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Review of Artificial Intelligence Based Beam Tracking Techniques for mmWave 5G and Beyond Networks

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ABSTRACT

Wireless networks of the future can take advantage of beamforming techniques in the millimeter wave (mmWave) and terahertz (THz) bands to effectively handle the immense bandwidths required. This opens up a world of possibilities for the advancement of wireless technology and the potential to create even faster and more efficient networks. To achieve directional beamforming gain, it is essential to have a reliable beam management (BM) framework that can track the best uplink and downlink beam pairs using traditional exhaustive beam scans (EBS). However, this requires extensive beam measurement, which can result in a significant overhead, especially for higher carrier frequencies and narrower beams. To tackle this issue, machine learning (ML) algorithms based on artificial intelligence (AI) are being created to detect and understand intricate mobility patterns and environmental changes. This article presents an overview of the current AI-based ML beam tracking (BT) techniques used in mmWave/THz bands for 5G and future networks, highlighting the essential features of an effective beam tracking framework.

Key words: mmWaves, Artificial Intelligence, Machine learning, Beam Tracking

1. INTRODUCTION

The ever-increasing demand for bandwidth-heavy applications, such as Virtual Reality (VR), Augmented Reality (AR), and Ultra-High Definition (UHD) 3D video is leading to a steady rise in wireless data traffic, doubling every year. This trend is expected to continue, indicating a massive surge in the demand for ultra-high data rates in the foreseeable future [1]. Predictions suggest that by 2030, global data traffic demand could reach up to 5 Zettabytes (ZB) each month, by 2030 with data rates expected to peak at 100 Gbps. However, due to limited availability of spectrum resources poses a significant challenge in meeting the increasing demand for high-bandwidth requirements of next generation wireless communication [2]. The challenge is to provide enough wireless bandwidth to support the growing demand for high-speed data transmission. The upcoming 6th Generation (6G) of wireless technology is expected to provide significantly higher data rates and more reliable connectivity than current legacy systems. The upcoming 6G wireless technology is expected to offer much higher peak data rates of 1 Tbps, which is approximately 50 times faster than the current 5G technology, this improved speed is predicted to enable new applications such as autonomous driving, holographic images, and telemedicine. Additionally, the latency of 6G is expected to be one-tenth of 5G which is 0.1 ms [3]. To fulfill the demanding need for enhanced transmission capacity, there exist two solutions that can meet the stringent data requirements.

One solution to address the challenge of limited spectrum resources is to improve spectrum efficiency by utilizing techniques such as large-scale Multiple Input Multiple Output (MIMO) and high-order modulation. The second approach involves techniques such as dual connection, non-orthogonal multiple access (NOMA), and carrier aggregation, which can expand system bandwidth substantially and improve the data service capacity [4]. However, despite the advances made in these technologies, overcoming the bottleneck of wireless bandwidth scarcity remains a challenge. To tackle this problem, researchers are investigating the use of mmWave /THz frequency bands because they provide an abundant amount of bandwidth resources that can fulfill the need for high transmission capacity [5]. Despite its potential benefits, mmWave/THz communication presents some difficulties and obstacles.

1) Limited range of communication: This is because the high frequency of mmWave bands leads to significant attenuation in free space, which ultimately restricts the effective range of communication.

2) Low diffraction capability: The practical application of mmWave is significantly affected by its sensitivity to be blocked by obstacles. This is because mmWave links are highly directional, making it challenging for the signal to propagate through diffraction and other means.

The use of beamforming and large-scale phase antenna array technology can be a possible solution to address the challenges of limited spectrum resources in wireless communication. By utilizing a large-scale phased antenna array combined with beamforming techniques, it is possible to generate a highly focused beam directed toward a specific direction [6].

