5G-A Ambient Power-enabled IoT Positioning Technology White Paper

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1 Executive Summary

Ambient power-enabled IoT technology, as a critical carrier of 6G massive connection technology, is anticipated to achieve a trillion-scale connection scope. Positioning services, following inventory management, represent a fundamental application of AIoT. Leveraging advantages such as low cost, no power supply, ease of deployment, maintenance-free operation, and compact size, AIoT effectively addresses the constraints of active positioning. It is poised for broad application across warehousing logistics, retail, smart manufacturing, and personnel management, achieving multi-functionality through a single network. In this white paper, China Mobile has collaborated with the industry and academic institutions to explore 6G AIoT positioning technology.

This white paper starts with typical positioning application scenarios of 6G AIoT, deeply analyzes end-to-end key technologies for AIoT positioning, introduces practical cases of positioning, and provides references and guidelines for the industry to explore 6G AIoT applications, promote the evolution of passive positioning technology, and innovate passive positioning solutions.

2 Abbreviations

Abbreviation	Explanation
3GPP	3rd Generation Partnership Project
4G	4th generation mobile networks
5G	5th generation mobile networks
5G-A	5th Generation Advanced Mobile Communication Technology
ADC	Analog-to-Digital Converter
AOA	Angle of Arrival
APP	Application
ASK	Amplitude shift keying
AIoT	Ambient power-enabled Internet of things
Beacon	Beacon
BLF	Backscatter Link Frequency
BPSK	Binary phase shift keying
CFR	Channel Frequency Response
CTE	Channel Timing Extension
DTW	Dynamic Time Warping
EPC	Electronic Product Code
ESPRIT	estimating signal parameter via rotational invariance techniques
FDD	Frequency Division Duplexing
FD-PDOA	Frequency-Difference of Arrival - Phase-Difference of Arrival
GPS	Global Positioning System
IFFT	Inverse Fast Fourier Transform
IoT	Internet of Things
IQ	In-phase and Quadrature
KNN	K-Nearest Neighbor
LMF	Location Management Function
LNA	Low Noise Amplifier
Lora	Long Range Radio
LoS	Line of Sight
MO	Material Order
MUSIC	Multiple Signal Classification
NB-IoT	Narrow Band Internet of Things
NLoS	None Line of Sight
QPSK	Quadrature phase shift keying
RAN	Radio access network
RFID	Radio Frequency Identification
RSSI	Received Signal Strength Indicator

SD-PDOA	Space-Difference of Arrival - Phase-Difference of Arrival
SFO	sampling frequency offset
SLO	Signal from Local Oscillator
SMLC	Serving Mobile Location Center
STO	Sampling Time Offset
TDoA	Time Difference of Arrival
TD-PDOA	Time-Difference of Arrival - Phase-Difference of Arrival
TOA	Time of Arrival
UDM	Unified data management
UE	User equipment
UHF	Ultra High Frequency
UWB	Ultra Wide Band
VAA	Virtual Antenna Array

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4 Overview of AIoT

IoT, with the vision of 'connecting everything,' has facilitated interconnectivity among billions of devices via communication technologies such as 4G/5G, NB-IoT, LoRa, Bluetooth, and WiFi. However, as the IoT market continues to expand, and connectivity extends to everyday objects in mass production and daily life, new challenges emerge. These include energy supply, battery life, maintenance, size, and cost. Overcoming these challenges to achieve self-power generation, low power consumption, low cost, and maintenance-free operation at the IoT endpoints is key to unlocking the massive connectivity market.

AIoT emerges in this backdrop, where end devices harvest energy from the environment, converting it into electrical energy to drive their circuits while communicating through backscatter, eliminating dependence on batteries or power supplies. As shown in **错误!未找到引用源。**, AIoT complements the high, medium, and low-speed IoT scenarios at the bottom of the "everything connected" pyramid, enabling sensing of massive IoT terminals and opening up a market worth hundreds of billions.

