Digital Twin Empowered Wireless Positioning: Prospects, Architecture, and Challenges

Xiufang Shi, Xinlu Xuan, Xinyu Huang, Jianzhe Xue, and Xuemin Shen

Abstract

Achieving precise and reliable positioning in complex and dynamic environments is very challenging due to multi-path propagation, environmental changes, and system limitations. This article explores the role of digital twin (DT) in wireless positioning and provides comprehensive study on the prospects of DT in enhancing positioning performance with respect to accuracy, coverage, latency, and reliability. Particularly, a general architecture for DT-empowered wireless positioning is proposed. The powerful simulation and prediction capabilities of DT are leveraged for fine-grained multi-path feature extraction, dynamic model update, seamless-transition, and system optimization. A case study based on fingerprinting positioning is presented to demonstrate the enhancement due to DT in feature extraction and model update. Some open research issues in DT-empowered wireless positioning are also discussed.

Introduction

High-precision positioning has become essential for a vast amount of applications such as navigation, asset tracking, emergency response, autonomous driving, and other location-based services [1], [2]. Existing wireless positioning technologies, e.g., Global Navigation Satellite Systems (GNSS), WiFi, ultra-wideband (UWB) and cellular-based positioning, have contributed significantly to the development of location-based applications. However, there still exist evident performance gaps between the provided services and the expected ones from the aspects of accuracy, coverage and latency, etc. The challenges in bridging the performance gaps mainly come from the impact of complex and dynamic environments, and the system limitations. In complex environment, wireless signals may undergo blockage, multipath propagation, etc., which can bring large measurement errors and degrade the positioning performance. The change of environment can make positioning models or algorithms inapplicable or significantly reduce their accuracy and effectiveness. Moreover, since each positioning system has its own limitations, no single positioning system meets the needs of all scenarios.

Digital twin (DT), as a virtual replica of the physical system, can continuously update with real-time data, enabling simulation, analysis, and optimization of the system's performance. Integrating DT into wireless positioning would be a powerful tool to overcome the existing challenges. By simulating the positioning environment and signal propagation, including attenuation, reflection, and diffraction, DT can help extract fine-grained features and correct measurement errors, leading to more precise positioning. In dynamic environment, DT can predict the movement of users or devices, and efficiently adapt to environmental changes, ensuring consistent performance even in challenging conditions. By integrating multiple positioning technologies within the DT, it is potential to provide continuous and seamless positioning services as users move across diverse areas.

The DT approach was originated in the area of smart manufacturing [3] for product lifecycle management, fault detection and intelligent decision. Recently, it has been extended to the area of wireless communication networks [4], [5], [6], facilitating decision-making for various layers, like channel predication in the physical layer, access control and beam management in the access layer, network configuration in the network layer, and proactive caching in the application layer. In the context of wireless positioning, only a few efforts are devoted to explore the potentials of DT in improving positioning performance. In [7], a seven-layer localization-oriented DT paradigm, named LocDT, is proposed to characterize the integrated localization and communication features in the sixth-generation (6G) networks. LocDT reveals device-wise importance-differences in channel features, which contribute to improving positioning accuracy. In [8], a DT model is constructed for indoor UWB positioning system, where the anchor layout is optimized by the DT model to improve the positioning accuracy. In [9], a DT radio frequency (RF) map is constructed and leveraged to generate RF fingerprints, reducing the data collection cost for fingerprinting-based positioning. Existing studies have covered some topics about DT construction [7], data generation [9], system deployment and optimization [8], primarily focusing on improving positioning accuracy and reducing costs with the aid of DT. However, the potential of DT for wireless positioning extends beyond just accuracy and cost. Key performance metrics, including coverage, latency, and reliability, also present substantial potential for improvement through DT-enabled solutions.

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Xiufang Shi (corresponding author) and Xinlu Xuan are with the College of Information Engineering, Zhejiang University of Technology, Hangzhou 310023, China; Xinyu Huang and Xuemin Shen are with the Department of Electrical and Computer Engineering, University of Waterloo, Waterloo, ON N2L 3G1, Canada; Jianzhe Xue is with the School of Electronic Science and Engineering, Nanjing University, Nanjing 210023, China.

Despite these opportunities, current studies remain insufficient to fully explore the potential of DT in advancing wireless positioning systems.

This article aims to explore the potentials of DT for wireless positioning, and narrow the performance gaps between the existing technologies and the demands for accurate and reliable location services. The main contributions of this article are summarized as follows.

- To the best of our knowledge, this is the first work to comprehensively investigate the prospects of leveraging DT to improve wireless positioning performance across multiple dimensions, including accuracy, coverage, latency, and reliability.
- A modularized architecture for DT-empowered wireless positioning is proposed. By integrating DT into the wireless positioning system, the powerful simulation and prediction capabilities of DT are leveraged for fine-grained feature extraction, dynamic model update, seamless-transition, and system optimization.
- A case study based on fingerprinting positioning is conducted to demonstrate the performance enhancement brought by DT. The results show that the positioning accuracy can be significantly improved through DT-aided feature extraction and model update.

