AoA) under dynamic circumstances. Therefore, adjusting the estimator from the AoA to the rate of change in AoA is necessary. The updated algorithm is significantly more flexible for higher angular speeds and can achieve higher tracking accuracy. The authors then developed a two-path recursive beam tracking (TPRBT) algorithm in specific scenarios. According to simulations, the TPRBT method achieved rapid tracking speed, high tracking accuracy, and minimal pilot overhead by solving the tracking problem induced by interference between two pathways.

Palacios et al. (2017) discussed beam training and tracking in directed mobile mmWave networks. The authors developed two techniques—a probabilistic method for beam tracking and a deterministic method for beam training—to swiftly ascertain the optimal transmit/receive directions at the Tx and Rx sides. The goal of the study was to optimize the communication rate over time. Based on the simulation results, rates can increase by 0.4–1.5 times while using simpler technology.

Using the dynamic model for the AoA and the angle of departure (AoD) for the mobility scenario in mmWave band communications, Bae et al. (2017) suggested a beam-tracking technique. The study indicated that monitoring the time-varying AoD requires two training beams. The numerical findings showed that the suggested beam-tracking technique outperforms the traditional one with minimal overhead training.

An auxiliary beam pair (ABP) design that offers high-accuracy channel AoD and AoA estimations for mmWave multiple-input multiple-output (MIMO) systems was earlier presented (Zhu et al., 2017). In that study, the estimated AoD and AoA enabled a directional process, while hybrid precoding allowed for spatial multiplexing of the data channel. The suggested approach obtained excellent angle estimation performance under various channel circumstances and signal-to-noise ratio (SNR) levels.

1.2 Adaptive filter

This method uses different types of adaptive filters for beam tracking. It is more efficient when only partial state observations are available in the mobile systems. The least mean squares (LMS) and normalized least mean squares (NLMS) algorithms for mmWave channel tracking have been examined and assessed (Asi et al., 2021). These adaptive filters typically trade off accuracy and convergence. The outcomes demonstrated that, although the LMS method is one of the simplest, it requires large numbers to converge quickly and provide a stable system. The NLMS algorithm explicitly implements the LMS algorithm when selecting an average step size, leading to a more stable and convergent adaptive process. The research found that the current step, or the gradient decline size, dramatically affects the quality of the tracking results, as measured by the mean squared error (MSE).

Using adaptive filters, Al-Ibadi and Mahmood (2022) looked at a multipath channel packet-tracking problem in an extensive mmWave MIMO communication system. The main focus was on how well the recursive least squares (RLS) and LMS algorithms outperformed the extended Kalman filter (EKF) when a few strong paths or a single wireless channel line dominated the line of sight (LOS). The study's conclusions suggest that BF systems in the mmWave frequencies should consider several paths rather than just one primary LOS channel. Researchers also have examined low-complexity channel and packet-tracking algorithms for mmWave communications (Yapıcı, 2018). Yapici used the LMS and bidirectional LMS (Bi-LMS) algorithms for mobile mmWave transmission. In this case, the unknown AoA and AoD changed the channel measurement in a way that was not linear. The simulation results showed that LMS works better than the well-known EKF method for tracking mmWave beams when AoA/AoD and channel gains are set up incorrectly (i.e., using noisy channel estimations). Bi-LMS did better than both LMS and EKF in MSE performance, which suggests that it could be used as a channel-tracking algorithm in situations where mobile mmWave transmission is needed. The study also showed that the LMS and Bi-LMS algorithms are better than EKF because they converge faster, have higher SNR, and are less likely to break when antenna array sizes are not perfect.

Using the modified ABP structure, a low-complexity beam-tracking technique for mobile mmWave systems using BF architectures, EKF, and ABP was presented in Kim et al. (2019)—the suggested approach enhanced the angle estimation performance in a low SNR area. By using the EKF and the ABP scaling ratio as the EKF's scaling function, the researchers successfully reduced the tracking MSE.

A tracking algorithm based on the Kalman filter (KF) and a method to detect sudden change (such as occlusion) has been previously proposed (Lim et al., 2021). The suggested method maintains excellent tracking accuracy at low SNR and experimental loads. According to the simulation findings, if the AoDs and the AoAs are very quick, the tracking algorithm and the abrupt change detection approach perform effectively in the suggested framework. Furthermore, acquisition error deteriorates the performance of the proposed techniques, permitting expansions by taking tracking, rapid change detection, and channel acquisition into account simultaneously.

1.3 ML approach

Recently, advanced ML and deep learning (DL) techniques have been used widely to solve wireless telecommunication problems that are hard to solve with heuristic or traditional optimization techniques. By designing robust and intelligent methods based on ML/DL, beam-based mmWave communications can achieve high performance and transmission stability. Reinforcement learning (RL), unsupervised learning (USL), and supervised learning (SL) are the three general categories into which learning models fall (Goodfellow and Bengio, 2016). For USL models that use sample data correlation, prelabeling is not needed. But for training deep-layered neural networks (NNs) with SL methods, ground truth labeling and fixed-size input are needed (Elbir and Mishra, 2020; Huang et al., 2020).

RL, on the other hand, is flexible and adapts to an agent's interaction with the environment by learning from past actions and the associated reward or punishment (Shen et al., 2021). ML/DL shows excellent outcomes in many applications, including mmWave, satellite, and unmanned aerial vehicle (UAV) communications. It is more suited for applications because of its outstanding capacity to learn representations in real-world settings. ML uses the UAV for several civilian applications and various other uses. However, body-centric communication systems also use ML/DL to enhance their capabilities (Khan MM et al., 2022).

Wang Y et al. (2019) suggested using ML classification and previous beam-training data to determine the best beam pair index using the receiver (Rx) vehicle's and its surrounding vehicles' positions and kinds (situational awareness). Using custom features that capture situational awareness in several locations, they structured mmWave beam selection as a multiclass classification issue. Thereafter, they thoroughly analyzed the various situational awareness levels and categorization models.

The track-finding algorithm's development and implementation on the publicly accessible dataset created for the Kaggle TrackML challenge was the main emphasis of the authors in another work (Lad, 2023). The preliminary findings relating to purity measures and track rebuilding efficiency were presented and discussed. The authors set out to create a practical graph neural network (GNN)-based method to facilitate quick-track discovery in future particle detector experiments with high brightness.

To achieve high resolution in tracking and vertex reconstruction, previous research suggested using GNN to track reconstruction using beam dump experiments (Lu et al., 2023). The results showed that the GNN technique works much better than the traditional approach in a typical three-track situation with the visible decay mode, boosting the three-track reconstruction efficiency by up to 88% in the low mass zone.

An approach to optimize the weighted sum rate (WSR) of a reconfigurable intelligent surface (RIS)-aided downlink multiuser multiple-input single-output (MISO) system has been presented earlier (Jin et al., 2024). The algorithm relies on weighted minimum MSE optimization and power iteration. The researchers created a DL approach with trainable variables and GNNs to accelerate the convergence of the suggested method and further enhance its performance.

A previous work talked about an autoencoder (AE) NN-based intelligent hybrid beamforming (HB) design approach (Tao et al., 2020) to solve the nonconvex optimization problem of designing digital and analog beamformers together, which is caused by the hardware limitations of analog shifter arrays. The authors solved the initial nonconvex optimization issue and translated it into an NN training process by mapping the HB system to an AE NN. The NN's training procedure might automatically create the beamformer and the combiner. Additionally, they covered the selection of hyperparameters and offered guidelines for the HB design of the AE NN.

Principal component analysis (PCA) can efficiently estimate the eigenvalues and eigenvectors of a high-dimensional dataset. A method for evaluating and tracking the channel parameters for 2D MIMO systems with uniform planar arrays (UPAs) of antennas has been proposed (Wang A et al., 2019). Numerical simulations confirm that the suggested technique, which applies the adaptive PCA method, has minimal complexity and excellent accuracy for tracking and estimating. The problem of joint user–cell association and the selection of several beams to maximize the aggregate network capacity has been addressed (Elsayed et al., 2021). The paper proposed three ML-based algorithms: Q-learning, transfer Q-learning (TQL), and the best signal-to-interference-plus-noise (SINR) association with density-based spatial clustering of applications with noise (BSDC) algorithms. In the mobility scenario, TQL and Q-learning outperformed BSDC by 12% in terms of rate. Q-learning and BSDC performed better in stationary circumstances than TQL; however, TQL achieved a roughly 29% speedup in convergence.