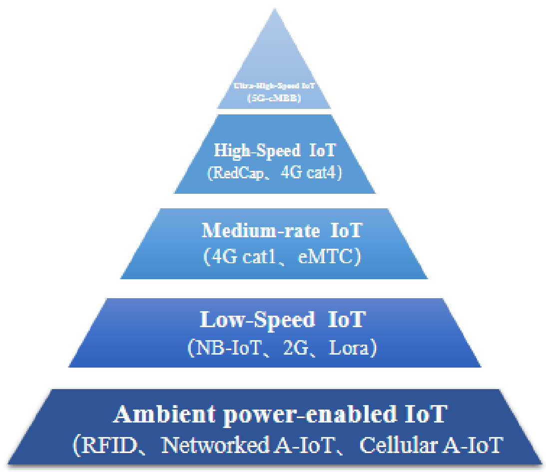


Figure 1 IoT Connectivity Pyramid Model

The advantages of AIoT are reflected in the following aspects:

- **Power-Free Operation:** devices convert RF communication signals into electrical energy to meet their own power requirements. In addition, environmental energy sources such as solar, wind, pressure, and temperature differences can be utilized as supplementary energy sources, enabling self-energy harvesting for devices without the need for batteries or power supplies.

- **Low Cost:** AIoT enables self-energy harvesting, eliminating the constraints of batteries. By employing a simplified communication technology based on backscatter, the design of RF circuitry is greatly simplified, leading to significantly lower costs compared to other communication technologies. Currently, a typical AIoT product, such as a UHF (Ultra High Frequency) RFID tag, costs only a few cents, whereas the cheapest Bluetooth tags cost several dollars, and other technology products are even more expensive.
- **Compact Size:** Without the constraints of a battery, IoT devices can achieve smaller sizes and more flexible forms, even in the form of flexible patches, which facilitates a wider range of applications.
- **Easy Deployment:** Devices do not require a power source, are available in multiple forms, and can be easily attached to various items, allowing them to work in complex environments such as high or low temperatures.
- **Maintenance-Free:** Since devices do not require battery replacement, once deployed, they can be used permanently without the need for maintenance.

With the continuous evolution of AIoT technology, the industry has developed AIoT communication technologies based on RFID, Bluetooth, WiFi, and LoRa. Among them, the theoretical transmission range of UHF RFID systems is between 1 to 10 meters. UHF RFID features a wide variety of devices, a mature ecosystem, and a well-established supply chain. It also exhibits significant advantages in terms of power consumption and cost, making it the most widely used technology across multiple industries, including logistics, manufacturing, and retail. China Mobile is also actively promoting the development of AIoT technology, proposing an evolutionary roadmap consisting of single-point AIoT 1.0, networked AIoT 2.0, and cellular-based AIoT 3.0. This evolution aims to transition AIoT from traditional "single-point reading" with UHF RFID to "network coverage," achieving breakthrough development [1].

The **networked AIoT system** enhances traditional RFID infrastructure by introducing a hierarchical architecture with central nodes and distributed nodes. The central node orchestrates the network by issuing inventory commands to the distributed nodes. These distributed nodes relay commands from the central node to AIoT AIoT readers and provide power to the devices. The central node is also responsible for receiving and demodulating signals from the AIoT devices, enabling the reading and collection of inventory data. This architecture supports one-to-one, one-to-many, and many-to-many network configurations, offering flexible and scalable operation. The system is designed to be compatible with ISO 18000-6C compliant UHF RFID tags, facilitating a seamless upgrade path for enterprises looking to enhance network coverage and management capabilities. It has already been successfully deployed in indoor localized applications such as warehouse logistics and retail environments, demonstrating its robustness and efficiency in real-world scenarios.