In the following sections, we first provide an overview about the existing positioning techniques, and summarize the main performance gaps. Then, the prospects of DT in wireless positioning are discussed. Subsequently, the proposed architecture for DT-empowered wireless positioning is introduced. Afterwards, the case study and some open research issues are provided.

Overview of Wireless Positioning

Existing Positioning Techniques

The existing wireless positioning techniques can be generally divided into two categories: model-based positioning and data-driven positioning.

Model-based positioning can be also called geometry-based positioning, it relies on well-defined mathematical or physical model, and utilizes the geometrical relationship between the transmitter and the receiver to estimate device locations. It performs well when the environments are relative stable and measurement models are accurate. However, in complex environments, such as urban canyons or indoor areas, its performance will severely degrade due to multipath and interference effects. According to the specific geometrical measurements, model-based positioning mainly consists of three kinds of methods:

- Time-based methods, which use the signal transmission time, e.g., time-of-arrival (ToA), time-difference-of-arrival (TDoA), and round-trip-time (RTT), to estimate the range or range difference between transmitters and receivers. They are generally applied in GNSS, cellular and UWB positioning systems.
- Angle-based methods, which use angle-of-arrival (AoA) or angle-of-departure (AoD) to estimate the angular-relationship between the transmitter and the receiver. The emerging technologies like massive multiple-input multiple-output (MIMO) would be of great potential to increase the accuracy of angle estimation.
- Phase-based methods, which use the received carrier phase (CP) to estimate the range between the transmitter and the receiver. Phased-based methods have been widely applied in GNSS real-time kinematics (RTK), providing centimeter-level accuracy. Considering the potential use of millimeter wave, Terahertz-Band in next-generation networks, phased-based methods would be of great potential to achieve centimeter or even millimeter-level accuracy [10].

Data-driven positioning generally uses machine learning (ML) techniques, to create predictive models for location estimation. One of the most common forms of data-driven positioning is fingerprinting. For fingerprinting, a fingerprint database or a radio map should be first built by collecting spatial fingerprints at known locations. The fingerprints generally consist of the received signal strength (RSS) or channel state information (CSI) from different access points (AP) or base stations (BS). By establishing the mapping relationship between locations and fingerprints, the system estimates the location with real-time collected fingerprint data. This kind of method requires extensive data collection, which can be time-consuming and costly. Moreover, the model training should be adaptive to environmental change.

Performance Gaps

Table 1 provides an overview of mainstream wireless positioning systems, listing the applied methods, achievable accuracy, latency, limitation factors, and corresponding use cases. It should be noted that the ranges of accuracy and latency are obtained from the literature work and commercial systems. The actual achievable accuracies and latencies might vary with application scenarios, hardware/software configurations and positioning algorithms. The emerging applications, e.g., immersive extended reality, and robotic interaction, have much higher requirements for positioning performance [2], [11]. The gaps between the achievable performance and the emerging requirements mainly lie in the following aspects:

1) Accuracy: Applications like autonomous driving, cooperative robotics often require centimeter-level or even millimeter-level accuracy. Although some positioning systems, e.g., GNSS-RTK can provide centimeter-level accuracy in open stable environment, the accuracy will severely degrade in highly dynamic and complex scenarios, e.g., autonomous driving in tunnels.

2) Coverage: When the users/devices move across different areas, they are expected to receive continuous and seamless positioning services. Most of the existing positioning systems can only offer limited coverage. GNSS generally works in outdoors. WiFi and UWB are mainly applied in indoors. Although cellular-based positioning can provide positioning services in both indoors and outdoors, the positioning performance are quite different in diverse environments.

3) Latency: Positioning latency refers to the time delay between sending a positioning request

System	Technique	Measurements	Accuracy	Latency	Limitation Factors	Use Cases
GNSS	Model-based	ToA CP+ToA	Meter-level Centimeter-level	1-10s	Signal loss Multipath effect	Outdoor
WiFi	Data-driven Model-based	RSS, CSI RSS, RTT	Meter-level	100ms-10s	Environmental change Multipath effect	Indoor
Bluetooth	Data-driven Model-based	RSS RSS, AoA	Meter-level	100 ms -1s	Environmental change Multipath effect	Indoor
UWB	Model-based	ToA, TDoA	Centimeter-level	10ms-100ms	Deployment cost Multipath effect	Indoor
4G	Model-based	ECID, RTT UTDoA, OTDoA	Tens of meters	100ms-10s	Cell size Multipath effect	Indoor & Outdoor
5G	Model-based	ECID, RTT UTDoA, OTDoA AoA, AoD	Sub-meter to meters	10ms-100ms	Cell size Multipath effect	Indoor & Outdoor

TABLE 1. Overview of Mainstream Positioning Systems.

and receiving the final position estimate. For time-sensitive applications, low latency is crucial for timely response and action. For the envisioned positioning use cases in the next-generation networks, the most stringent latency for positioning can be as low as 0.1 ms [2], [11], which is much less than the achieved latency of existing positioning systems.

