A Review on Machine Learning Applications in Localization in 5G and Beyond Wireless Communications

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***Abstract*— Location is the process of estimating the position of a device or user in a wireless network. Location is critical for many applications and services in 5G and beyond wireless communications. However, localization faces many challenges in complex and dynamic environments, such as multipath propagation, non-line-of-sight (NLOS) conditions, and limited bandwidth and power resources. Machine learning (ML) is a promising technique that can improve location performance and efficiency by exploiting the large amount of data available in wireless networks. In this article, state-of-the-art ML localization techniques are reviewed. In addition, recent ML localization techniques are compared, and observations from the comparison are delineated. Additionally, challenges with possible recommendations are presented.**

Keywords—B5G, machine learning, localization, localization in B5G

I. INTRODUCTION

Location in wireless communications is the process of determining the position and orientation of wireless devices or users in a wireless network [1]. Location in wireless communications can be used for various purposes, such as location-based services, network optimization, resource allocation, security, and navigation. Location in wireless communication can be done by various methods, such as using Global Positioning System (GPS), using wireless signals such as received signal strength, angle of arrival, arrival time, etc. [2], [3], using machine learning algorithms (such as deep learning, reinforcement learning, etc.), or using hybrid methods that combine multiple methods [4]. Location is important in B5G because it enables a variety of new applications that rely on location information, such as autonomous driving, smart city, industrial automation, virtual reality, e-health, etc. [5]. In 5G and beyond (B5G) wireless communications, location is critical to enable various applications and services that require high location accuracy, reliability, scalability and efficiency, such as connected communities, smart environments , vehicle autonomy, asset tracking, medical services, military and crowd detection [6], [7]. Performance improvement should be made possible through beamforming, interference management, resource allocation and network optimization [5].

One of the challenges of localization in B5G wireless communications is the complexity and variability of the radio propagation environment, especially at mmWave and THz frequencies. To overcome this challenge, some emerging techniques have been proposed, such as reconfigurable intelligent surfaces (RIS), integrated communication and localization (ICL), and machine learning (ML) [5]. These techniques aim to exploit the potential of SIFs to control the radio environment, take advantage of the synergy between communication and location signals, and apply data-driven methods to learn from channel measurements [5], [8]. . These techniques are expected to enable high-precision, low-latency localization in B5G networks [8], [9]. The following sections provide a brief overview of state-of-the-art ML localization techniques, factors that influence localization, comparison of localization techniques versus factors that influence localization, challenges of ML localization techniques, and recommendations for making progress in this area. Finally, an overview of the article is presented in the conclusion.

II. ML LOCALIZATION TECHNIQUES IN B5G

Here are some of the cutting-edge machine learning location techniques that are being applied to 5G and beyond wireless communication:

A. Machine Learning for Fingerprinting-based Localization

Fingerprinting is a technique that uses a database of reference signals (such as received signal strength, angle of arrival, time of arrival, etc.) and their corresponding locations to match measured signals and estimate the position of mobile nodes. Deep learning can help create and update the fingerprint database, reduce the dimensionality of fingerprint data, and improve the matching accuracy. Some examples of deep learning architectures used for fingerprint-based localization are convolutional neural networks (CNN), deep de-noising neural networks (DDNN), auto-encoders (AE), antagonists (GAN), long-short-term memory networks (LSTM), deep recurrent neural networks (DRNN) and hybrid deep learning models [10].

B. Machine Reinforcement Learning for RIS-Assisted Localization

RIS are passive devices capable of reflecting and manipulating wireless signals to improve communication and location performance. Deep reinforcement learning (DRL) can help optimize RIS phase shifts, estimate RIS channel state information, and design RIS beam patterns for localization. DRL is a combination of deep learning and reinforcement learning, which can learn from high-dimensional data and optimize complex policies in dynamic environments [11].

C. Machine Learning for ICL

ICL is a technique that integrates communication and location signals into a single waveform, reducing signaling overhead and latency. Deep learning can help design the ICL waveform, extract location features, and estimate the position of mobile nodes. Some examples of deep learning architectures used for ICL are CNNs, AEs, GANs, LSTM networks, and hybrid deep learning models [12].