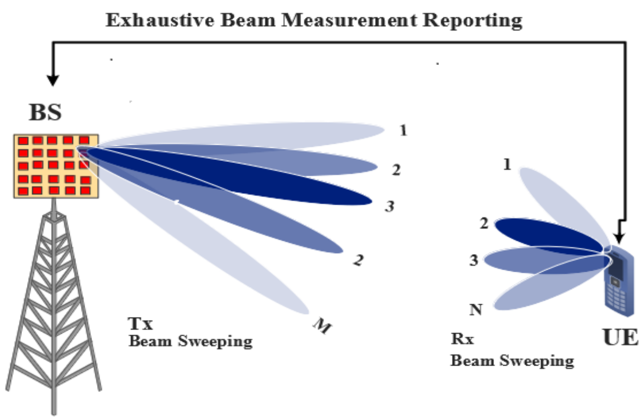

Figure 1: Exhaustive beam search for finding optimal Tx/Rx beam

The energy of the mmWave signal can then be focused into a narrow pencil beam, which allows for efficient data transmission over a greater distance. The beamforming technique also enables space division multiplexing (SDM) of spectrum resources, which can significantly improve the allocated spectrum utilization [7]. This SDM techniques converge the signal coverage from all directions to a precise directional service, minimizing interference between beams and enabling the provision of different communication links in the same space, leading to significant improvement in the performance of the base station (BS).

For directional transmission to be efficient, it is crucial that the beams of both the receiver and the transmitter are accurately aligned shown in Figure 1. The process of beam training, which involves obtaining current channel state information (CSI) and identifying the strongest channel path, can help in achieving this alignment. However, there are several challenges to achieving successful beam training and BT. Firstly, the frequent fluctuations in the wireless channel make beam training a time-consuming process, particularly in high-mobility scenarios. Secondly, the misalignment of beams can significantly decrease the link budget, resulting in decreased throughput or connection loss. Finally, in high mobility scenarios, it is essential to frequently switch to the optimal beam to ensure uninterrupted communication and seamless coverage for users. This process is crucial for maintaining the quality of the communication link. [8].

These processes of beam training and tracking must be executed with speed, precision, and reliability to establish a robust communication link capable of efficiently meeting the requirements of high data rates in future wireless communication networks. The changes in the Angle of Arrival (AoA) and Angle of Departure (AoD) over time can be utilized to facilitate the process of beam training by tracking their temporal correlations [9]. Recently, AI has gained immense popularity in wireless communication systems due to its impressive achievements in computer vision and natural language processing. In computer vision, AI has achieved exceptional performance in tasks such as object detection, segmentation, and recognition, in natural language processing, AI has made significant strides in areas like speech recognition, machine translation, and sentiment analysis. Furthermore, AI has been instrumental in advancing research enabling sophisticated applications like autonomous vehicles, medical diagnosis, and robotics. AI success in these domains has encouraged more researchers to explore its potential in wireless communication systems, AI research in wireless communication has demonstrated promising results in enhancing beam management, resource allocation, and other crucial aspects.

To keep up with the fast paced progress in the field of mmWave/THz communication, we have integrated up-to-date research on BT using AI based ML techniques in this article. This study aimed at improving the understanding of the latest trends in the development of mmWave BT techniques using ML. The remaining sections of the article are organized as follows Section 2 discusses the general application scenarios of mmWave/THz beams. Section 3 provides a general introduction to ML. Section 4 is the main part of the article, and it presents a general overview of ML applications for beam tracking. Section 5 discusses some open research challenges in mmWave/THz beam tracking. Finally, section 6 concludes the paper.

2. APPLICATION OF MMWAVE/THZ BEAM TRACKING IN DIFFERENT SCENARIOS:

To achieve optimal beamforming gain, beam training is utilized to specify the strongest channel path. However, frequent beam training in a fast-changing environment results in significant overhead. Once the strongest channel path is identified and the directional link is formed, even minor beam misalignment can lead to performance loss, reducing data rates or even causing unexpected link outages [10]. Reliable and efficient BT techniques, which result in maintaining the quality of directional communication links and reducing the overall beam training overhead, are crucial. Nonetheless, BT's effectiveness and dependability need to be further enhanced, particularly in highly dynamic environments. Before delving into existing research on BT technologies, this article begins by outlining various application scenarios that take advantage of mmWave/THz beamforming technologies. The overview of different application scenarios is shown in Figure 2.

2.1 WLAN/WPAN:

The 60 GHz band has been utilized for Wireless Local/Personal Area Network (WLAN/WPAN) communication technologies through the development of IEEE 802.11ad and IEEE 802.15.3c standards. This unlicensed bandwidth enables high-speed data transmission by utilizing mmWave bands for broadband multimedia applications over short distances at a low cost. However, in this high frequency band, excessive path loss reaching (15 dB/km) poses a significant challenge to the link budget, improves link security, and reduces interference. Additionally, beamforming, which results in a pencil narrow beam, causes a high speed connection. However, it becomes very sensitive to misalignment leading to interruptions which results in wireless link instability [11].