Overall, the existing positioning systems still face significant performance gaps in terms of accuracy, coverage, and latency. Bridging these gaps will drive future advancements in positioning systems for diverse applications.

Prospects of DT in Wireless Positioning

DT can be deemed as a digital representation of the physical world, reflecting the real-time states and behaviors of the entities therein. In the area of wireless communications, DT constructs a digital replica of the physical environment and can emulate the wireless signal propagation within the physical environment [5], [12], providing new opportunities for positioning systems. The potential prospects of DT in wireless positioning include:

1) Enhancing Accuracy: By providing a detailed and evolving view of the environment, DT can help extract fine-grained features, reduce measurement errors, and fuse muti-source data, so as to enhance positioning accuracy. Specifically, by simulating the propagation of wireless signals in complex environments, DT can help extract subtle signal features, e.g., ToA, AoA and CP from overlapping paths, that are often challenging to isolate in real-world measurements. Moreover, by predicting and analyzing the signal blockages, interference and multipath effects, DT helps identify potential sources of error and allows for real-time corrections. Furthermore, DT can act as a data integration hub, allowing for adaptive fusion of various data from GNSS, 4G/5G, WiFi, and UWB, etc. This fusion enhances positioning accuracy by leveraging the strengths of multiple positioning systems.

2) Extending Coverage: DT can facilitate seamless transition of positioning systems across different areas, such as moving from outdoors to indoors. In contrast to the current transition methods that rely on the received signals and conduct reactive switching between different positioning systems based on predefined switching rules, DT can predict the user's trajectory and the upcoming signal environment, and provide proactive assistance during the switching between different positioning systems, resulting in more consistent and continuous coverage. Moreover, DT can help simulate large-scale deployments of positioning systems in smart cities, factories, or other environments. By modeling the physical layout, network topology, and expected device density, DT can be used to optimize the placement of signal transmitters (e.g., WiFi AP, UWB anchors) to ensure maximum coverage without gaps.

3) Reducing Latency: For positioning system, the latency mainly comes from data transmission and processing delay. DT can aid to reduce both transmission delay and processing delay. One hand, with the current and historical data, DT can predict a device's movement and update its position proactively, effectively reducing the processing delay for future positioning requests. On the other hand, DT can be also utilized for real-time simulation of positioning networks. Using twin models to predict congestion, pre-optimize data transmission routes and resource allocation will facilitate the reduction of transmission delay. The main value of using a DT to reduce positioning latency is that it enables the system to think ahead rather than simply react.

4) Improving Reliability: DT provides a continuous and evolving representation of the environment, allowing positioning systems to adapt in real time to changes such as new obstacles, movement of people or vehicles. By employing online or incremental learning techniques, DT allows the system to quickly refine and update positioning-related models, e.g., channel model, feature exaction model, and location estimation model, ensuring more reliable performance under dynamic conditions. Moreover, when sudden inaccuracies or signal losses occur, DT can help identify potential causes, such as interference, hardware failure, or environmental changes, thereby enhancing system resilience and reliability.

Architecture of DT-Empowered Wireless Positioning

Regarding how to integrate DT into wireless positioning system, we propose an architecture of DT-empowered wireless positioning, as shown in Fig. 1, which includes three modules: DT construction, model training & updating, and decision-making.

DT Construction

For positioning system, DT is expected to provide a holistic understanding of the positioning environment and fine-grained site-specific information to enhance positioning and optimization capabilities. The construction of DT should capture complete information about physical environment, positioning infrastructure, radio propagation, and the devices or people being tracked. By referring to [5], the enabling technologies mainly include high-fidelity sensing, precise 3D mapping and real-time ray-tracing.

1) High-Fidelity Sensing: The physical space is equipped with multiple sensing devices, e.g., cameras, RF transceivers, which can capture information about the physical environment, such as location, object properties, signal propagation, and other contextual details. High-fidelity sensing enables accurate data acquisition to ensure that DT can be dynamically updated and adapt to any changes in the physical world.

2) Precise 3D Mapping: The collected sensing data are used to create a precise 3D model of the physical environment. By converting the physical entities, e.g., buildings, objects, devices, infrastructures, into their digital counterparts and embedding their geometrical and electromagnetic properties, 3D mapping can ensure the virtual environment accurately mirrors the real world.