Beam tracking is essential in modern wireless communications, particularly in high-frequency bands such as the mmWave and terahertz frequencies. The practical implementation of beam tracking necessitates several requirements and encounters numerous obstacles to providing reliable and effective communication. These challenges include high mobility, latency constraints, channel dynamics and blockages, hardware limitations, power consumption, complexity in multiple scenarios, and environmental sensitivity. Therefore, beam tracking needs advanced algorithms that can quickly adapt to changing environments, leveraging ML and RL to predict and adjust beams dynamically. Moreover, the demand for techniques that minimize the time required for beam adjustments, such as parallel processing or faster hardware implementations, is essential for real-time applications.

In summary, effective beam tracking in practical scenarios involves a combination of advanced algorithms, low-latency processing, efficient power management, and robust hardware solutions. Addressing these challenges is critical to enabling the next generation of high-speed, reliable wireless communication systems. In this paper, we examine the beam-tracking techniques used in real-world scenarios and elucidate the benefits and drawbacks of each method, providing a foundation for future research to comprehend beam tracking in mmWave and terahertz communications.

The main points covered in this paper can be summarized as follows:

1. This study comprehensively reviews different beam-tracking techniques used in mmWave communications and compares various beam-tracking methods in terms of performance and suitability for mmWave communications. Further, it evaluates conventional tracking techniques (LMS, RLS, and KF) and explains why they are less effective in the mmWave band due to higher frequency and shorter coherence time.

2. This study recommends improved tracking strategies better suited for mmWave vehicular communications.

Fig. S3 demonstrates the general paper structure.

2 Challenges for mmWave bands in different scenarios

mmWave bands offer significant advantages for modern wireless communication systems because they support high data rates, a large bandwidth, and reduced congestion. However, several challenges are associated with the use of mmWave bands in different application scenarios. The unique features of mmWave signals, such as their power loss in free space, easy absorption by the atmosphere, and limited travel distance, primarily cause these problems. Below is a list of challenges associated with mmWave bands across various application scenarios.

2.1 High path loss

One finds a significant propagation loss when comparing mmWave communications to other communication systems with lower carrier frequencies. Rain attenuation and atmospheric and molecular absorption features limit the mmWave communication range (Niu et al., 2015). The wavelength's reciprocal square root influences the rise in accessible space route loss. When using isotropic propagation, the mmWave frequencies cause substantial route losses and reduced communication range. The increasing diffraction and penetration losses make the reflected and diffused signals more critical. Permeation losses in building materials range from a few decibels (dB) to >40 dB (Mohamed et al., 2019). In addition, there is a frequency-dependent absorption by the atmosphere; for example, the oxygen absorption in the 60 GHz band peaks at 15–30 dB/km. However, raindrops scatter radio signals because their size resembles the size of radio wavelengths (Khan F and Pi, 2011). Rappaport et al. (2013) carried out a 28 GHz urban propagation study in New York City, with a range of 75–125 m between the transmitter (Tx) and the receiver (Rx). The findings indicated that out of all the measurements made in New York City, the LOS path loss exponent was 2.55. In the non-LOS (NLOS) scenario, the average route loss exponent was 5.76. Additionally, they carried out an outage study in Manhattan, New York, which involved measuring propagation at 28 GHz using steerable beam antennas for outdoor cellular communications in New York City. Most failures occurred at distances of >200 m from the TX, and 57% of the sites had obstruction-related outages. Rx obtained a signal in all situations within 200 m distance. Rappaport et al. (2012) carried out 38 GHz cellular propagation measurements at the main campus of the University of Texas at Austin, Texas. For the 25 dBi horn antennas, the measured LOS path loss exponent was 2.30, while the NLOS path loss exponent was 3.86. A lower antenna gain has been demonstrated to result in a more extensive delay in the root mean squares (RMS) value. An outage study revealed that lower-altitude bases provide superior close-in coverage, with the most outages occurring at distances >200 m from the base stations. Additionally, the results indicated that the AoAs are primarily found when Rx azimuth angle falls between $-20°$ and $+20°$ with reference to the foresight.

2.2 Sensitivity to blockage

When faced with obstructions much bigger than the wave's wavelength, electromagnetic waves are weaker at diffraction around these obstacles (Niu et al., 2015). Because mmWave signals have a tiny wavelength, they cannot pass through most solid objects. Thus, connections operating in the 60 GHz band are susceptible to obstruction by objects such as people and furniture. For instance, a human obstruction costs the connection budget 20–30 dB (Singh et al., 2009). Certain materials, such as those used for constructing external brick walls, significantly reduce the penetration. The development of small cells and dispersed interior antennas is driven by the wall insulation effects, which inhibit outside base stations from covering indoor users (Giordani et al., 2017). Therefore, the channel may appear or vanish quickly depending on the movement of reflectors and barriers and changes in the handset's orientation in relation to a body or a hand. According to recent research, path loss in LOS propagation can rise to 20 dB/10 years with increasing Tx and Rx distances. However, it can also be reduced to 40 dB/10 years with an extra blockage loss of 15 dB for nonvisibility (Mohamed et al., 2019).

2.3 Beam directivity

Most transmissions in vehicle-to-everything (V2X) communication technologies today are omnidirectional, although BF or other directed broadcasts can be carried out if a physical link has been established between the nodes. However, as previously established, isotropic transmission at mmWave frequencies results in significant path loss. Typically, BF gain directs mmWave lines to address this issue. Nonetheless, there is a substantial chance of deafness because of beam misalignment in directional connections, as they may need exact alignment of the Tx and Rx beams (Giordani et al., 2017). Several experiments have determined mmWaves' properties, the effects of high free space propagation losses at these frequencies and the high noise levels due to the larger bandwidths. The outcome needs higher SNRs unless directional antenna arrays, BF technology, and small-cell deployment are used (Mohamed et al., 2019). It is possible to build electronically steerable antenna arrays as circuit board metal patterns. The antenna array then electronically directs its beam in any direction, achieving a high gain in one direction while providing a meager gain in all other directions by adjusting the phase of the signal broadcast by each antenna element. Several beam-training algorithms have been developed to shorten the necessary beam-training period to get the Tx and Rx to direct their beams toward each other (Niu et al., 2015; Hassan et al., 2020; Mollel et al., 2021).

2.4 Atmospheric absorption

mmWave signals are highly susceptible to atmospheric absorption, especially by rain, fog, snow, and water vapor. Weather conditions affect mmWave communication more than lower frequency bands, as absorption increases with frequency. Weather phenomena such as rain and fog can severely degrade the signal strength, leading to increased attenuation and higher error rates, especially in outdoor environments (Banday et al., 2019). In some cases, it can result in a total loss of communication. Adaptive modulation and coding schemes, which adjust the data transmission rate based on environmental conditions, can help mitigate some of these effects. Using hybrid systems that combine mmWaves with lower-frequency bands (e.g., sub-6 GHz) can also ensure more reliable communication during adverse weather (Han C and Duan, 2019).

2.5 Limited coverage range

The high path loss also limits the effective coverage range of mmWave signals. Unlike lower frequency bands (e.g., sub-6 GHz), which can travel further with fewer obstacles, mmWave signals are much more sensitive to distance. In urban or large rural environments, mmWave signals may only cover small distances, requiring the deployment of many small cells or relay stations to maintain seamless coverage (Rappaport et al., 2013). This increases both operational and capital expenditures. Dense cell deployment, small cell networks, and technologies such as mmWave BF and massive MIMO are key strategies to extend coverage and improve range (Zhang L et al., 2019).

2.6 Multipath propagation

Multipath propagation refers to the phenomenon where a transmitted signal arrives at Rx via multiple paths, typically due to reflections from objects such as buildings, vehicles, or the ground. At mmWave frequencies, multipath can occur more frequently due to the high sensitivity of the signal to reflectors. In specific scenarios such as BF and spatial diversity, multipath can be helpful. However, multipath can also result in interference, mainly when signals arrive out of phase, leading to destructive interference. This can result in signal degradation, especially in dense urban environments with many reflective surfaces (Rappaport et al., 2017). Massive MIMO, which uses large antenna arrays to direct and focus beams more precisely, can help manage multipath interference. Additionally, advanced signal-processing techniques, including equalization and interference cancellation, can be used to improve the signal quality (Molisch et al., 2016).

2.7 LOS dependency

mmWave communication typically requires a clear LOS between the Tx and Rx. Due to their high frequency, mmWaves do not penetrate obstacles easily and are more susceptible to attenuation and blockage in NLOS situations. Maintaining LOS in practical urban or indoor environments can be difficult due to walls, floors, or other obstructions. This results in decreased signal quality or even complete loss of connection in certain circumstances. Advanced BF and relaying techniques can overcome the LOS requirement and establish NLOS communication by reflecting the signal via various paths. In some cases, hybrid systems that combine mmWave with sub-6 GHz frequencies can provide fallback coverage in NLOS scenarios (Rangan et al., 2014).