D. Machine Learning for Cooperative Localization

Mobile nodes can communicate position data and measurements with one another or with anchor nodes (nodes whose coordinates are known) using the cooperative localization technique to increase the accuracy of their location. The most effective cooperative partners may be chosen, cooperative data can be merged, and mobile node positions can be estimated with the aid of machine learning [13].

E. Machine Learning for Hybrid Localization

In order to take advantage of their complementary strengths and minimize their flaws, hybrid tracking is a methodology that integrates various tracking methods (such as range-based, non-range, fingerprint, etc.). Machine learning can be used to integrate location data from many sources, determine the position of mobile nodes, and choose the optimum location approach for various scenarios [12].

F. Machine Learning for Localization-Aware Resource Allocation

Location-based resource allocation is a technique that optimizes the allocation of wireless resources (such as power, bandwidth, time slots, etc.) based on location information of mobile nodes. Machine learning can help learn the optimal resource allocation policy, adapt to dynamic network conditions, and balance the trade-off between communication and location performance. [11].

III. ML LOCALIZATION TECHNIQUES IN B5G

Some of the factors considered for localization in machine learning localization in 5G and beyond wireless communications are:

A. The Wireless Technology

The wireless technology used for location affects the type and quality of signals that can be measured and used for location. For example, different wireless technologies may have different frequency bands, modulation schemes, bandwidths, transmit powers, or antenna configurations. These factors influence the propagation characteristics, coverage range, multipath effects, interference levels, and signal-to-noise ratios of wireless signals. Therefore, machine learning localization techniques must consider wireless technology and its impact on localization performance [11].

B. The Localization Method

The localization method's complexity and accuracy are influenced by the localization technique utilized. For instance, different localization techniques may make use of various measurements (such as received signal strength, angle of arrival, time of arrival, etc.), models (such as fingerprint, geometric, probabilistic, etc.), or techniques (such as range-based, non-range, cooperative, hybrid, etc.). The processing needs, communication costs, scalability problems, and localization errors of the localization method are influenced by these variables. As such, machine learning localization algorithms must to take into account the localization method and its applicability in various contexts [10], [14].

C. The Environment

The unpredictability and uncertainty of wireless signals and position data depend on the environment in which they are measured. For instance, various settings could have varying degrees of interference, obstructions, reflections, diffractions, noise, and shadows that interfere with wireless signals. Furthermore, the mobility, dynamics, and heterogeneity of various environments may vary, which could also have an impact on positional data. Machine learning localization techniques must therefore take the environment into account as well as its localization issues [11].

D. The Network Architecture

The scalability and effectiveness of the location system are impacted by the network architecture. Different network architectures could, for instance, use different kinds of nodes (such as anchors, sensors, or relays), connections (such as wired, wireless, or cellular), or topologies (such as centralized, distributed, or hierarchical). These variables affect the coordination of the location system and network coverage, connection, and capacity. As a result, network architecture and its effect on localization performance must be considered by machine learning localization approaches [11].

E. The Application Requirements

The trade-offs and limitations of the localization system are impacted by application needs for localization. For instance, various applications may have various specifications for location dependability, accuracy, latency, scalability, security, or privacy. These criteria have an impact on the location system's design decisions, optimization targets, and performance indicators. Therefore, application requirements and their implications for localization should be taken into account by machine learning localization techniques [10], [14].

F. The Machine Learning Algorithm

The machine learning algorithm used for localization affects the learnability and complexity of the localization system. For example, different machine learning algorithms may have different types of learning (such as supervised, unsupervised, reinforcement, etc.), different types of models (such as linear, nonlinear, deep, etc.), or different types techniques (such as regression, classification, grouping, etc.). These factors influence the learning efficiency, accuracy, robustness and generalization of the localization system. Therefore, ML localization techniques must take into account the machine learning algorithm and its suitability for localization [11].

Table 1 presents comparisons and contrasts of state-of-the-art ML localization techniques using the following factors discussed earlier in this section.