3) Real-Time Ray-Tracing: Ray-tracing is used to simulate the propagation of wireless signals in the environment. Through traversing from the transmitter to the receiver, and locating the interaction points between wireless signals and spatial entities, ray-tracing can calculate the possible propagation paths, such as direct transmission, reflection, diffraction, and refraction, based on the electromagnetic properties of physical entities. The significant improvement in hardware computing power enables ray-tracing in real-time, which will facilitate accurate positioning and channel modeling.

The DT construction module forms the foundation for creating a replica of the physical world that supports various tasks, including but not limited to positioning related tasks. By having a highly accurate digital representation, DT can generate synthetic data and conduct simulations, which are then used for model training, updating, and decision-making. The simulation capability of DT is particularly useful for understanding the interaction between signals and buildings, obstacles, or other objects, thereby facilitating positioning performance improvement.

Model Training and Updating

The module of model training & updating provides a model base for efficient decision making. The model base includes channel model, feature extraction model, and fingerprinting model. Different models play different roles in positioning system.

1) Channel Model: The channel model describes how signals propagate from the transmitter to the receiver through the environment. It characterizes the impact of the transmission medium on the transmitted signals, including various factors, e.g., pathloss, shadowing, and multipath propagation, that affect signal quality and integrity. Channel model is crucial for the design, optimization and maintenance of wireless communication systems. For wireless positioning, accurate channel model can help optimize system deployment and configuration so as to improve positioning performance. Moreover, channel models can provide guidelines for efficient fusion of mutisource data, and seamless transition when the devices being tracked move cross different areas.

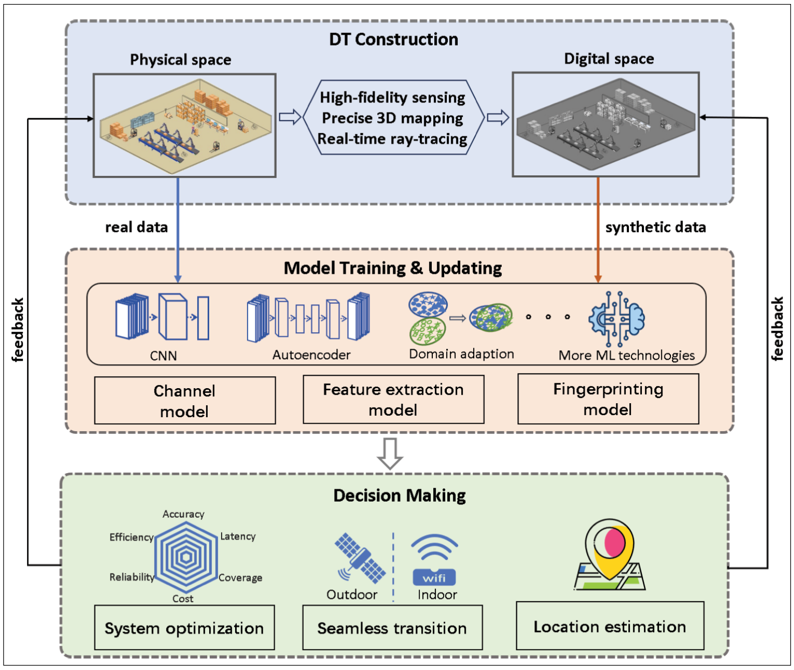

FIGURE 1. Architecture of DT-empowered wireless positioning.

2) Feature Extraction Model: The feature extraction model is responsible for extracting fine-grained site-specific information to improve positioning accuracy. In practical environments, multipath propagation is site-specific and varies at different sites. It is challenging for traditional signal processing methods to accurately estimate multipath features (MPF) in complex environment, since they are sensitive to noise, interference, and model mismatches. In contrast, ML-based methods can learn robust features even in the presence of noise, interference, and signal variability. DT incorporates site-specific geometry, materials, and dynamic elements in the physical environment, and can simulate the propagation of wireless signals, enabling the generation of realistic synthetic datasets that capture site-specific propagation effects. By establishing the mapping relationship between the received signals and the corresponding multipath components, including pathloss, propagation delays, AoAs, AoDs, phase shifts, etc., along different propagation paths, feature exaction model can be trained via advanced ML technologies.

3) Fingerprinting Model: For fingerprinting-based positioning, the fingerprinting model establishes the mapping relationship between locations and RF fingerprints. Since DT aids to extract fine-grained MPF, rather than corse-grained

RSS or CSI, fingerprinting model takes MPF as the input and the corresponding location as the output. Multiple kinds of ML networks, e.g., Convolutional Neural Network (CNN), AutoEncoder, can be utilized to train the fingerprinting model.

The above models are environment-specific, and should be robust to environmental changes. Therefore, besides of robust pre-training, adaptive model updating is also necessary to keep the models up to date. The data source for model training and updating include the synthetic data generated from the digital space and the real data collected from the physical space. Synthetic data are created using simulations and ray-tracing within the constructed DT, which provides diverse scenarios and environmental conditions for robust training. This helps the system simulate conditions that may be rare or difficult to replicate in the physical space. The real data, captured by sensing devices, are used to train and refine the models so that they can accurately represent the physical environment. By taking advantage of well-designed ML model structures and domain-adaption techniques, we can obtain environment-adaptive models for efficient real-time decision-making.