3 Fundamental principles of the beam-tracking technique

This section explains the fundamental principles of the beam-tracking technique. These principles form the foundation for designing and implementing robust beam-tracking systems in modern wireless networks, which are as follows:

1. Beam alignment. The alignment of the Tx and Rx beams to maximize the effective channel gain necessitates real-time adjustments due to mobility, blockage, or environmental dynamics.

2. Direction of arrival (DoA) estimation. It determines the angle at which the signal arrives at Rx. Accurate DoA estimation underpins efficient beam alignment.

3. BF codebooks. It defines a set of predesigned beam patterns that cover the spatial area. Beam tracking often involves searching for the optimal beam pattern within this codebook. Larger codebooks provide finer resolution but require more computation and search time.

4. Feedback mechanisms. It involves two types: closed-loop systems and open-loop systems. In

closed-loop systems, Rx reports the optimal beam indices or other metrics to the Tx. In open-loop systems, Rx predicts or preconfigures beams without real-time feedback. Feedback increases the overhead but improves the tracking precision.

5. Adaptive algorithms. User mobility, environmental changes, or obstacles trigger beam adaptation. Methods such as HBF combine ABF and DBF techniques for greater adaptability.

Before explaining the beam-tracking techniques, we must illustrate the problem. Beam tracking in mmWave for vehicular communications presents a unique challenge due to the high level of movement and the rapidly changing environment. The vehicle's movement increases tracking errors, leading to tracking failures. The vehicular communications' short coherence time imposes stringent time constraints on beam tracking at mmWave frequencies. The beam-tracking problem for mmWave bands can be expressed as an optimization problem in the following way:

$$\begin{gathered}\min_{\theta} |e(\hat{\theta})|^2 \\ \text{s.t. } \frac{-\theta_{3\mathrm{dB}}}{2} \leq \hat{\theta} \leq \frac{\theta_{3\mathrm{dB}}}{2}, \\ T_{\mathrm{c}} \geq \tau,\end{gathered}$$

where $\hat{\theta}$ means the estimated angle, T_{c} means the coherence time, and τ represents the user's required time to be within $\theta_{3\mathrm{dB}}$. $e(\hat{\theta}) = |y(\theta) - \hat{y}(\hat{\theta})|$, $e(\hat{\theta})$ refers to the error of tracking, $y(\theta)$ indicates the actual measurements or the current observation, and $\hat{y}(\hat{\theta})$ means the predicted measurements using the model $(A \times x + n)$. Fig. S4 illustrates the $\theta_{3\mathrm{dB}}$ constraint.

4 Beam-tracking techniques

Beam tracking, a CSI estimation technique, maintains beam alignment over time in high-mobility scenarios. It considers the previous information, whereby the CSI estimation updates recursively by using the prior and present estimated CSI (Han C et al., 2019; Anooz and Pourrostam, 2023). In practical MIMO channels, there is a time correlation between the channel realizations, and when the channel is temporally correlated, the current CSI depends on the prior CSI. Note that the prior CSI enhances the quality of the current channel estimation with a high temporal correlation.

Because frequent beam training causes massive overhead, beam-tracking techniques reduce the overhead of beam training by using only a small number of training beams to serve the user (Lim et al., 2020). For highly dynamic environments, we still need to enhance the quality and robustness of beam tracking. Therefore, we summarize the present beam-tracking techniques and split them into two categories and four subcategories, as presented in Fig. S5.

4.1 Model-based schemes

Model-based schemes for beam tracking involve using a mathematical model of the wireless channel to predict the optimal direction for the antenna beam based on information about the location and movement of Rx. One approach to model-based beam tracking is to use a physical model of the wireless channel, considering factors such as the location and orientation of the Tx and Rx, the frequency of the wireless signal, and the user's velocity. Another approach is to use a statistical model of the wireless channel based on the signal strength and quality measurements at different points in the environment. The structure of the tracking slot is shown in Fig. S6. In this section, we review several beam-tracking strategies. As presented earlier (Asi et al., 2021), the model is divided into ray tracing and adaptive filter.

4.1.1 Ray-tracing scenarios

This scenario includes several Txs and Rxs distributed in a specific outdoor or indoor environment. In this scenario, Txs and Rxs are equipped with omni or quasi-omni antennas, and the simulation output includes channel parameters such as AoA, AoD, and path. The Tx transmits a beam in all directions to acquire the channel response, enabling accurate capture of a 2D or 3D picture. Although these beams go in a straight path, they can also pass through various environmental materials or diffract, reflect, or scatter. Note that these beams are tracked to determine whether they can reach Rx. The disadvantage of these methods is their high complexity (Asi et al., 2021). There are different methods, and Table S1 recaps these techniques.

1. Beam tracking based on observation

An observation method is a feedback-based approach for beam tracking, in which Rx feeds the estimated BF vector to the Tx (Bae et al., 2017). Consequently, the Tx updates its BF vector based on the feedback. This method is mentioned in Table S2. The observation method is straightforward and requires minimal complexity for implementation. However, it requires feedback from Rx, increasing the system overhead. It is also sensitive to feedback delay and quantization errors, which can affect the accuracy of the beam tracking. Therefore, the observation method is more suitable for scenarios where the channel changes slowly, with minor feedback delays and quantization errors. We use the multistage observation method for scenarios where the channel changes rapidly, and the feedback delay and quantization errors are significant. This method uses multiple stages to enhance the accuracy and robustness of beam tracking using a combination of observation-based and feedback-based approaches. Other than that, the main drawback of multistage channel estimation is the error propagation problem. If the estimated AoD/AoA pair is erroneous in any given period, it will undoubtedly lead to an error in every posterior estimation period. Furthermore, compounding this problem, a reduced SNR will result from the directivity gain loss for the beam patterns used at the early time (Kokshoorn et al., 2016).

2. ABP-based beam tracking

The ABP algorithm can be used as a beam-tracking technique to catch the angle variations and repair the steering direction beams toward it. It is used in literature by assuming a single-path channel or adopting single and multiple channels (Haykin, 2013; Zhu et al., 2017). Note that the ABP is a pair of beams used to estimate the AoA of the incoming signal and update the BF direction accordingly. The ABP comprises a primary beam and a secondary beam, with the former serving for data transmission and the latter for beam tracking.

There are two types of ABPs: auxiliary-full (AF) and auxiliary-half (AH). Afterward, AH divides a uniform linear array (ULA) equally, forming two beams simultaneously at the Tx and the AoA for device detection. The discovery process generates the antenna's scan sequences. Moreover, AF scans the same sector twice in a time-division fashion using the entire antenna array to create one beam at a time at Rx and Tx. The AH uses two synchronous directional beams, while AF uses one at each slot time to search the region depending on the generated scan sequences (Nawaz and Hassan, 2020; Nawaz et al., 2020). The steps of this method are listed in Table S3.

3. Beam tracking using adaptive tracking with stochastic control (ATSC)

ATSC adapts its tracking rate to the average angular change. Assume an mmWave communication system in which both the Txs and Rxs use ABF and are outfitted with ULAs with omnidirectional antennas and a single RF chain (Liu C et al., 2021). The steps of this method are listed in Table S4. Fig. S6 shows the tracking slot structure.

4. Sequential adaptive (SA) and parallel adaptive (PA) beam-training methods

The SA and PA beam-training methods are distinct approaches for adaptive beam training in wireless communication systems. The SA approach tracks a single optimal beam direction, while the PA tracks multiple optimal beam directions simultaneously. Both methods adjust the beam direction based on the RSS until they determine the optimal beam direction(s). On the other hand, PA can track multiple desired signals more efficiently than SA by adapting multiple beams in parallel. However, it requires more computational resources and hardware (De Donno et al., 2017). The steps of these methods are listed in Table S5.

4.1.2 Adaptive filter schemes

The adaptive filter comes in handy when the signal's or the channel's unexpected dynamics shift over time. Several algorithms, such as LMS and RLS (Asi et al., 2021), regulate how the adaptive filter functions. When random problems are present and only partial observations are available, the filtering challenge involves estimating the internal states of the mobile systems (Dehkordi et al., 2021). Table S6 explains some of these techniques.