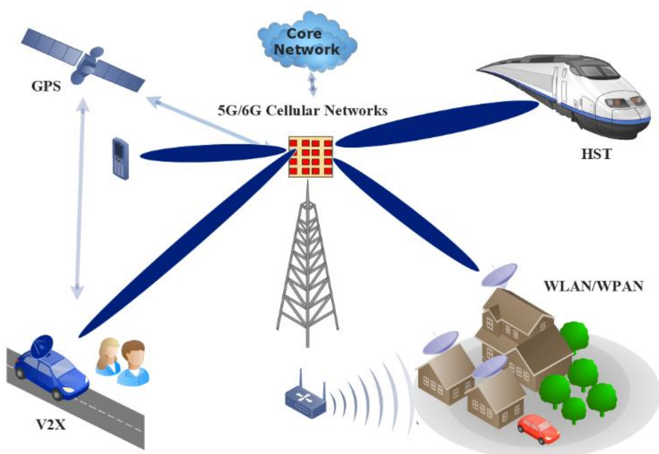

Figure 2: mmWave/THz beam application scenarios

2.2 Cellular Networks

The 3rd Generation Partnership Project (3GPP) has standardized the New Radio (NR) access technology for Release 15 to address the surge in data traffic and connectivity [12][3]. The increasing mobile communication volume and connection density of up to $10^6/km^2$ have raised the maximum data rate requirement to 10 Gb/s, leading to a need for wider wireless channel bandwidth. To meet these challenges, mmWave/THz technology with its narrow beam, short wavelength, and flexible properties is a promising solution for ensuring reliable communication quality [13].

2.3 V2X Communications

As the number of vehicles on the road has increased, traffic congestion and related issues such as safety and environmental preservation have become significant problems. Intelligent Transportation Systems (ITS) using V2X (Vehicle to Everything) communication have emerged as a potential solution. Dedicated Short-Range Communication (DSRC) based on Vehicular Ad hoc Networks (VANET) and Cellular-V2X (C-V2X) have been studied as two main types of V2X communication protocols [14]. For high-level autonomous driving cars, 3GPP Release 16 requirements specify a transmission rate of more than 1 Gbps with a delay of less than 3 ms for collision avoidance in the collective perception of environment scenario [15]. However, BT in mmWave/THz V2X communication is time-consuming and challenging in mobile scenarios. Sensing information can help obtain the relative positions of vehicles, reducing beam searching space and decreasing latency. Accurate and low-latency BT is still a challenge due to significant changes in the AoD and AoA in mobility scenarios. [16].

2.4 High Speed Train (HST)

It is anticipated that the HST will provide a sufficient quality of service while enabling rapid mobility up to a speed of 500 km/h. However, the HST scenarios present challenges such as rapid movement, frequent channel changes, and significant Doppler frequency offsets. The use of mmWave/THz and BT technology can effectively address these challenges and provide high-quality data services in HST scenarios [17].

3. MACHINE LEARNING FOR MMWAVE BEAM TRACKING

There has been extensive research conducted on traditional beam tracking techniques, which employ Bayesian statistics such as the Kalman Filter [18], Extended Kalman Filter [19], Unscented Kalman Filtering [20], and Particle Filter [21]. These methods have been studied extensively in the literature and are widely adopted for BT in various applications. However, this paper does not provide an in-depth analysis of conventional BT approaches. Instead, it focuses more on AI based ML solutions for mmWave/ THz frequency bands in the following sections. The reason behind this is that AI/ML is believed to be a crucial aspect of 5G and beyond networks and is expected to overcome the shortcomings of traditional BT methods.

ML allows computer systems to learn and improve automatically from experience without being explicitly programmed, it involves training algorithms on data. There are several types of machine learning algorithms, including Supervised Learning (SL) - In this type, the algorithm is trained on labeled data with known inputs and corresponding outputs. Unsupervised Learning (USL) - In this type, the algorithm is trained on unlabeled data and identifies patterns and relationships within the data without any prior knowledge of what it represents. Reinforcement Learning (RL) - This type of algorithm learns by trial and error. It is trained to make decisions based on a set of rules, and it receives feedback on its actions to improve its decision-making abilities.