Decision Making

The decision-making module is responsible for making intelligent decisions based on the insights provided by the DT and trained models. From the aspects of system efficiency, user experience, and positioning accuracy, the corresponding decisions generally include system optimization, seamless transition, and location estimation.

1) System Optimization: System optimization involves making adjustments to ensure the overall system performs efficiently. It uses the information from the channel model to adjust system configurations, communication parameters, and resource allocations to improve signal quality, reduce interference, and enhance positioning accuracy. Particularly, the objective of optimization should jointly consider the communication and positioning performance. The optimization process can include tasks like power control, antenna configurations adjustment, frequency bands selection, or system deployment optimization to ensure reliable communication and high-precision positioning.

2) Seamless Transition: Considering the application scenarios of different positioning systems are different, when the devices or users move across different zones, for example, from outdoor to indoor, the positioning system generally needs to switch from GNSS to other indoor positioning systems. Seamless transition needs to decide when and how to switch the positioning system so as to provide continuous and reliable positioning service. Through dynamic simulation in DT, based on the prediction results of user's location and the corresponding channel information, the seamless transition module can provide seamless handover decisions.

3) Location Estimation: This module refers to real-time positioning with the collected data. The fine-grained MPF, extracted via feature extraction model, can benefit both fingerprinting-based methods and geometry-based methods. For fingerprinting-based methods, MPF provides higher dimensional information and the fingerprinting model can output more precise location estimates. For geometry-based methods, the geometrical measurements are more accurate. Through geometrical transformation, the non-line-of-sight measurements can be transformed into line-of-sight measurements from virtual anchors, which can be fused to improve the location estimation accuracy.

The decision-making module incorporates a feedback loop, which helps the system adapt to environmental changes, enhance positioning accuracy, and provide better overall system performance. The system optimization strategies will be sent to the physical space for system adjustment and the digital space for DT update. Besides, the location estimation results can be regarded as the labels of collected data. Although the labels may not be accurate, the existing semi-supervised or weakly supervised learning techniques can cope with imperfect labels. The feedback of location-labeled data can be utilized to continuously improve the performance of DT construction and model training modules.

Case Study: CSI-Based Fingerprinting

To verify the benefits brought by DT, we conduct a case study regarding CSI-based fingerprinting. The DT is constructed via DeepMIMO [13], which is based on accurate Remcom 3D Ray-tracing [14], and can support simulations about wireless signal propagation under various scenarios. We leverage the synthetic data generated by DeepMIMO for model training. In our case study, we will firstly show the enhancement brought by fine-grained MPF extraction, then the enhancement brought by model update in dynamic environment.

DT-Aided MPF Extraction

To verify the benefits brought by DT in MPF extraction, we compare the localization performance in CSI-based fingerprinting with different fingerprints: 1) CSI, the raw CSI measurements; 2) Perfect MPF, which are generated via accurate ray-tracing; 3) SP-based MPF, which are extracted from CSI measurements using traditional signal processing methods, including angle-delay channel response [15], etc. 4) DT-aided MPF, which are extracted from CSI measurements via the feature extraction model. In DT-aided MPF extraction, the input of feature extraction model include locations of reference points and the corresponding CSI, and the output are MPF. As shown in Fig. 2, the process of location estimation, combined with DT-aided MPF extraction, includes three steps: initial location estimation with CSI measurements, then MPF extraction with CSI measurements and initial location estimates, and in the end, final location estimation with MPF. All the modules are based on CNN, and the structure of each module is shown in Fig. 2. The extracted MPF consists of the azimuth and elevation AoDs from BSs, the azimuth and elevation AoAs at the user, the received powers, the propagation delays, and the path phases. MPF is constructed as a channel matrix and input into the CNN-based location estimation model. During the training of each module, major hyper-parameters are configured as follows: Batch Size = 32, Optimizer = Adam, Learning Rate = 0.001, Epochs = 50.