TABLE I. COMPARISON OF STATE-OF-THE-ART LOCALIZATION TECHNIQUES

Technique Name	**Wireless Technology**	**Network Architecture**	**Application Requirement**	**Machine Learning Algorithm**	**Localization Method**	**Environment**
WiDeep [15]	WiFi	Distributed	Indoor localization with high accuracy and robustness	Deep learning (CNN)	Fingerprinting	Dynamic and Heterogeneous
SemanticSLAM [16]	WiFi and Camera	Centralized	Indoor Localization with semantic information	Unsupervised learning (clustering) and supervised learning (classification)	SLAM	Unsupervised learning (clustering) and supervised learning (classification)
Hybloc [17]	WiFi and Bluetooth Low Energy (BLE)	Distributed	Indoor localization with high accuracy and scalability	Ensemble learning (random decision forest)	Hybrid (range-based and fingerprinting)	Dynamic and heterogeneous
Deep learning for RIS-assisted localization [4]	mmWave or THz	Centralized or distributed	Outdoor localization with high accuracy and low latency	Deep learning (CNN, AE, GAN, LSTM) or deep reinforcement learning (DRL)	Range-based or fingerprinting	Complex and variable
Deep learning for ICL [4], [18]	mmWave or THz	Centralized or distributed	Outdoor localization with high accuracy and low latency	Deep learning (CNN, AE, GAN, LSTM) or hybrid deep learning models	ICL (integrated communication and localization)	Complex and variable
Deep learning for fingerprinting-based localization [18], [19]	WiFi or BLE or UWB or RFID or LiFi or mmWave or THz or acoustic signals or magnetic signals or inertial signals or hybrid signals	Centralized or distributed	Indoor or outdoor localization with high accuracy and robustness	Deep learning (CNN, DDNN, AE, GAN, LSTM, DRNN) or hybrid deep learning models	Fingerprinting	Dynamic and heterogeneous

In developing Table 1, the following observations were made.

- Most of the techniques use deep learning algorithms for localization, which can learn from high-dimensional data and optimize complex policies in dynamic environments.
- Most of the techniques use fingerprinting methods for localization, which can exploit the rich functionality of wireless signals and achieve high accuracy without requiring geometric models.
- Most techniques use WiFi signals for location, which are widely available and compatible with most devices. However, some techniques also use other signals such as mmWave, THz, BLE, UWB, RFID, LiFi, acoustic, magnetic, inertial, or hybrid signals to improve location performance.
- Most techniques are designed for indoor locations, where wireless signals are more affected by noise, interference, multipath effects, and environmental changes. However, some techniques also work for outdoor locations, where wireless signals have greater coverage range and line-of-sight paths.
- Some of the techniques use hybrid methods for localization, which combine multiple localization methods (such as range-based, non-range, fingerprint, etc.) or multiple machine learning algorithms (such as supervised, unsupervised, reinforcement, etc.) to exploit their complementary strengths and overcome their weaknesses.
- Some of the techniques use new localization methods, such as RIS-assisted localization and ICL. The RIS-assisted location uses reconfigurable smart surfaces to control the radio environment and improve communication and location performance. ICL integrates communication and location signals into a single waveform to reduce signaling overhead and latency.

IV. Challenges of ML Localization Techniques

Some of the open challenges or limitations of the machine learning localization techniques are:

A. *Data Quality and Availability*

Machine learning localization techniques rely on large amounts of data to train and test their models. However, data collected from wireless signals may be noisy, incomplete, or outdated due to environmental factors, device heterogeneity, mobility patterns, or network dynamics. Additionally, data may not be easily accessible or shared for privacy or security reasons. Therefore, machine learning localization techniques must address data quality and availability issues using methods of pre-processing, data augmentation, transfer learning, federated learning, or preservation of data. private life [20], [21].

B. *Model Robustness and Security*

Machine learning localization techniques can face adversarial attacks that aim to manipulate the data or model to degrade localization performance or leak sensitive information. For example, an attacker can inject false signals, scramble the signals, or modify the fingerprint database to trick the tracking system. Additionally, machine learning models may not be robust to changes in the environment or network conditions that affect wireless signals. Therefore, machine learning localization techniques must ensure the robustness and security of the model by using anomaly detection, encryption, authentication, verification or adversarial defense methods [18].