4. STATE OF THE ART

This section covers a brief introduction of ML/AI based mmWave/THz BT approaches, prior research on ML-based BT techniques can be categorized into three primary groups: USL, SL, and RL. Furthermore, SL techniques can be categorized into two groups based on their use of auxiliary information: auxiliary information-assisted BT and non-auxiliary information-assisted BT, Table 1 shows the overall summary of BT related research, presented in this article.

Table 1: A brief summary of ML based beam tracking algorithm with dataset tools and performance evaluation

Category	Algorithm	Ref.	Data Generation	Performance Evaluation	Pros & Cons
Without Auxilary information Assisted Supervised Learning	**Deep Neural Networks**	[22]	DeepMIMO [45] Ray tracing Wireless Insite[49]	MMSE, Effective achievable rate	**Higher Precision and wide applicability at the cost of huge training data and long training time. Lower online complexity due to offline training. In case of environmental change retraining is required**
		[23]	Ray Tracing DeepMIMO [45]	Spectral Efficiency	
		[24]	Ray Tracing Wireless Insite[49]	Avg. SNR, beam Alignment Accuracy	
		[25]	Real world Data Deep Beam[46]	Beam Alignment accuracy, AoA accuracy	
	Long Short-Term Memory Networks	[27]	Ray tracing QuaDRiGA[51]	Outage probability AoA Error	
		[28]	Ray tracing Wireless insite[49]	Spectral Efficiency	
		[29]	Simulations	Prediction accuracy, beamforming gain	
		[30]	Cost200 Channel	MSE, AoA	
Auxiliary Information Assisted Supervised Learning	**Location Information**	[31]	Wireless Insite[49] Ray Tracing	MSE, beam Power	**Relying solely on additional information makes these methods less reliable if the information used is either inaccurate or not available.**
		[32]	Wireless Insite[49] Ray Tracing	Spectral Efficiency, beam training, power loss	
		[33]	Wireless Insite[49] Ray Tracing	Misalignment Probability	
	Sub 6 GHz CSI	[34]	Ray tracing	accuracy, spectral efficiency	
		[35]	Simulation	Accuracy of Prediction	
	Other Sensory Information	[37] [38]	Simulation, ViWi Framework [52]	Beam Prediction Accuracy	
Reinforcement Learning	**Deep Q-Networks and Q-Learning**	[39]	Simulation	Spectral efficiency, alignment probability	**No need for large training data, and lower accuracy due to the online training process. Able to adapt to changing environments at the expense of increased online complexity and longer convergence time.**
		[40]	Simulation		
	Multi Armed Bandit	[41]	Real World data	Misalignment Probability	
		[42]	Simulation	Spectral efficiency	
		[43]	Simulation	Misalignment Probability, spectral efficiency	

4.1 Supervised Learning without Auxiliary Information

Among the various ML techniques, SL is commonly used because of its simplicity. In addition to BT, it has multiple applications in wireless communication networks such as data compression, error correction codes, power management, mobility management, and channel estimation. Several well-known supervised learning algorithms include long short-term memory (LSTM), recurrent neural networks (RNNs), convolutional neural networks (CNN), support vector machines (SVM), and K-nearest neighbors (KNN).

4.1.1 Deep Neural Networks (DNN)

DNN is a type of artificial neural network that consists of multiple layers of interconnected nodes or neurons consisting of weight and biases. DNNs refine their precision by analyzing training data and gaining the ability to perform intricate tasks. Because of their effectiveness in AI and computer networks, they have been extensively studied to enhance BT processes. In [22], the author presented a combined scheme that utilizes a DNN and LSTM, where DNN is utilized to learn the intricate relationship between the received beam patterns and CSI. After channel estimation, LSTM is utilized to track the specific channel with decreased training overhead. In [23], a DNN-based solution for hardware constrained MIMO system is proposed where the predefined DFT codebook is utilized and DL learns the specific codebook for the surrounding environment and location where more users are located, this environment adaptability results in overall improvement of BT. Similarly, in [24], a hierarchical beam alignment technique combined with DNN was used to design a probing codebook by learning the environmental features of the specific location. While training, the BS captures the CSI channel matrix by scanning wider beams. The DNN then utilizes this matrix to modify the weights of the beam forming antennas for the wider beams.