1. RLS algorithm

Beam tracking uses the RLS algorithm, which uses the least squares method. The main feature of RLS is that its convergence rate is faster than that of the standard LMS algorithm. However, RLS's excellent performance fails to handle sudden changes in the state, necessitating a reset to track the beam again. The RLS algorithm is quite costly in terms of computational complexity (Haykin, 2013). The forgetting factor (λ)'s parameter selection influences the algorithm's stability and convergence (Al-Ibadi and Mahmood, 2022). Table S7 explains the basic RLS algorithm.

2. LMS algorithm

The LMS algorithm, sometimes called a stochastic gradient-based algorithm, is a type of adaptive filter that converges to the best Wiener solution using the gradient vectors of the filter weights. People commonly use it due to its ease of computation. Therefore, it is a good benchmark for judging all other adaptive filter algorithms. Further, its key qualities include ease of coding and resilience. The disadvantage of the LMS algorithm is that it is unsuitable for unstable systems because it has a fixed step size (Asi et al., 2021). Since the input vector $\boldsymbol{x}_k$ drives the updating of the LMS algorithm's weights, high values of $\boldsymbol{x}_k$ increase the likelihood of a gradient noise amplification issue. In addition, the LMS algorithm's convergence is somewhat sluggish (Abualhayja'a and Hussein, 2021). The LMS algorithm is often used in nonstationary environments because of its ease of use, resilience, and ability to track changes effectively. Even though the RLS method is more accurate in stationary conditions, it might become excessively complicated and unstable when the environment changes quickly. Although the trade-offs between both algorithms vary depending on the application, LMS is usually the superior option for nonstationary systems due to its smoother adaptability and lower computational burden (Haykin, 2013). Table S8 shows the basic LMS algorithm.

The NLMS technique solves the gradient noise amplification problem, considerably boosting convergence rates. By making the step size adaptive to the status of the vector, the NLMS can work in a dynamic environment (unstable) as well as a fixed domain (static). The NLMS method's step size changes over time compared to the LMS algorithm. The weight corrector term is normalized based on the input vector weight's update norm (Abualhayja'a and Hussein, 2021):

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \frac{\mu}{||\boldsymbol{x}_k||^2} \boldsymbol{e}_k^{\mathrm{T}} \frac{\partial \boldsymbol{h}(\boldsymbol{x}_k)}{\partial \boldsymbol{x}_k}, \tag{1}$$

where $\boldsymbol{e}_k$ means the error for time k, μ denotes the AF step size, and $||\boldsymbol{x}_k||^2$ indicates the normalized norm vector of $\boldsymbol{x}_k$.

Another form of the LMS algorithm is the Bi-LMS algorithm, which uses forward and backward LMS. As long as there is no sudden change in the channel characteristics, each new channel estimation and beam alignment is considered an additional initialization after the tracking period. This plan makes it possible to use the Bi-LMS algorithm, which is provided as follows (Yapıcı, 2018):

$$\hat{\boldsymbol{x}}_{k+1}^{\mathrm{F}} = \hat{\boldsymbol{x}}_k^{\mathrm{F}} + 2\mu \boldsymbol{e}_k^{\mathrm{T}} \frac{\partial \boldsymbol{h}(\hat{\boldsymbol{x}}_k^{\mathrm{F}})}{\partial \boldsymbol{x}_k^{\mathrm{F}}}, \tag{2}$$

$$\hat{\boldsymbol{x}}_{k+1}^{\mathrm{B}} = \hat{\boldsymbol{x}}_k^{\mathrm{B}} + 2\mu \boldsymbol{e}_k^{\mathrm{T}} \frac{\partial \boldsymbol{h}(\hat{\boldsymbol{x}}_k^{\mathrm{B}})}{\partial \boldsymbol{x}_k^{\mathrm{B}}}, \tag{3}$$

where $\hat{\boldsymbol{x}}_{k+1}^{\mathrm{F}}$ and $\hat{\boldsymbol{x}}_{k+1}^{\mathrm{B}}$ denote the forward and backward guesses of the unknown parameter vector $\boldsymbol{x}_k$, respectively. Hence, the final guess is

$$\hat{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_k^{\mathrm{F}} + \hat{\boldsymbol{x}}_k^{\mathrm{B}}. \tag{4}$$

We cannot use the Bi-LMS algorithm for beam tracking to determine whether we need to update the BF directions. This is because backward adjustments require the starting value of the unknown parameter vector at the end of the tracking interval. However, the innovative tracking duration can improve the estimations.

3. KF algorithm

The KF method is a recursive, linear, unbiased, and less-error-variance technique that finds the best estimate of the unknown state of a linear dynamic system from noisy data collected at discrete real-time intervals (Zhang Z, 1997). It is a set of mathematical formulas that provides an active recursive computing rate to minimize the MSE while estimating the state of an operation. KF assumes that the density at every step of time is Gaussian. Therefore, it is characterized by two parameters: the mean and the covariance (Ristic et al., 2004).

The KF algorithm has critical drawbacks in dynamic models, whereby it needs information, such as the model of transition of state, the process covariance, and observation noise, for these models (Kim et al., 2020). The advantages of the KF algorithm are that it estimates the dynamic system state, even if its precise form is unknown, supporting estimations of past, present, and even future cases (Zhang C et al., 2016). Moreover, due to its extremely low computing complexity, it has drawn much interest in the mmWave field (Liu G et al., 2020). Table S9 presents the summary of the KF algorithm.

The choice of the supposed covariance matrices $\boldsymbol{Q}$, $\boldsymbol{R}$, and $\boldsymbol{P}$ affects the performance of the estimation of a KF. Note that the selection of $\boldsymbol{P}$ affects the initial filter convergence. For simplicity, we often arbitrarily initialize the $\boldsymbol{P}$ effect to an identity matrix despite its unimportance. Even though their impacts are far more significant, $\boldsymbol{Q}$ and $\boldsymbol{R}$ affect the total performance of the filter; the output (measurement) equations and the state prediction equations are weighed differently by the noise covariances $\boldsymbol{Q}$ and $\boldsymbol{R}$ (Rhudy et al., 2017).

4. EKF algorithm

Nonlinear systems use the EKF for state estimation. The advantages of the EKF are that it has low complexity and good performance if the nonlinearity is moderate (Va et al., 2016). To use the EKF method for beam tracking in vehicular communications, the state evaluation model and the observation expression are necessary components of the system model (Shaham et al., 2020). Furthermore, the EKF uses the linearization approach (Montella, 2011) to rely on the linear KF to roughly convert the system filtering problem from a nonlinear problem to a linear filtering one.

EKF aims to estimate the channel parameters using the measurement model iteratively and the observed signal. This strategy's computational complexity is excessive, necessitating numerous directed beams to perform omnidirectional scanning on the channel throughout the iterative process. It then adjusts the beam pointing depending on the scanning results to ensure the correctness of the measured value (Liu G et al., 2020). The EKF algorithm follows Table S10 (Liu F et al., 2019).

5. EKF with modified ABP

In this method, the choice of auxiliary beams and their associated measurement noise covariances R1 and R2 can significantly affect the tracking accuracy. Generally, we should choose the auxiliary beams to obtain additional information about those beam parameters that the primary measurement alone cannot provide. Furthermore, their noise covariances should be set to reasonable values based on the expected measurement accuracy (Kim et al., 2019). The summary of this technique is presented in Table S11.

6. Particle filter (PF)

PF, also known as the Monte Carlo (MC) method, is a sequential MC algorithm that solves recursive Bayesian integrals. The advantages of PF are its simplicity, flexibility, and ease of dealing with non-Gaussian and multimodal system models. Moreover, PF does sequential MC estimation using a point mass (particle) representation of the probability densities (Ristic et al., 2004).

The beam tracking using a PF estimates the CSI (gain and angle) using the received signal z_k for every time slot. The overhead and increased complexity of massive MIMO systems and high-mobility channels are the drawbacks of PFs. Note that the PF is better than the KF methods because it works well in nonlinear cases if the nonlinearity is high (Dehkordi et al., 2021). Table S12 illustrates the steps of the PF algorithm.

7. Unscented KF (UKF) algorithm

A UKF spreads sigma points. The sigma points accurately represent the mean and the covariance for the state distribution. They propagate through a nonlinear system, and their propagation calculates the posterior mean and covariance. We accomplish this by using the unscented transformation (UT). The UT computes the random variable statistics, which succumb to a nonlinear change through function evaluations (Pasek and Kaniewski, 2020).

Furthermore, because the UT chooses the sigma points deterministically, it differs from the MC estimate. This method differs from the EKF algorithm, which follows a linear model. The advantages of UKF are that it is easy to implement, is more precise, and uses the same order of calculations. Furthermore, it does not require the system model's gradients (Gustafsson and Hendeby, 2012). Table S13 explains the UKF algorithm.