C. *Computational Complexity and Energy Consumption*

Machine learning localization techniques can involve complex algorithms that require high computing power and memory resources. However, some of the mobile nodes may have limited capabilities and battery life. Additionally, machine learning models can incur high communication overhead and latency due to the exchange of large amounts of data or model parameters. Therefore, machine learning localization techniques should reduce computational complexity and power consumption by using model compression, model pruning, model quantization, model distillation, or model compression methods. model compression. advanced computing [21].

D. *Model Generalization and Adaption*

Machine learning localization techniques may not be able to generalize well to different environments, devices, or scenarios that differ from the training data. For example, a machine learning model trained on one building may not perform well on another building with a different layout, materials, or interference. Additionally, machine learning models may not be able to adapt quickly to changes in the environment or network conditions that affect wireless signals. Therefore, machine learning localization techniques should improve the generalization and adaptation of their model using transfer learning, online learning, active learning or meta-learning methods [18].

E. *Model Interpretability and Explainability*

Machine learning localization techniques can be difficult to interpret or explain due to their complex and nonlinear nature. For example, a deep neural network may have thousands of parameters and hidden layers that are difficult to understand or justify. Additionally, machine learning models may not provide any measure of confidence or uncertainty for their location estimates. Therefore, machine learning localization techniques should improve the interpretability and explainability of their model using visualization, attention mechanism, salience map or Bayesian inference methods [20].

F. *Model Evaluation and Validation*

Machine learning localization techniques can be difficult to evaluate or validate due to the lack of benchmarks or standardized metrics. For example, different studies may use different data sets, experimental settings, parameters, or performance indicators to evaluate their ML models. Additionally, machine learning models may not be validated in real-world scenarios or large-scale deployments that reflect the practical challenges and requirements of location systems. Therefore, machine learning localization techniques should establish the evaluation and validation of their model using common benchmarks, metrics, protocols or platforms [22].

V. Recommendation

Some possible recommendations to address the limitations of machine learning localization techniques are:

A. *Using Hybrid Techniques*

Hybrid techniques are techniques that combine multiple location methods (such as range-based, range-free, fingerprinting, etc.) or multiple machine learning algorithms (such as supervised, unsupervised, reinforcement, etc.) to exploit their complementary strengths and mitigate their weaknesses. For example, a hybrid technique can use a range-based method to provide coarse location and a fingerprint method to provide precise location. Or, a hybrid technique can use a supervised algorithm to train a model offline and an unsupervised algorithm to update the model online. Hybrid techniques can improve the accuracy, reliability, scalability and adaptability of ML location systems [21], [22].

B. *Using Federated Learning*

Federated learning is a technique that allows multiple mobile nodes to collaboratively train a machine learning model without sharing their data with each other or with a central server. Federated learning can address data quality and availability issues using each node's local data, model robustness, security issues by avoiding data leakage or manipulation, and computational complexity issues and energy consumption by distributing the computation between the nodes [23].

C. *Using Edge Computing*

Edge Computing is a technique that allows mobile nodes to perform computations at the edge of the network, such as on nearby devices or base stations, rather than on remote servers or clouds. Edge computing can reduce communication overhead and latency caused by machine learning models by avoiding the transmission of large amounts of data or model parameters. Edge computing can also reduce the power consumption of mobile nodes by offloading some of the computational tasks to more powerful edge devices [22], [21].

CONCLUSION

Machine learning location is a promising location technique for 5G wireless communications and beyond, as it can improve the accuracy and efficiency of location algorithms by learning from wireless signals and measurements. However, ML localization also faces many challenges and limitations, such as data quality and availability, model robustness and safety, computational complexity and power consumption, generalization and adaptation. . models, model interpretability and explainability, and model evaluation and validation. In the improvement of ML localization techniques, several factors, such as wireless technology, network architecture, application requirements, machine learning algorithm, localization method and environment, and the use of appropriate methods are adopted to address the challenges and limitations. Some of the leading machine learning localization techniques are WiDeep, SemanticSLAM, Hybloc, deep learning for RIS-assisted localization, deep learning for ICL and deep learning for localization based on fingerprints. These techniques use different types of wireless signals, network architectures, application requirements, machine learning algorithms, location methods and environments to achieve high performance location in wireless communications. . 5G and beyond. Going forward, this study would discuss the integration of ML with other emerging technologies, such as massive MIMO, mmWave, drones, and blockchain.

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