Once the site-specific codebook for wider beams has been learned, the DNN predicts narrower beams for data transmission without any additional training. Simulation results, which were conducted using both ray tracing and the

DeepMIMO [45], reveal that this approach to designing a site-specific probing codebook outperforms traditional hierarchical methods with decreased overhead and resulting in better accuracy. However, the approaches presented in references [22] and [23] require knowledge of the CSI, which can be a high-dimensional complex channel matrix because of large scale MIMO utilization and extremely challenging to obtain in the mmWave/THz band. CNN has been developed to decrease the computational complexity of DNN by utilizing sharing parameters. Traditionally, they are used in tasks such as image classification, pattern recognition, and computer vision [25]. The DeepBeam solution, presented in [26], is a BM method based on a CNN that leverages the useful information extraction capabilities of CNN to passively eavesdrop on data transmissions in a network and infer the AoA and beam identifier. The simulation results demonstrate that DeepBeam CNN achieves high accuracy in beam prediction, with up to 77% and 99% accuracy for 12 and 5-beam codebooks, respectively. Moreover, the study indicates that for a 12-beam codebook, avoiding excessive search during the initial beam establishment can reduce the latency by seven times. Another significant contribution of this study is the release of an experimental dataset that is publicly available for further research purposes [46].

4.1.2 Long Short-Term Memory Networks (LSTM)

LSTM, which is a type of RNN architecture, is designed to handle the issue of vanishing and exploding gradient descent in standard RNN. LSTM networks use a memory cell to keep track of information over a sequence of inputs, allowing them to selectively forget or remember certain pieces of information and hidden details as needed. This makes them well-suited for tasks that involve processing sequential data, such as natural language processing, speech recognition, and time series analysis, as a result of its capability to learn hidden details and recognize long-term relationships within input data, the LSTM approach has been widely studied to improve beam management and BT procedures [47] [22]. In [27], a solution based on LSTM was proposed for beam tracking and estimating the AoA over certain paths. The LSTM model takes the received signal as input and past AoA estimations as input and leverages the fact that certain paths exhibit sequential changes in UE parameters due to mobility. In [28], the LSTM approach for BT in a multi-input single-output (MISO) vehicle mmWave system is presented. This technique comprises two stages of channel tracking. In 1st stage, the UE sends pilots signals to all BS where each BS estimates the channel and predicts the optimal beamforming vector. At the same time, all the BSs sent the estimated channel to a centralized cloud where all channels are integrated and fed as input to the LSTM model where LSTMs are trained based on integrated channels. In the 2nd stage, the trained LSTM model will predict the next channel in upcoming coherence time, where there will be no need for further pilot training signals In [29] to take advantage of the feature extraction abilities offered by a CNN, it is employed alongside LSTM to capture spatial correlations present in beam domain images of both high and low resolutions , by employing a multi-resolution codebook, which consists of wide and narrow beams, low-resolution beam domain images are acquired through wide beam measurements, Subsequently, these images serve as input to an LSTM-based CNN model, which learns the correlation between low-resolution and high-resolution beam domain images and predicts the quality of narrow beams, Simulation results are performed using wireless Insite [49].. In a recent study [30], a combination of a sequential Bayesian estimation framework and an LSTM prediction model is described to enhance the performance of the BT method. The method utilizes a DFT codebook-based approach, which relies on the channel power leakage property to estimate the AoD and main LOS path deviation. The model also proposes optimal neighboring criteria (ONC) and maximum probability criteria (MPC) for selecting narrow beams while the user is moving at high speed. The ADAM optimizer [50] with a cross-entropy loss function for backpropagation is implemented. The simulation results achieved perform better compared to the traditional Kalman filter [48] and LSTM [27] methods in terms of BER and beamforming gain.

4.2 Auxiliary-Information-Assisted SL

In high-speed scenarios, measuring beams can be time-consuming, leading to increase overhead. One potential solution is to utilize ML techniques to predict optimal beams based on auxiliary information shown in Figure 3, such as the location and orientation of the user equipment and sub-6 GHz CSI. Furthermore, sensor-based information, such as LIDAR and radar, is increasingly being employed for beam management in mmWave/THz networks.