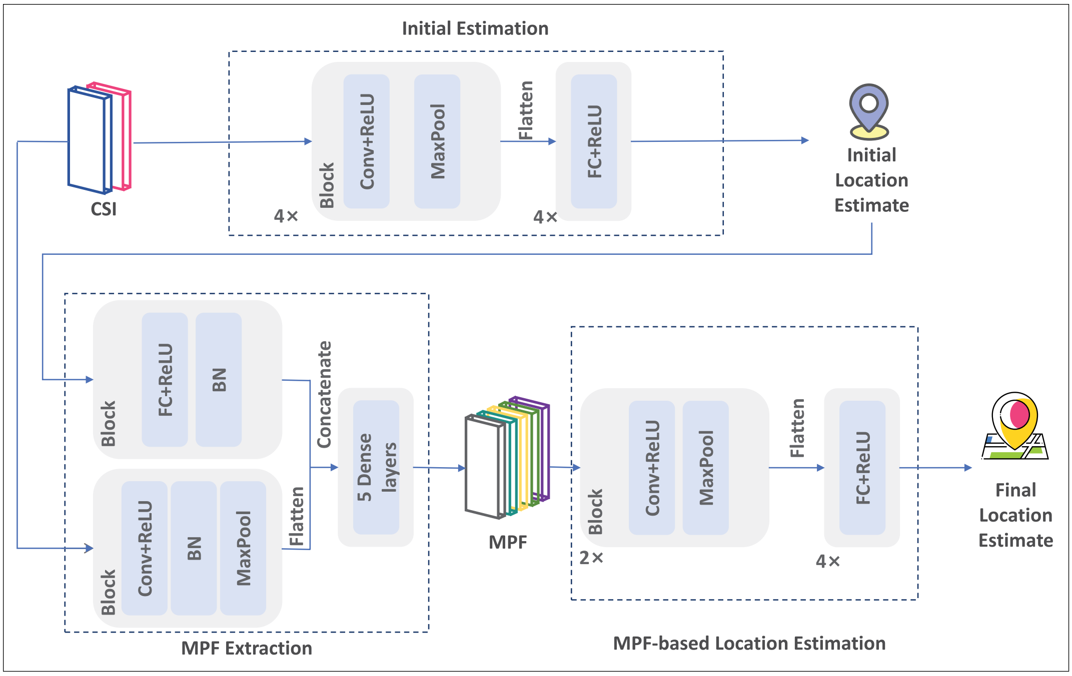

FIGURE 2. The process of location estimation based on MPF.

We select an indoor room scenario in DeepMIMO, *"I2 (Indoor 2) Blockage Scenario"* for performance evaluation. In this scenario, there exists one BS with operation frequency at 28 GHz and a line-of-sight blockage between the BS and the users. From the BS to the receiver at each candidate user location, the maximum number of propagation paths is 5. Along each propagation path, the wireless signal undergoes a maximum of 4 reflections and 1 diffraction. The DT simulates the propagation of signals in this scenario, generating CSI and MPF data at each reference location. The synthetic dataset covers more than 140 thousand reference locations, with 1 cm spacing between adjacent locations. Fig. 3 shows the cumulative density function (CDF) of the position errors with different fingerprints. We can observe that with perfect MPF as fingerprint, the positioning accuracy can be improved to a great extent. With respect to the positioning results with SP-based MPF, about 90% of them are better than those with raw CSI measurements, and about 10% of them are worse than those with raw CSI measurements. The reason for this is SP-based MPF extraction methods are sensitive to noises and interferences, and their performances are not robust in complex environments. In contrast, with the aid of DT, we can obtain the mapping relationship between CSI and MPF, thereby facilitating the training of feature extraction model, which can provide robust, fine-grained MPF and further improve the positioning accuracy.

DT-Aided Model Update

For fingerprinting-based localization, one of the main limitations is the sensitivity to environmental changes. Continuous data collection is generally required to keep the localization model up-to-date. DT can track the trajectories of the moving devices, predict the change of signal propagation and conduct channel model update, reducing the data collection overhead.

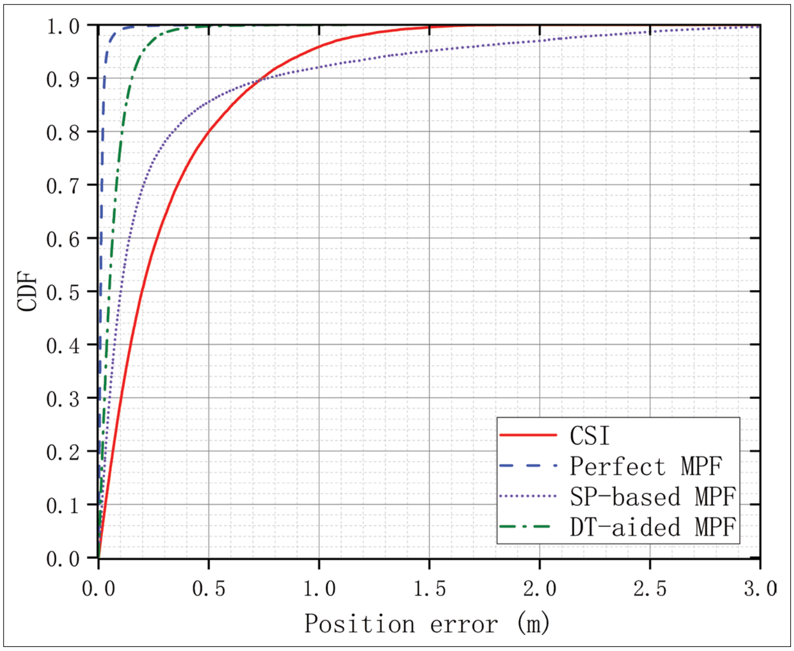

FIGURE 3. CDF of position error with different fingerprints.