The **cellular-based AIoT** system leverages base stations or relay nodes to power and collect data from AIoT devices, enabling long-range transmission and scalable coverage through comprehensive network reach and mobility management. By utilizing full-area coverage capabilities, the system facilitates efficient mid- to long-distance communication. The relevant 3GPP standards are progressing in an orderly manner. In the finalized 3GPP Release 18, the concept of 5G-Advanced and the inclusion of cellular-based AIoT have been introduced. The upcoming Release 19 is actively investigating topics related to the cellular-based AIoT air interface and core network integration, with the standard expected to be finalized in the second half of 2025. Upon completion, cellular-based AIoT will be fully integrated into the cellular communications industry, unlocking significant market potential for AIoT technologies.

This white paper explores positioning technologies based on these three **AIoT** architectures: **single-point**, **networked**, and **cellular-based** AIoT systems.

5 Overview of AIoT Positioning

5.1 Definition of AIoT Positioning

AIoT positioning refers to the process of determining the location of AIoT devices within the AIoT architecture. In this system, AIoT readers measure positioning metrics such as backscatter signal strength and phase from the devices, and the data is processed by a positioning computation platform to determine the device's location. In the cellular-based AIoT architecture, AIoT reader may include base station, relay nodes, or smartphones, as illustrated in Figure 2 From an application perspective, positioning is the second most important use case for AIoT, following inventory management. It offers several key advantages, including low cost, wide applicability, non-line-of-sight (NLOS) capability, battery-free operation for the terminal devices, and high performance. These attributes make AIoT positioning a promising candidate to become one of the most widely adopted indoor positioning technologies.

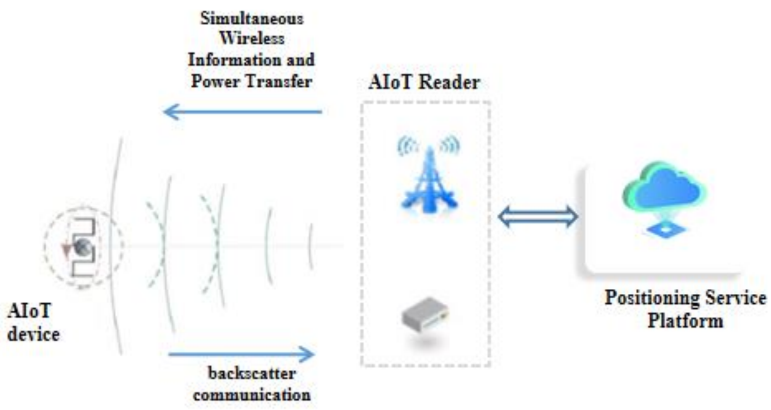


Figure 2 Schematic diagram of AIoT positioning

AIoT positioning can be categorized based on positioning dimension, positioning mode, positioning state, and positioning outcome as follows:

1. Positioning by Dimension

- **Zero-Dimensional (0D) Positioning:** Also known as presence detection, it determines whether a target (e.g., a person or an object) is within a specific area. This method typically requires only one AIoT reader and a device, making it suitable for applications such as presence monitoring.
- **One-Dimensional (1D) Positioning:** Suitable for linear or elongated environments like corridors, pipelines, or tunnels, where the real-time relative position of the target along a single axis is sufficient. Due to the narrow width of the region, the positioning typically focuses only on the length axis without considering the width.
- **Two-Dimensional (2D) Positioning:** Determines the X, Y coordinates of the target within a plane. This type of positioning usually requires three or more AIoT antennas to accurately

calculate the real-time position of devices within a standard 2D plane.

- **Three-Dimensional (3D) Positioning:** Extends 2D positioning by including the height dimension, providing the X, Y, Z coordinates of the target. This allows for the precise spatial localization of the target in three-dimensional space.

2. Positioning by Mode

- **Active Positioning:** In active positioning, the target carries a device that interacts with the AIoT reader through signal exchange, either by measuring the distance (ranging) or by using non-ranging methods to determine the target's position. Most AIoT positioning applications are based on active positioning due to the need for the target's active participation in the process.
- **Passive Positioning:** In passive positioning, the target does not directly interact with the AIoT readers. Instead, the position is inferred by analyzing the impact of the target on the signal metrics of surrounding reference devices. This method is useful in scenarios where the target cannot or does not engage in direct signal exchange.