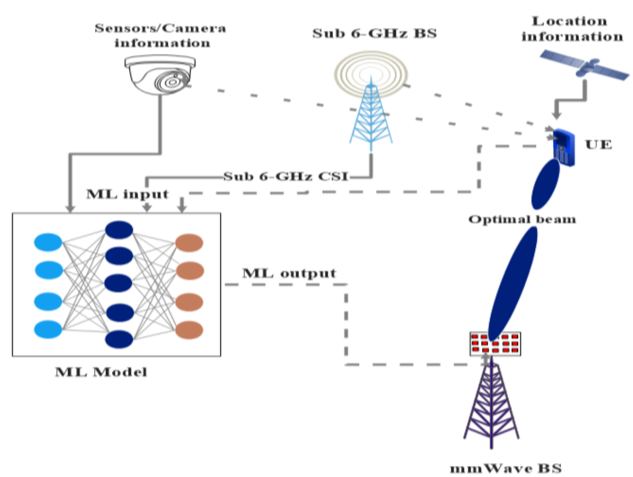

Figure 3: Auxiliary information assisted ML model

4.2.1 Location Information

To effectively track the optimal beam the UE location can be utilized to decrease the overhead of beam training. In [31], the authors proposed a coordinated beamforming approach that utilizes radio frequency signatures obtained from received pilots at multiple base stations. On the basis of the received pilots, they trained a CNN model to forecast the highest possible rate for each base station beam. The method then chooses the beam with the best rate of prediction. The use of auxiliary information in the form of location was further explored to address BT challenges in V2I [32] [33]. In [32] the author developed a database for storing beam pairs and quantized location bins. In [33], they proposed a learning model that could handle receiver locations that are not discrete. In [34], the author exploited an SL approach that involved SVM, KNN, and logistic regression algorithms for 5G new radio (NR) mmWave beam tracking. They utilized the CSI matrix and UE location information collected at the base station to train the ML models. During the prediction phase, the optimal narrow beam is accurately predicted without the need for additional CSI reports, which allows for more data transmission to take place.

4.2.2 Sub 6 GHZ CSI

The channel gains of the mmWave and sub-6 GHz interfaces exhibit spatial correlation in line-of-sight situations, as per the experimental results in [53]. In [35], this correlation was utilized to obtain fingerprints for UE by acquiring a power delay profile from sub-6 GHz CSI. During the training phase, an EBS is performed shown in Figure 1, then using a DNN technique that estimates the correlation between the best beam in the mmWave link and the sub-6 GHz power delay profile. After training, with sub-6 GHz CSI as input, DNN was used to indicate the optimal beam indices for the mmWave link. Simulation results show that compared to other traditional BT, this approach achieves a higher probability for predicting optimal narrow beam. In [36], a similar method was suggested, where a CNN was applied to a multi-classification task for forecasting the mmWave optimal beam. In [37], a novel approach was introduced that leverages previously obtained sub-6 GHz CSI instead of instantaneous low frequency CSI. Additionally, an LSTM model was employed to predict the best beam between two sub-6 GHz CSI estimation instances, aiming to enhance the accuracy for beam alignment and beamforming gain. According to simulation results, this method results in an overall enhancement of the beamforming gain.

4.2.3 Sensors/Camera Information

To reduce the overhead of beam management in the mmWave/THz bands, environmental sensing/camera information can be used. In [38], a technique is introduced that predicts the best narrow beam index using a residual network. This network employs visual data acquired from cameras installed in mmWave base BS to make this prediction. Likewise, in [39], cameras mounted on drones were utilized to gather visual data, which enabled rapid beam prediction in mmWave frequency bands. The authors validated their approaches by testing them on publicly available datasets [53] and found that they were able to accurately predict the best beams.

4.3 Reinforcement Learning (RL)

The methods discussed in sections 4.1 and 4.2 require significant training and are supervised, meaning they may not perform well in untrained situations, which limits their usefulness. To address this issue, RL, which involves online learning, is better suited to more general scenarios. In this section, we will have a brief discussion of mmWave/THz BT techniques using RL.