We select a dynamic outdoor scenario, *"O2 Dynamic (Outdoor 2) Scenario"* in DeepMIMO, to verify the enhancement brought by model update. In this scenario, there are three streets and two intersections. Buildings/houses are located on both sides of the streets. Mobile vehicles are moving on the main street along 4 lanes (2 in each direction). There are 2 BSs working at operating frequency 3.5 GHz and 116,303 candidate user locations. From the BSs to the receiver at each candidate location, the maximum

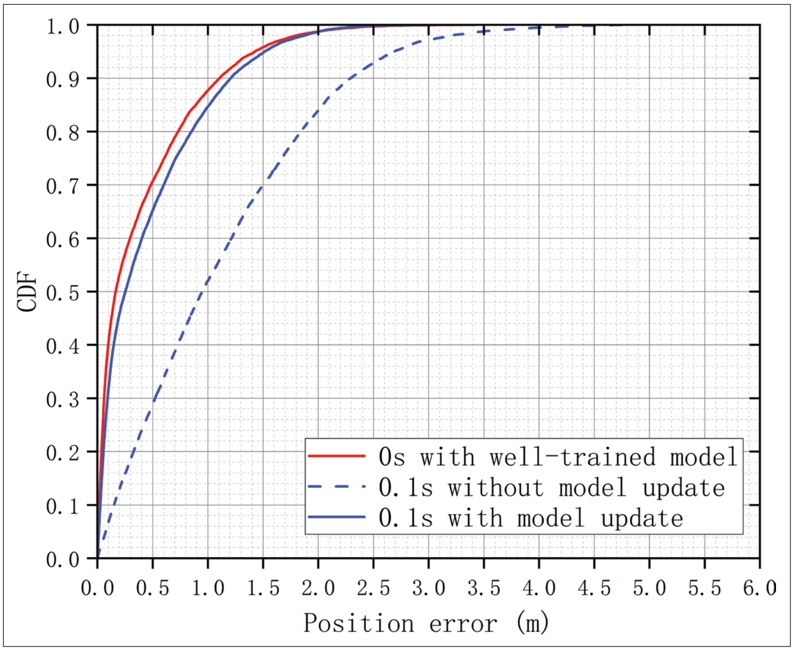

FIGURE 4. CDF of position error with different models in dynamic environment.

number of propagation paths is 5. Along each propagation path, the wireless signal undergoes a maximum of 2 reflections. The CSI samples are continuously generated every 100 ms. In our simulation, we select the CSI samples at 58,621 candidate locations as the training (80%) and testing (20%) data. Fig. 4 illustrates the enhancement brought by model update. At the start point (0s), DT generates a synthetic dataset and trains a positioning model. Based on the well-trained model, the positioning errors of approximately 88% of the location estimates are within 1 meter. After 0.1 seconds later, due to the vehicles' movement, the signal propagation changes and the positioning model trained at the start point is out-of-date. Without model update, the positioning accuracy severely degrades. With the aid of DT, the positions of the vehicles can be predicted. Through predictive ray-tracing, DT updates the synthetic dataset and further updates the positioning model. With the updated model, the positioning accuracy has been greatly improved.

This case study preliminarily illustrates the benefits of DT in enhancing positioning accuracy and improving system robustness. Specifically, it demonstrates how the simulation and prediction capabilities of DT can be leveraged to extract fine-grained MPF features and update positioning model. These findings provide valuable insights for designing practical DT-empowered wireless positioning systems. As we stated before, DT is prospective in multiple aspects including accuracy, coverage, latency, and reliability, etc. Comprehensive verification about the benefits brought by DT is necessary but challenging, since a few open research issues regarding system optimization and mechanism design should be addressed in the future.

Challenges and Open Research Issues

The proposed architecture shows the integration of DT into wireless positioning system. Implementing DT-empowered wireless positioning also presents several challenges. Substantial issues are open for further research.

1) Efficient Data Collection: Although DT is capable of predicting some environmental dynamics, e.g., regular movement of vehicles, unforeseen environmental changes pose challenges for accurate prediction. The interaction between the physical and the digital worlds is necessary for dynamic model update. Continuous large-scale data collection would induce very high overhead. Although the advanced ML technologies, e.g., transfer learning, domain adaption, enable model update with small-scale data, it is still challenging to balance the performance of model update and the cost of data collection. Efficient data collection strategies, with regards to what, where, and when to collect, should be well designed. Potential solutions for efficient data collection include implementing adaptive sampling techniques that prioritize data from high-impact or changing environments, and integrating reinforcement learning algorithms to optimize the timing and location of data collection.