3. Positioning by State

- **Static Positioning:** Refers to scenarios where the device's position remains unchanged over a period of time. It is commonly used in retail environments or museum exhibitions to determine the fixed location of people or objects.
- **Dynamic Positioning:** Refers to scenarios where the device’s position changes continuously over time, such as in warehouse logistics or smart manufacturing. In dynamic positioning, the speed of the target’s movement needs to be considered to ensure accurate tracking and to account for its impact on the positioning algorithms.

4. Positioning by Outcome

- **Relative Positioning:** Determines the relative position between the device and the AIoT reader. This method is often used in asset search applications where knowing the relative distance or direction to the device is sufficient to locate the item.
- **Absolute Positioning:** Determines the AIoT device's absolute coordinates within a network or

real-world environment. Absolute positioning is required in applications like asset tracking or pet location, where the precise global position of the AIoT device is necessary for effective tracking or searching.

5.2 Advantages and Challenges of AIoT Positioning

The primary advantages of RFID-based positioning lie in its cost-effectiveness, convenience of battery-free operation, and broad applicability across diverse use cases. It has been widely deployed in scenarios where high positioning accuracy is not critical, such as in logistics, warehousing, and retail, and it continues to function reliably even in extreme environments characterized by high temperatures, radiation, and humidity. AIoT positioning inherits these benefits and further enhances them in the following ways:

- **Expanded Application Scenarios:** AIoT positioning requires no manual maintenance and can operate sustainably and stably, addressing the challenges of extreme environments while significantly reducing post-deployment maintenance costs. This expands the range of IoT applications and makes it feasible in previously inaccessible scenarios.
- **Extended Positioning Range:** Unlike traditional RFID systems, which are limited by short-range communication, AIoT positioning leverages the advantages of cellular networks in terms of coverage, manageability, control, and secure authentication. This enables a low-power, secure, and high-performance positioning capability, unlocking new potential applications.
- **Improved Positioning Accuracy:** The introduction of phase-based positioning technologies enhances the accuracy of AIoT device localization, facilitating better integration between the physical and digital worlds, particularly in applications involving massive numbers of items.
- **Fusion of Positioning Terminals:** AIoT positioning supports integration with other technologies, such as combining positioning data with camera systems. This enables multimodal applications, such as identifying objects tracked by cameras, and enhances the overall versatility and capability of the solution.
- While the fundamental physical principles of AIoT positioning are similar to those used in widely recognized technologies such as Bluetooth, UWB, and 5G — all based on the channel

characteristics of wireless signals — the unique nature of backscatter communication in AIoT introduces several specific technical challenges:

- **Limited Capabilities of AIoT devices:** Unlike active AIoT devices that can transmit uplink positioning signals and extract measurement metrics, AIoT devices lack these capabilities. In an AIoT system, all positioning signals are transmitted by the AIoT readers, reflected by the AIoT devices via backscatter, and then received again by the AIoT readers. The AIoT readers must extract the relevant positioning metrics and compute the location information. This process is entirely driven by the AIoT readers, with the AIoT devices only playing a passive role.
- **Multiple Sources of Measurement Error:** The positioning process in AIoT involves signal transmission and reception by the AIoT readers, the round-trip signal time between AIoT readers and the devices, and the processing time of the devices. Inherent errors during signal transmission and reception, as well as sampling frequency deviations during the backscatter modulation process, can significantly affect the accuracy of the positioning measurements.
- **High Susceptibility to Environmental Interference:** Due to the low transmission power of backscatter signals, AIoT positioning is highly susceptible to multipath effects and environmental noise. These factors can degrade the quality of the received signal at theAIoT readers, reducing the accuracy of the extracted positioning metrics and adversely impacting the overall positioning performance.