8. UKF with improved ABP (Liu G et al., 2020)

In this method, the UKF first estimates the AoA/AoD, after which the improved ABP algorithm modifies the UKF algorithm and then the AoA/AoD. This technique efficiently increases the robustness of the same kind of algorithm while reducing the estimation error significantly (Liu G et al., 2020). The summary of this technique is presented in Table S14.

4.2 Data-based schemes

Beam tracking is used to solve the beam prediction problem by using sequences of beams without the need for visual images of the scenery by having the Txs of the scenery data (Srinivasan, 2020). One method that shows promise for extracting data from the training history is ML, which can reduce the overhead of beam training by reducing the space of beam search in future training. There are offline and online learning ML approaches for beam-tracking purposes. The online learning trackers dynamically modify their models of appearance.

Meanwhile, offline learning trackers use pre-trained appearance models from other datasets (Wang X et al., 2022). The beam-tracking techniques based on ML can be split into SL, USL, and RL approaches. Consequently, beam tracking based on ML makes the tracking policies more accurate and obviates the need to solve beam optimization problems periodically. The main advantages of ML over other techniques in beam tracking are that it captures the channel and environmental parameters well and has low mathematical complexity (Burghal et al., 2019).

4.2.1 SL approach

This method works with labeled data. SL models provide more precise outcomes relative to USL because the programmer explicitly instructs the machine on what to look for in the given data (Naeem et al., 2023). The main feature of this technique is the capability to gather data or create the output of data from previous knowledge. The disadvantage of this technique is that it requires a high number of training samples in advance. However, gathering training data is frequently expensive (Zhang J et al., 2021). Table S15 illustrates the SL techniques used for beam management of mmWave wireless communications.

1. NN approach

This type depends on the deep SL (DSL) method. There are various DSL techniques, such as feedforward NNs (FNNs), convolutional NNs (CNNs), recurrent NNs (RNNs), and GNNs. In addition, the RNN class contains the long short-term memory (LSTM) and gated recurrent unit (GRUs) approaches.

(1) FNN method

FNN, also known as a fully connected deep NN (fully connected DNN), is a type of artificial NN (ANN). It has more hidden layers that help it understand or recognize things better, as one can see in Fig. S7. Its features are the capacity to learn massive amounts of data and that it has good tools for modeling complex nonlinear systems. At the bottom, there is the input layer. In the figure, each node at the input layer denotes the number of inputs in the FNN. At the top, there is the output layer. The number of nodes indicates the number of outputs in the FNN. Some hidden layers in the middle of the FNN have a strong relationship with its design. FNN models nonlinear complex relations using multiple hidden layers (Lim et al., 2021). In the FNN, the neuron in the hidden layer performs a nonlinear transform known as the activation function. FNNs use different activation functions, such as the sigmoid function. The sigmoid function receives real numbers as input, while its output falls between zero and one. The curve of the sigmoid function is S-shaped and is defined as $f_{(x)_{\mathrm{sigmoid}}}=\frac{1}{1+\exp^{-x}}$. The tanh function is like a sigmoid, while its output is between "-1" and "1" and is represented as $f_{(x)_{\tanh}}=\frac{\exp^{x}-\exp^{-x}}{\exp^{x}+\exp^{-x}}$, and the rectifier linear unit (ReLU) function is defined as $f_{(x)_{\mathrm{ReLU}}}=\max(0,x)$. It transforms all input values into positive numbers. The ReLU's features include fewer data requirements, rapid convergence, and sparse activation, all of which are essential for short-time response systems such as wireless communication systems. Thus, the FNN output z is a combination of nonlinear transformations of the input data I, which is expressed as follows (Wang R et al., 2021):

$$z=f_{(I)}=f^{(L-1)}(f^{(L-2)}(...f^{(1)}(I))), \tag{5}$$

where L denotes the number of layers; in FNN, we must optimize the neurons during the training process. Usually, the number of hidden layers and nodes in an FNN is large. Therefore, it becomes more complex. Table S16 explains the FNN algorithm for AoA and DoA prediction.

(2) CNN method

CNN is a DSL approach with the advantage of its excellent performance in task classification. CNNs are more robust than RNNs because CNNs have more advantages than RNNs. The disadvantage of the CNN DL model is that the broad beam training imposes a significant overhead. The CNN strategy consists of three phases: the training phase, the prediction phase, and the training beam, thus dividing the data group into a training group and a test group. We train the classifier using the training group and verify the DL model's performance using the test group. We obtain a well-trained DL model by optimizing the parameters. In the prediction phase, the trained DL model classifies and predicts the beams to obtain the best pair. After finishing the work of the two stages, the training model is used for selecting the actual beam (Zhang L et al., 2022). Different popular CNN architectures, such as the LeNet-5, focus on digit recognition. AlexNet pioneered DL success in large-scale image classification tasks (Krizhevsky et al., 2017). Visual geometry group network (VGGNet) emphasized depth by stacking small (3×3) convolution filters (Simonyan and Zisserman, 2015). Residual neural network (ResNet) revolutionized DL by solving vanishing gradient problems in DNNs (He et al., 2015). EfficientNet scales networks efficiently by balancing width, depth, and resolution (Tan and Le, 2019).

(3) RNN method

RNN exploits the correlation time between the measurement data and updates the channel states using some memory. Applications containing temporal delays of signals, such as speech processing, process control, non-Markovian control (Hochreiter, 1998), and translation, use the RNN. The RNN's disadvantage is its sensitivity to the vanishing and exploding gradient. In other words, during the training operation, the multiplication of various small or large derivatives causes the steepest one to explode or decay, a condition known as short-term memory (STM). When the network logs a new input, it loses its sensitivity over time because it no longer remembers the previous ones. LSTM solves this problem. Fig. S8 shows the RNN architecture.

(a) LSTM network

LSTM is a new structure with a suitable gradient-based learning algorithm (Guo J, 2013). LSTM networks facilitate the generation of large recurrent networks, addressing time-series data issues in ML and delivering the latest results. The training of the LSTM networks uses the backpropagation through time method, which makes it possible to overcome the vanishing gradient problem. Instead of neurons, the LSTM networks contain memory blocks called cell states connected by layers.

Each block comprises three gates that regulate its output and state, thereby shaping the memory state for the current sequences. Additionally, the LSTM governs the resolution of the gates, which in turn provides the activation function for the input values. Based on previous channel estimates and signals from the inertial measurement unit (IMU), the LSTM predicts the distribution of the AoA and AoD states during the current beam transmission cycle.

Two main beam-tracking processes use this distribution. First, the current cycle of beam transmission uses the distribution of AoA and AoD to determine the sounding beams of Rx and Tx. Second, based on previous information, we use the predicted channel distribution to update the channel estimation. The observed signal z at frame K serves as the sequence of input data for the LSTM, which we refer to as input features. The network uses these input features to train under an SL structure and estimate the future state of the user equipment. Typically, we use the MSE to determine errors. The disadvantages of the LSTM technique are the complexity of the structure and the fact that it takes a long time to train (Jeong et al., 2021). Another form of the LSTM algorithm is the Bi-LSTM algorithm, which uses forward and backward LSTM. An example of training of the LSTM model is shown in Fig. S9, which shows the block diagram of the LSTM technique.