4.3.1 Deep Q-Networks and Q-Learning

Q-Learning is an ML algorithm employed in RL to determine the best policy for an agent in a given environment. It is a model-free approach that updates a Q-function (quality) iteratively, which estimates the expected future reward for each state-action pair. The Q-function is updated utilizing the Bellman equation, and the agent selects the action with the highest Q-value in each state to optimize its total expected reward. Q-Learning is valuable in complicated and dynamic environments where it is difficult to define a mathematical model of the system. However, it often requires multiple iterations before it can converge to the optimal solution, which can limit its usefulness in fast-moving UE scenarios. To speed up the beam-tracking process in such scenarios, researchers have proposed running multiple Q-learning agents in parallel, as described in the reference [40]. Additionally, a BT method based on deep Q-networks (DQN) was suggested in [41]. This approach can adapt to changes in the environment by adjusting the range of beam probing, making it suitable for UE with high speed. The assessment of this approach, considering both slow- and fast-moving UE, shows that it converges and learns faster than Q-learning.

4.3.2 Multi-Armed Bandits (MAB)

Multi-armed bandit (MAB) is a type of ML algorithm commonly used in decision-making scenarios that involve a trade-off between exploration and exploitation. It is named after a hypothetical scenario where a gambler is faced with a row of slot machines, referred to as one-armed bandits, and must decide which one to play. The initial research studies that presented BT as a multi-armed bandit problem can be found in references [42] and [43]. In these studies, researchers proposed using MAB algorithms for BT solutions in different scenarios, such as utilizing auxiliary information and high-speed scenarios. However, these approaches may lead to beam misalignment in mmWave channels that frequently change. To overcome this issue, the authors of reference [44] proposed a new approach that combines the beam scanning subspace and the beam index difference as an arm. This approach can better adapt to fast-changing channels and reduce the BT overhead.

5. OPEN RESEARCH PROBLEMS

5.1 Machine Learning

By utilizing its abundant spectrum resources, mmWave communication can achieve data rates of Gbps through the use of large antenna arrays. However, due to the rapid changes in the channels in high speed scenarios, beam tracking can result in excessive overhead that is not desirable. Unlike traditional methods of beam training and tracking, ML aims to equip algorithms with the ability to gather and use relevant data automatically, thereby reducing the need for extensive beam search. Leveraging ML capabilities results in achieving fast and efficient establishment of mmWave connections, while also acquiring situational awareness. Specifically, DL has enormous potential in acquiring situational awareness, including capturing channel responses and identifying unused spectrums. DL can also be utilized in tasks like classification and optimal beam selection. However, it causes huge complexity in identifying beam weight. In contrast, RL is advantageous in addressing problems that involve sequential decisions. By combining DL and RL, beam training and tracking technologies can become intelligent, flexible, and capable of efficiently adapting to rapidly changing environments.

5.2 THz Bands Beam Tracking

As wireless communication systems experience a rapid increase in data traffic, the frequency range (0.1-10) THz band is being considered for future cellular as one of the possible solutions to support data rates of up to 10 Gbps. In THz communications, implementing the beamforming technique is critical to counteract signal fading and distortion that occur due to the loss of signal strength and the multi-path effect during wireless transmission. So, one of the future challenges for THz wireless communication includes the effective beamforming design strategies, where more robust and accurate beam tracking techniques utilization will be required implementing AI and ML can effectively solve these problems. As beamforming depends on CSI, information about the AoD and AoA is critical. However, due to the higher frequencies and larger antenna arrays used in THz communication, information about AoA, AoD, and beam tracking require significant computational complexity. Developing efficient, accurate, and reliable beam tracking techniques is an urgent problem that needs to be addressed.

6. CONCLUSION

The demand for wireless communication with high capacity and data rates has grown rapidly, and mmWave/Thz frequency bands are seen as a solution for 5G and beyond. However, due to the small wavelength of these frequencies, directional communication using beamforming is necessary to overcome path loss. If the beam is not tracked properly, it may result in significant training overhead, which is not desirable. In conclusion, beam tracking is a crucial aspect of mmWave /THz communication systems that aims to maintain high data rates and improve system reliability. Various BT techniques have been proposed, including supervised learning and reinforcement learning. The use of auxiliary information, such as location, sub-6 GHz CSI, and sensor-based information, can significantly reduce the overhead of BT. Reinforcement learning, especially MAB, and DQN, can adapt to changes in the environment and are better suited for general scenarios. However, the effectiveness of each technique depends on the specific scenario, and further research is necessary to develop more robust and efficient BT methods for mmWave and THz communication systems.

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