2) Resource-Performance Trade-Off: The construction and maintenance of DT introduce additional resource consumption, including communication, computation and storage. It is necessary to balance resource consumption and positioning performance enhancement. Particularly, it is crucial to quantitatively evaluate the positioning performance enhancement and the resource consumption brought by DT. Moreover, positioning performance and resource consumption employ distinct metrics, making it difficult to directly compare resource consumption and positioning performance enhancement. Therefore, developing tailored trade-off strategies to meet the specific requirements and constraints of different scenarios becomes essential. One potential solution is to adopt multi-objective optimization and adaptive algorithms that dynamically adjust DT model detail based on real-time resource availability and performance needs. Lightweight ML techniques and edge computing can also reduce resource usage while maintaining positioning performance.

3) Privacy and Security: Implementing DT-empowered wireless positioning involves collecting and processing vast amounts of sensitive contextual data from the environment, users, and devices. Detailed contextual data can be taken advantage by adversaries, raising concerns about user privacy. Besides, DT can become target of attacks like spoofing, jamming, or unauthorized access. Robust data encryption, secure communication protocols, and access controls are critical, but often introduce computational and latency overheads. To address these challenges, decentralized data processing and privacy-preserving methods, such as federated learning and differential privacy, are promising to keep sensitive data local and reduce the risk of interception or unauthorized access. Furthermore, lightweight cryptographic algorithms and adaptive security protocols can be designed to reduce the computational and latency overheads.

Conclusion

This article has investigated the prospects of DT in enhancing positioning accuracy, extending coverage, reducing latency, and improving reliability of wireless positioning systems. A modularized architecture of DT-empowered wireless positioning has been proposed, consisting of DT construction, model training & updating, and decision-making. In the proposed architecture, the interaction between the physical world and the digital world facilitates continuous improvement of positioning systems and models, thus providing accurate and reliable positioning results. A case study about CSI-based fingerprinting has demonstrated the accuracy enhancement brought by DT-aided MPF extraction and DT-aided model update. A few open issues for future research have also been identified. This study should promote further development of DT-empowered wireless positioning.

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Biographies

Xiufang Shi (Member, IEEE) (xiufangshi@zjut.edu.cn) received the B.Sc. degree in automation from the East China University of Science and Technology, Shanghai, China, in 2011, and the Ph.D. degree in control science and engineering from Zhejiang University, Hangzhou, China, in 2016. She was a joint Ph.D. Student with The University of Sydney, Sydney, NSW, Australia, in 2015. From 2016 to 2018, she was a Post-Doctoral Researcher with the College of Control Science and Engineering, Zhejiang University. She is currently an Associate Professor with the College of Information Engineering, Zhejiang University of Technology, Hangzhou. Her major research interests include wireless localization, target tracking, and the Internet of Things.

Xinlu Xuan (yyqxxxlwjk@foxmail.com) received the B.S. degree in mechanical and electronic engineering from Shaoxing University, Shaoxing, China, in 2022. She is currently pursuing the M.S. degree in control engineering with the Zhejiang University of Technology, Hangzhou, China. Her research interests include indoor positioning systems, multimodal feature fusion, and intelligent location-based services.

Xinyu Huang (Student Member, IEEE) (x357huan@uwaterloo.ca) received the B.E. degree from Xidian University, Xi'an, China, in 2018, and the M.S. degree from Xi'an Jiaotong University, Xi'an, in 2021. He is currently pursuing the Ph.D. degree in electrical and computer engineering with the University of Waterloo, Waterloo, ON, Canada. His research interests include digital agents, generative AI, and network resource management.

Jianzhe Xue (Student Member, IEEE) (jianzhexue@smail.nju.edu.cn) received the B.S. degree in communication engineering from Xidian University, Xi'an, China, in 2021. He is currently pursuing the Ph.D. degree with the School of Electronic Science and Engineering, Nanjing University, Nanjing, China. His current research interests include low-altitude information networks, orthogonal time frequency space modulation, and machine learning for wireless communications.

Xuemin (Sherman) Shen (Fellow, IEEE) (sshen@uwaterloo.ca) received the Ph.D. degree in electrical engineering from Rutgers University, New Brunswick, NJ, USA, in 1990. He is currently a University Professor with the Department of Electrical and Computer Engineering, University of Waterloo, Canada. His research interests include network resource management, wireless network security, the Internet of Things, AI for networks, and vehicular networks. He is a registered Professional Engineer of Ontario, Canada, an Engineering Institute of Canada Fellow, a Canadian Academy of Engineering Fellow, a Royal Society of Canada Fellow, a Chinese Academy of Engineering Foreign Member, an International Fellow of the Engineering Academy of Japan, and a Distinguished Lecturer of the IEEE Vehicular Technology Society and Communications Society.