At time slot t, the inputs of the LSTM technique are $\boldsymbol{x}_t$ and the hidden state of the previous time slot $\boldsymbol{h}_{t-1}$. After the computation of the outputs, the cell state $\boldsymbol{c}_t$ and the hidden state $\boldsymbol{h}_t$ are updated depending on Eqs. (6)–(12). Then, the hidden state $\boldsymbol{h}_t$ feeds off the LSTM model at the posterior time step and the cell state $\boldsymbol{c}_t$. The learning is done by updating every weight repeatedly to reduce the loss function $l(\boldsymbol{y}_t, \overline{\boldsymbol{y}}_t)$, which punishes the distance between the target $\overline{\boldsymbol{y}}_t$ and the output $\boldsymbol{y}_t$. The following recursive equations update the information in the cell state when the input sequence enters the LSTM (Guo Y et al., 2019):

$$\widetilde{\boldsymbol{c}}_t = \phi(\boldsymbol{W}_{cx}\boldsymbol{X}_t + \boldsymbol{W}_{ch}\boldsymbol{h}_{t-1} + \boldsymbol{b}_c), \tag{6}$$

$$\boldsymbol{i}_t = \sigma(\boldsymbol{W}_{ix}\boldsymbol{X}_t + \boldsymbol{W}_{ih}\boldsymbol{h}_{t-1} + \boldsymbol{b}_i), \tag{7}$$

$$\boldsymbol{k}_t = \sigma(\boldsymbol{W}_{kx}\boldsymbol{X}_t + \boldsymbol{W}_{kh}\boldsymbol{h}_{t-1} + \boldsymbol{b}_k), \tag{8}$$

$$\boldsymbol{o}_t = \sigma(\boldsymbol{W}_{ox}\boldsymbol{X}_t + \boldsymbol{W}_{oh}\boldsymbol{h}_{t-1} + \boldsymbol{b}_o), \tag{9}$$

$$\boldsymbol{c}_t = \widetilde{\boldsymbol{c}}_t \odot \boldsymbol{i}_t + \boldsymbol{c}_{t-1} \odot \boldsymbol{k}_t, \tag{10}$$

$$\boldsymbol{h}_t = \tanh(\boldsymbol{c}_t) \odot \boldsymbol{o}_t, \tag{11}$$

$$\boldsymbol{y}_t = \sigma(\boldsymbol{W}_t\boldsymbol{h}_t), \tag{12}$$

where $\boldsymbol{W}_{cx}$, $\boldsymbol{W}_{ch}$, $\boldsymbol{W}_{ix}$, $\boldsymbol{W}_{ih}$, $\boldsymbol{W}_{kx}$, $\boldsymbol{W}_{kh}$, $\boldsymbol{W}_{ox}$, and $\boldsymbol{W}_{oh}$ refer to the weighted matrices for the linear transformation. $\boldsymbol{X}_t$ means the input at time t. $\widetilde{\boldsymbol{c}}_t$

denotes the intermedial vector for cell state. $\boldsymbol{c}_t$, $\boldsymbol{b}_c$, $\boldsymbol{b}_i$, $\boldsymbol{b}_k$, and $\boldsymbol{b}_o$ indicate the bias vectors. $\boldsymbol{i}_t$ means the input gate, $\boldsymbol{k}_t$ means the cell memory, and $\boldsymbol{o}_t$ means the output gate. $\sigma(.)$ and $\phi(.)$ refer to the sigmoid functions for each gate; $\odot$ shows the elementwise multiplication.

For the channel-tracking system, the present channel estimation at the base station $\widetilde{\boldsymbol{h}}_t$ will be the input of the LSTM. The estimated channel for the posterior time slot $\widetilde{\boldsymbol{h}}_{t+1}$ will be the required output of the current time, which agrees with $\boldsymbol{x}_t$ and the desired output $\overline{\boldsymbol{y}}_t$ in the LSTM model, respectively. This training process will discard a significant amount of past useless information and continuously improve the prediction results based on advanced memory. The LSTM output will be the predicted vector $\widetilde{\boldsymbol{h}}_{t+1}$ of the channel, and the difference between it and the actual channel vector at the posterior time $\boldsymbol{h}_{t+1}$ is negligible.

(b) GRU network

The GRU model is a facilitated version of the LSTM model, which minimizes the complexity of the RNN and solves traffic problems. Every recurrent unit uses a GRU to pick dependencies for different time scales adaptively. Similar to the LSTM unit, the GRU has gates that adjust the unit's information flow without having a separate memory cell. Fig. S10 illustrates the GRU network structure. The GRU has two gates. The first gate is for updating, which controls and updates the present cell content with the new candidate cell state. The second gate is for resetting, which rests on the closed cell's memory. The state equations of the GRU are expressed in Eqs. (13)–(17) (Mazin et al., 2018).

Reset gate equation:

$$\boldsymbol{r}_t = \sigma(\boldsymbol{W}_r\boldsymbol{h}_{t-1} + \boldsymbol{R}_r\boldsymbol{x}_t + \boldsymbol{b}_r); \tag{13}$$

Current state equation:

$$\boldsymbol{h}'_t = \boldsymbol{h}_{t-1} \odot \boldsymbol{r}_t; \tag{14}$$

Candidate state equation:

$$\boldsymbol{z}_t = g(\boldsymbol{W}_z\boldsymbol{h}'_{t-1} + \boldsymbol{R}_z\boldsymbol{x}_t + \boldsymbol{b}_z); \tag{15}$$

Update gate equation:

$$\boldsymbol{u}_t = \sigma(\boldsymbol{W}_u\boldsymbol{h}_{t-1} + \boldsymbol{R}_u\boldsymbol{x}_t + \boldsymbol{b}_u); \tag{16}$$

New state equation:

$$\boldsymbol{h}_t = (1-\boldsymbol{u}_t) \odot \boldsymbol{h}_{t-1} + \boldsymbol{u}_t \odot \boldsymbol{z}_t. \tag{17}$$

Here, $g(.)$ is a nonlinear function implemented using the hyperbolic tangent, $\sigma(\cdot)$ denotes the logistic sigmoid, $\boldsymbol{W}_r$, $\boldsymbol{W}_z$, and $\boldsymbol{W}_u$ indicate the weight matrices, which are set to input $\boldsymbol{x}_t$, $\boldsymbol{R}_r$, $\boldsymbol{R}_z$, and $\boldsymbol{R}_u$ are square matrices that determine the weights of the recurrent connection, $\boldsymbol{b}_r$, $\boldsymbol{b}_z$, and $\boldsymbol{b}_u$ denote the bias vectors, and $\odot$ distinguishes the Hadamard product. Next, we use the MSE to minimize the loss function. The MSE measures the model output and how much it matches the genuine output signals. Another form of the GRU algorithm is the Bi-GRU algorithm, which uses forward and backward GRU.

(4) GNN method

Models for reasoning about precisely organized data, particularly graphs, are called GNNs. A graph comprises distinct vertices representing objects or things, potentially connected by edges indicating connections. In particular, the graphs fed into a GNN (during training and test) do not have to follow strict structural rules. The numbers of vertices and edges between the graphs can differ because it can handle unstructured data and non-Euclidean data types. The popularity of GNNs in AI has lately increased (Ward et al., 2022). The graph-structured topology of wireless networks makes GNNs better at approximating the intended-to-transmit design. This is especially true in large or complex networks. In addition, GNNs may be immediately extended to other network settings without requiring retraining, a significant aspect of the practice (Li et al., 2024). GNNs are superior to traditional NNs primarily because of their extraordinary ability to generalize to other networks and configurations unseen during training. This capability is essential to implementing workable data-driven networking solutions. Despite being a straightforward method for handling generic graphs, GNNs have some drawbacks. Specifically, the shared transition function implies extracting features using the same weights in subsequent iterations, which may not be optimal for DL scenarios wherein the relationships between high-level features (later in the network) differ from those of low-level features (earlier in the network). Furthermore, GNNs have variable-length encoding networks because they iterate until convergence, which might complicate implementation (Ward et al., 2022). Graph convolutional networks (GCNs), graph attention networks (GATs), and message-passing NNs (MPNNs) are the foundations of the most-often-used GNN models in communication networks.

2. Support vector method (SVM)

SVM is an SL method for two-group classification issues. The theory of SVMs, initially presented by Vapnik, is based on structural risk reduction. It has been used for several communication challenges, including multiuser detection (Chen S et al., 2001) and blind equalization/identification (Santamaria et al., 2004; Gaudes et al., 2007). The SVM technique works incredibly well to overcome intersymbol interference (ISI) and cochannel interference because SVM was born out of identifying the optimal linear decision boundaries (hyperplane) to separate two classes maximally (Chen S et al., 2001). The strong generalization abilities of SVMs lead to an overestimation of the channel order. Moreover, this method can function under conditions of low diversity (Santamaria et al., 2004).

4.2.2 USL-based approach

USL approaches make the analysis of raw datasets more accessible and aid in producing analytical insights from unlabeled data. New advances in factor analysis, latent models, hierarchical learning, clustering methods, and finding outliers have made a big difference in the state of the art in USL (Usama et al., 2019). The USL finds patterns in datasets that contain unstructured or unlabeled data elements. Using this learning method, an AI system receives only the input data, not the corresponding output data. USL algorithms outperform SL techniques when handling complex jobs because intelligent machines need to be able to draw (independent) inferences from massive volumes of unlabeled data (Naeem et al., 2023). Table S17 explains the USL methods used for beam management of mmWave wireless communications.