These factors present significant challenges for the optimization of AIoT positioning algorithms and the enhancement of positioning accuracy. In-depth analysis is required to develop methods for mitigating measurement errors and identifying suitable approaches tailored for AIoT positioning. However, the advantages of low-cost and easy deployment associated with AIoT device-based positioning technologies also introduce unique positioning modes, such as using reference AIoT devices and AIoT device arrays. These distinctive techniques will be key topics of discussion in this white paper.

5.3 Market Outlook for AIoT Positioning

With the advancement of AIoT technologies and the increasing demand for indoor positioning, the global indoor positioning market is experiencing rapid growth. According to data from Huajing Industry Research Institute, the global indoor positioning market size reached approximately 10.5 billion RMB in 2021, with a compound annual growth rate (CAGR) of 4.12% from 2013 to 2021. The market size in China alone surged to 28 billion RMB in 2022, demonstrating the immense potential and rapid expansion of indoor positioning technologies within the Chinese market. It is anticipated that by 2028, continuous technological innovations and the expansion of application scenarios will drive further growth in the global indoor positioning market [7].

In terms of application sectors, indoor positioning technologies have been widely deployed across various industries, including smart manufacturing, warehousing and logistics, energy and power, public safety, healthcare, mining, hospitality, and airports. Among these, smart manufacturing and warehousing and logistics are the primary application scenarios and the main battleground for AIoT technologies. Additionally, the Chinese government has shown strong support for the development of indoor positioning technologies, introducing a series of policies to promote the adoption of IoT technologies. The future of indoor positioning is expected to evolve towards higher accuracy, lower power consumption, hybrid positioning technologies, and broader applications.

AIoT positioning, leveraging its inherent advantages of ultra-low power consumption, low cost, maintenance-free operation, and compact size, combined with the integration of cellular networks, stands to fully capitalize on the infrastructure and licensed spectrum benefits of cellular networks. This integration enhances communication reliability, reduces the cost ofAIoT readers, and simplifies business deployment, positioning AIoT to play an increasingly significant role in the indoor positioning market.

6 Typical Scenarios and Demand Analysis for AIoT Positioning

As AIoT technology gains widespread adoption across various industries, the AIoT devices attached to people, goods, and vehicles are increasingly required not only for identification but also for positioning purposes**.** Specific application needs include verifying whether individuals are within a designated Electronic fence, confirming whether items are in their designated locations, and ensuring that vehicles follow predefined routes. These are among the key insights users expect to gather from the AIoT management platform once the AIoT devices have been identified within a specific area.

The inherent advantages of AIoT, including ultra-low power consumption, low cost, and maintenance-free operation, make it suitable for positioning applications even in extreme environments such as high temperatures, radiation, and humidity. Moreover, the integration of cellular-based AIoT technology provides enhanced coverage, manageability, control, and secure authentication, further expanding its application scenarios. Additionally, the adoption of phase-based positioning technologies, as well as the integration of AI-enhanced positioning and multimodal fusion positioning technologies, will contribute to further improvements in positioning accuracy.

Building on these advantages, this chapter explores typical AIoT positioning scenarios, categorized as follows:

- **Enterprise Service Scenarios:** Including warehousing and logistics, retail, smart manufacturing, and intelligent parking, where AIoT positioning is used to enhance operational efficiency and asset management.
- **Government and Public Service Scenarios:** Covering applications such as museum exhibitions, mining tunnels, law enforcement and judicial processes, and healthcare and elderly care, where AIoT positioning meets the needs of public safety and service improvement.
- **Personal and Home Scenarios:** Addressing use cases related to family care and smart home environments, where AIoT positioning is used for personal safety and convenience.

For each scenario, this chapter will firstly introduce the typical applications, followed by a summary of the positioning performance requirements, as well as the needs for network infrastructure and device capabilities in AIoT systems.