In fields such as multimedia data analysis and bioinformatics, challenges involving data objects with many properties are becoming increasingly common. In these cases, it is frequently advantageous to lower the data's dimension—that is, to characterize it using fewer features—to increase the effectiveness and precision of data analysis (Fodor, 2002). The problems for which dimensionality reduction (DR) is necessary are when the explanatory variable numbers exceed (occasionally greatly exceed) the sample numbers. We often use DR strategies as a preprocessing or analytical step to simplify the data model. Finding an appropriate low-dimensional representation for the initial high-dimensional data collection is usually required. Tasks such as classification and clustering may frequently provide more accurate and understandable results when dealing with this simplified representation, and processing costs may also be significantly decreased (Cord and Cunningham, 2008). Depending on the data reduction method (projection), we can classify the DR algorithms into linear and nonlinear.

1. Linear projection

It is simply a projection from a high-dimensional space to a lower-dimensional space. Therefore, it can only do linear DR (Shah and Rangan, 2022).

PCA is a linear projection method, a method for showing the whole picture. PCA learns a set of features called principal components, which are linearly uncorrelated and show the different levels of the original data sample (Kasun et al., 2016). It is a fast-computational method for exploration and comparison. Beam-tracking techniques use PCA for data visualization, noise reduction, and feature extraction.

The main advantage of PCA is its ability to compress further patterns identified in the data while not significantly sacrificing information by lowering the dimensions. This makes it an extremely effective method for image compression. It guides how to reduce a complex dataset to a lower dimension with a little more work to reveal the frequently hidden, more straightforward structure underneath. PCA has traditionally been viewed as a "black-box" technique, although it is an effective tool for lowering dimensions and revealing correlations among complicated data items (Jolliffe, 2002).

It is laborious for the user to comprehend the underlying relation from the features that are extracted (Dash et al., 1997) only because of the coordinate transformation from the original data space into eigenspace. It is also referred to as the empirical orthogonal function (EOF) technique, the Hotelling transform, the Karhunen–Loève transform, and the singular value decomposition (SVD) in some other domains (Dash et al., 1997).

2. Nonlinear projection

Compared to linear approaches such as PCA, nonlinear DR (NLDR) methods are more effective in maintaining local neighborhood information in the data. In addition to preserving the data's global structure, NLDR techniques seek to retain the data's local structure (Shalal et al., 2023). Nonetheless, the quantity of chosen neighbors significantly influences the upheld structure and must be selected carefully.

AE is a USL DR technique that compresses (encodes) high-dimensional input data to create lower-dimensional data. This method can be integrated with another DL method for beam tracking, as shown previously (Shah and Rangan, 2022). Finding the low-dimensional feature representations that can most accurately recreate the original data is the goal of an AE. An AE does not distinguish between data and treats each sample uniformly because it makes a single transformation matrix for embedding all the data (Zhang J et al., 2018). AE uses an algorithm that produces output data identical to the input data. If the input layer neurons are more significant than the hidden layer neurons, the AE performs DR. Nonlinear AE learns nonlinear features.

In contrast, linear AE learns variance information in a manner akin to PCA (Kasun et al., 2016). An AE with identical weights for the input and output layers is known as a tied-weight AE (TAE). RL typically does not directly incorporate DR, but it can include AEs in a system for tasks that benefit from feature learning or DR. For instance, we can use AE in an RL context to preprocess high-dimensional input data, thereby enhancing the effectiveness of the learning process.

4.2.3 RL approach

RL is a subfield of DL in which the device interacts with the environment to achieve a goal, and learning occurs through successive interactions. The RL agent learns by experience and takes actions based on the environment, which causes changes in the environment's state, receiving a reward for the action taken to measure the success or failure of the movement (AlMahamid and Grolinger, 2022).

The agent follows instructions and gathers information from the environment, the present state, and the reward to assess whether it has achieved its goal. The reward is a scalar feedback signal, which the agent always aims to maximize. Fig. S11 explains the RL technique structure. In real life, Markov decision processes (MDPs) formally describe how people interact with their surroundings using a tuple with four parts: states, actions, transition probabilities, and a reward function (Elsayed et al., 2021).

The problem with RL is that it involves the direct mode of learning from the interaction between a decision-maker (i.e., an agent) and its environment (Elsayed et al., 2021). There are three categories of RL schemes: model-based, model-free, and policy-based algorithms. Table S18 shows the RL techniques used for beam management of mmWave wireless communications. Some works of literature integrate the RL techniques with other beam-tracking methods to obtain excellent performance for mmWave wireless communications beam tracking. Table S19 shows some of this literature.

1. Model-based RL

Model-based RL algorithms require an accurate depiction of the environmental dynamics in terms of the distribution of state-transition probability. These schemes calculate the best policy by solving system equations. In model-based RL, the agent has access to a model of the environment that describes the transition dynamics and reward function (Foster et al., 2000).

When the model is known, a value-iterative technique based on dynamic programming (DP) may efficiently update value functions after each strategy step (Yu et al., 2018). On the other hand, it is a general method for recursively solving combinatorial optimization issues on smaller sets (Mensch and Blondel, 2018). The advantages of DP include its durability against movements, sensor jitter, and impulsive noise, as well as its sensitivity to weak targets. This unique technique combines target tracking and identification into a straightforward optimization process that accounts for clutter, background noise, and statistical models of target motion. DP is a technique that systematically breaks down significant structured combinatorial problems into smaller subproblems to solve them. Many DP algorithms are not differentiable, so they cannot be used as backpropagation-trained NN layers (Mensch and Blondel, 2018), even though they are flexible. The disadvantage of DP algorithms is their slowness and high memory requirements (Vodopivec et al., 2017).

2. Model-free RL

Model-free RL mechanisms come into play when the model lacks an accurate description or possesses a more complex solution. These algorithms react with the environment directly, using trial-and-error schemes to learn the best policy, which means learning directly from experience without explicitly building a model of the environment; therefore, they are used when dealing with sequential decision-making control with unknown environmental information (Jiang et al., 2019). Although model-free RL can yield a workable solution based on responses to the surroundings, its accuracy is reduced without DNN model knowledge (Shen et al., 2021).

(1) MC method

MC RL technique considers sample trajectories, which helps it overcome the challenges posed by the unknown model estimate. This approach could be less efficient than the DP method because it only updates the strategy's value estimate after completing a sample trajectory (Yu et al., 2018). The MC algorithm gathers experience from taking samplings of the search space without needing any environment model (Vodopivec et al., 2017).

(2) Temporal difference (TD) method

TD learning (Foster et al., 2000) integrates DP and MC algorithms for more active model-free learning (Yu et al., 2018). Because of the need for many training samples of experience, often gathered by a trial-and-error process across many iterations, TD approaches, such as Q-learning, need to improve their convergence (Lillicrap et al., 2016). Therefore, the main driving force behind transfer learning in TD techniques is to shorten the convergence time and minimize the number of samples required to understand the target task (Elsayed et al., 2021). Although it raises bias and reduces evaluation variance, learning performance is often improved (Vodopivec et al., 2017).

(a) Q-learning

Q-learning is a model-free RL technique that lets an agent learn the best course of action and adjust to changing conditions without requiring any past information. It is appropriate in the event of a deterministic policy (Chen YJ et al., 2020), and it is an off-policy algorithm (Han Z et al., 2022). The Q-learning table (a Q-table) documents the experience. This table has three components: states, actions, and state–action values (Q-values). This experience stored in the Q-table provides enough information to solve the prediction problem (Chiang et al., 2021). The advantages of Q-learning are that it works well in dynamic contexts because it can adjust to nonstationary networks and changing channel circumstances. It can learn the optimum policies with little or without prior knowledge. It is a classic case of TD learning and solves the low-dimensional problem of discrete space (Yu et al., 2018). It is used in various scenarios due to its ease of comprehension and implementation. One of the main drawbacks of Q-learning is that it is limited to distinct action–space contexts. Moreover, the other disadvantage is that hyperparameters such as learning rate, discount factor, and exploration rate can significantly affect Q-learning performance and, hence, need to be carefully adjusted. It may overfit the training set if appropriate regularization or exploration techniques are not used, resulting in subpar generalization to novel contexts. Q-learning could take a long time in real-time applications due to the need for many iterations before reaching the optimal policy.

(b) Deep Q-network (DQN) method

DQN is an algorithm within the deep RL (DRL) algorithms and combines the DNN with the Q-learning algorithm (Anschel et al., 2017). The Q-function predicts the expected cumulative reward of choosing an action in a given state. By maximizing this expected cumulative reward, DQN learns to make judgments. The high-dimensional state and action spaces in beam tracking can be handled by DQN, which makes learning the ideal beam direction more effective. Moreover, DQN is a flexible and stable algorithm that breaks the RL problem into sequential SL tasks (Anschel et al., 2017). One of the disadvantages of this algorithm is that its performance may need to be carefully tuned because of its sensitivity to hyperparameters, including batch size, discount factor, learning rate, and network design. Furthermore, dealing with DNNs that may be complicated and need DL knowledge is a significant part of the implementation difficulty of DQN. While DQN improves the high-dimensional state space processing power, high-dimensional continuous action space remains beyond its capabilities (Yu et al., 2018).