6.1 Enterprise Service Positioning Scenarios

6.1.1 Warehousing and Logistics

In warehousing and logistics operations, location information plays a crucial role in enhancing order and efficiency in material handling, and thus requires a high degree of positioning accuracy [8]. As illustrated in Figures 3 and 4, AIoT-based positioning technology enables real-time tracking of the precise location and status of goods. This technology covers all aspects of material handling, including inbound processing, shelving, picking, outbound processing, searching, and tracking. By implementing AIoT positioning, businesses can address common challenges such as lengthy inspection times during inbound and outbound processing, low picking efficiency with a high risk of errors, and high rates of idle inventory. Ultimately, this leads to faster material turnover, improved inventory management efficiency, and enhanced accuracy in goods handling.

Figure 3 Warehouse logistics positioning real view

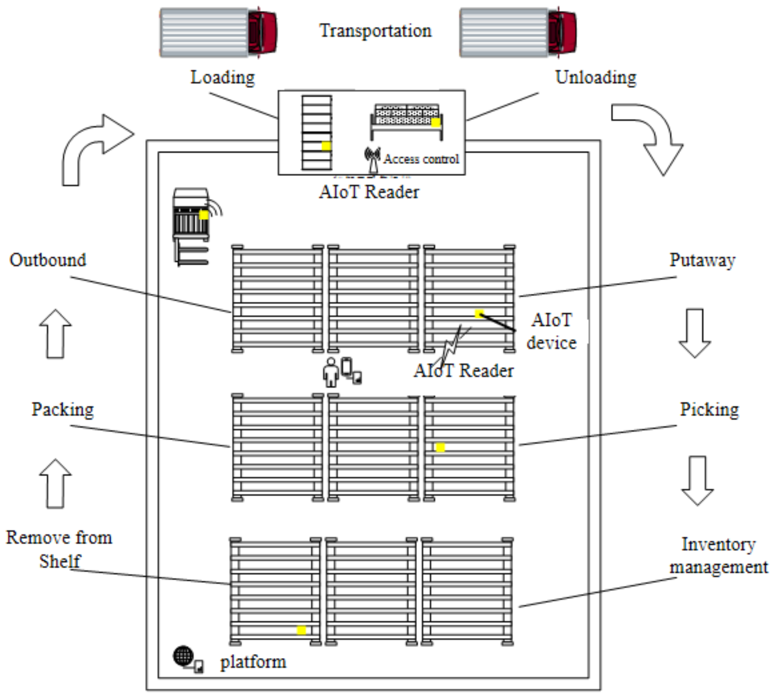


Figure 4 deployment of positioning in Warehouse logistics

Inbound and Outbound Management: By deploying AIoT devices on goods, automatic identification and tracking are achieved during the inbound and outbound processes, ensuring that all items are properly registered. The required positioning accuracy for these operations ranges from 1 to 3 meters. Additionally, businesses place a strong emphasis on minimizing false positive and false negative rates, aiming for 100% confidence in inbound and outbound positioning. Due to the high frequency of material flow, the frequency of positioning updates for inbound and outbound operations is also high.

- **Shelving and Picking Management:** AIoT devices deployed on both items and shelves facilitate the identification of goods and their precise location during shelving and picking operations. Information such as item details and storage locations is stored in a database, enabling easy search and retrieval. Since this process requires accurate identification of each individual item, the positioning accuracy must be closely related to the size of the storage slot, with a typical requirement of at least 1-meter accuracy or better.
- **Carrier Turnover Management:** Carriers refer to equipment such as pallets and bins used to transport goods. AIoT devices deployed on these carriers enable efficient location tracking, helping to prevent losses due to incorrect handling, misplacement, or forgetfulness. For this

type of application, the requirement for positioning accuracy is relatively low; it only needs to reliably detect changes in the carrier's location when it enters or leaves a designated area.

6.1.2 Shopping Malls and Retail

Shopping has always been a vital part of daily life. Typical shopping mall layouts include supermarkets, retail stores, and parking areas, often situated within multi-story buildings or even multiple interconnected structures. These shopping areas feature a wide variety of displayed products across different sections and shelves. As illustrated in Figures 5 and 6, AIoT-based positioning technology can assist consumers in quickly locating target products and stores. For operators, it provides valuable services such as inventory management, theft prevention, and display optimization. Additionally, AIoT positioning offers store managers customer flow data, enabling them to adjust store layouts effectively and uncover new commercial opportunities [8][9].