(3) State-action-reward-state-action (SARSA) method

Rummery and Nranjan introduced the model-free SARSA algorithm in 1994 (Liao et al., 2020). It is an on-policy time difference technique in RL. It was first referred to as an enhanced Q-learning algorithm before being dubbed the SARSA learning algorithm. The SARSA algorithm performs better in reducing security risks from malevolent radio sources. The advantage of this algorithm is that it is an on-policy algorithm (Han Z et al., 2022), which implies that it can constantly enhance its BF method when learning new information without needing to retrain. Another advantage of this algorithm is that it can learn immediately from environmental interactions. Therefore, it is particularly suitable when maintaining or acquiring accurate models, which is challenging. The conventional SARSA algorithm chooses a plan using the ε-greedyy strategy. When using the ε-greedyy technique, the cognitive user gradually approaches the ideal Q as the exploration process progresses. Large-scale investigation is not currently conducive to enhancing system efficiency and will result in excessive overhead (Liao et al., 2020).

3. Policy-based RL

Model-based and model-free RL techniques treat the action and state variables as discrete, which can lead to quantization errors and disruption of the continuity of space. As a result, it is challenging to identify the best control strategy for the continuous variable problem. We can use policy-based models for the RL problem of constant variables (Jiang et al., 2019). Their use is not limited to the deterministic policy scenario; it may also encompass stochastic policy scenarios (Chen YJ et al., 2020).

(1) Deep deterministic policy gradient (DDPG) method

We train the model in an easy-to-create virtual environment using DDPG, a DRL technique, to lessen its reliance on the sample data. It can also handle continuous input and continuous output model training, directly producing the control action and trajectory sequence. DDPG solves the challenge of constant state space and continuous action space (Lillicrap et al., 2016) by combining the benefits of DQN with the actor–critic (AC) architecture. It implements a deterministic strategy to guarantee further that the network is more convergent. DDPG adopts the AC structure and the AC framework. Here, the actor component consists of the target and online policy networks, which use a deterministic policy to extract a specific action from the current state. The quality of action is measured in the critic section using the Bellman equation of the action–state function Q, which comprises an online Q-network and a target Q-network (Yu et al., 2018).

(2) AC method

AC algorithm is a component of policy-based RL. Its fundamental idea involves applying gradient updates to optimize the policy, thereby enabling direct learning of the general stochastic policy. As it is, the AC algorithm ensures that certain items in the state and action vectors will always exist. The critic evaluates the policy using the estimate function and directs the actor to update it using the policy gradient that it has assessed. The actor is used to produce random actions (Jiang et al., 2019). Continuous action space can be handled using the AC approach. However, network convergence is hampered by the randomization strategy (Yu et al., 2018).

Fig. S12 illustrates the performance of MSE and the time index. This work uses a straightforward RNN architecture based on the LSTM or Bi-LSTM as an ML model (Anooz et al., 2024a). The RNN design comprises four layers, each having 128 nodes. ReLU activations are used in these layers. A dropout layer follows every layer to guarantee regularization and prevent the NN from overfitting. Ultimately, there is only one fully connected layer in the network with ReLU activation. The ML model exhibits distinct performance compared to the EKF and LMS MSE results. The MSE of ML decreases with time, whereas the MSE of EKF and LMS increases because ML models, especially those using RNNs, persistently learn from and adjust to new data. Consequently, their predictions can improve over time, leading to a reduction in the MSE as accuracy increases with additional data (Goodfellow and Bengio, 2016). Consequently, ML is used in beam tracking to address the challenges associated with traditional methods. One concern is that the MSE in beam tracking for mmWave communications escalates with time with conventional methods. This is apparent in the MSE performance of EKF and LMS (Anooz et al., 2024b). Based on the outcomes, ML surpasses EKF and LMS in mmWave communications, providing an effective means of monitoring a target over time with reduced errors. The EKF is based on the assumption that the system dynamics model is precise. Suppose that the dynamics of the system fluctuate or alter. In that case, the performance of the EKF can decline over time due to its inability to adapt to changes not forecast accurately, increasing the MSE (Simon, 2006). The LMS algorithm is intended to adjust to a stable environment. Nevertheless, in the case that the statistical properties of the noise or signal fluctuate, the algorithm may struggle to adapt well over time, leading to an increase in the MSE due to LMS's persistent inability to enhance its model during the initial adaptation phase (Haykin, 2013). The figure indicates that the performance of Bi-LSTM surpasses that of LSTM because Bi-LSTM uses both forward and backward processing, resulting in superior performance compared to LSTM, which uses only forward processing. Table S20 shows the comparisons among these techniques.

5 Suggestions and recommendations

Despite its limitations depicted in previous studies, the Gaussian mixture (GM) filter can be used in beam-tracking applications. A strong mathematical tool called the GM filter can show the probability density function (PDF) of variables with a complicated multimodal distribution (Hao and Shu-kui, 2019). Its accuracy depends on the complexity of the target distribution and the number of Gaussian distributions used in the mixture. Therefore, the specific application and signal characteristics may require algorithm tuning. Another competitor to the GM filter is the PF, but using many particles may result in a longer processing time. Apart from the role of tracking techniques, we also need to optimize the transmit antenna's location at the base station along the roadside. There is a need to enhance the height, position, and array orientation of the Tx in the ray-tracing process. The majority of studies and research on beam tracking have solely focused on tracking the AoD and AoA, with only a handful addressing the impact of velocity and distance on beam tracking. Therefore, researchers must study the effect of the Tx's height and position on beam tracking. Practical studies have shown that the maximum distance of Rx from the Tx for receiving a good signal is up to (roughly) 200 m (Rappaport et al., 2013).

Further, ML can help solve the beam-tracking problem, and many ML algorithms have been used in beam tracking. Applying ML in beam tracking requires estimating the channel coefficients only once. If there is a beam-tracking outage, the system can continue functioning as it relies on the stored channel coefficient data. These techniques can aid in reducing the beam-tracking time in mmWave vehicular communications, particularly during the short coherence time resulting from vehicles' high velocity. Scholarly investigations and studies are ongoing to better understand these trackers' performance in various settings. Though these algorithms have demonstrated encouraging outcomes, in specific scenarios, such as high-mobility vehicles, the availability of training data may make it more challenging to use them.

6 Conclusions

Beam-tracking techniques are essential for maintaining reliable communication links in mmWave mobile communication systems. Obstacles such as buildings, trees, and pedestrians easily block mmWave signals, necessitating these techniques. In this paper, we defined beam tracking and explained the fundamental principles of the beam-tracking technique. We summarized the significant beam-tracking techniques in mmWave communications recorded in the literature. Additionally, we proposed a few promising research gaps in this particular area of study. Given the literature presented above, we can claim that several approaches can achieve reliable and efficient beam tracking. These approaches include beam sweeping, beam refinement, and hybrid techniques that combine these approaches. Moreover, the effectiveness of these techniques depends on a range of factors, including the user's mobility, the complexity of the communication environment, and the base station's processing power. In general, hybrid techniques that combine beam sweeping and refinement offer the best trade-off between tracking accuracy and computational complexity. Moreover, based on the literature presented above, ML is superior to other methods in terms of reaction time, as the data are trained only once and can be refined online as new data become available. The direct multiplicative sum of the network weights and the data features can easily estimate the beam parameters. The main issue with this method is the amount of data used for training; the more data available for training, the more accurate the estimation result for the beam or channel. In the case of high-speed or rapid environmental changes, data-based techniques can estimate beam parameters without reestimating the channel, an essential advantage compared to other model-based methods. Some non-ML methods, such as the RLS technique, fail to trace the ray during rapid and sudden changes during the tracking process and require repeating the process from the beginning. In contrast, other methods can continue tracking at a lower-quality rate than data-based techniques depending on the literature.

Contributors

Ruaa Shallal Abbas ANOOZ conceived and designed the study, drafted the paper, and finalized the paper. Jafar POURROSTAM provided the guidance throughout the experimental phase and provided critical direction. Mohanad Al-IBADI provided the guidance throughout the experimental phase, supervised the research, and revised the paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

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List of supplementary materials