Figure 5 Supermarket retail passive positioning scene real picture

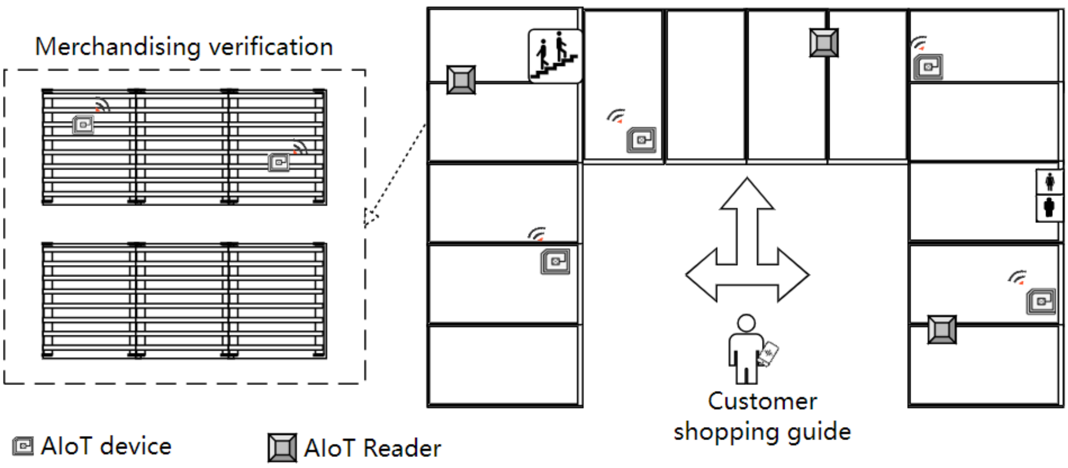


Figure 6 retail positioning deployment in a shopping mall

- **Consumer Shopping Guidance:** In supermarkets and key locations, a large number of low-cost, maintenance-free AIoT devices can be deployed. Consumers can use a shopping mall APP on their smartphones to determine their current location via interaction with these AIoT devices. The APP can then provide services such as navigation to specific stores, precise product recommendations for nearby shops, and finding companions, offering convenience and personalized assistance to enhance the shopping experience. This type of application does not require high positioning accuracy; typically, an accuracy of 1 to 3 meters is sufficient.
- **Automated Store Inventory and Display Check:** Traditional manual inventory using barcode scanners is labor-intensive and time-consuming. By integrating AIoT positioning capabilities, stores can achieve real-time, second-level inventory counts while simultaneously verifying whether items are displayed according to plan. This eliminates the need for employees to manually check each item against a display guide, simplifying and streamlining the process.
- **Store Layout Optimization:** For supermarket operators, the combination of in-store AIoT devices and consumer smartphones allows them to track changes in consumer movement and behavior. Key metrics such as customer traffic patterns, dwell time, and visit frequency can be analyzed, providing critical insights that support dynamic adjustments to store layouts and business planning, ultimately optimizing the overall shopping environment.

6.1.3 Smart Manufacturing

With the advent of Industry 4.0, the demand for automation, digitization, and unmanned operations in the manufacturing sector is rapidly increasing. Smart manufacturing plays a crucial role in enhancing productivity and promoting sustainability. In smart manufacturing environments, production line robots with three-dimensional mobility are expected to become the primary workforce in future intelligent factories [10]. During the production process, it is essential to track the real-time location of materials and robots to ensure the completeness of each production step. Accurate positioning helps robots avoid obstacles during movement and ensures that they perform tasks at precise locations, as illustrated in Figure 7.Smart manufacturing scenarios require high positioning accuracy, typically ranging from 10 to 30 centimeters. Additionally, these operational environments demand robust anti-interference and anti-blockage capabilities from the positioning technology to ensure reliable performance in complex industrial settings [8].

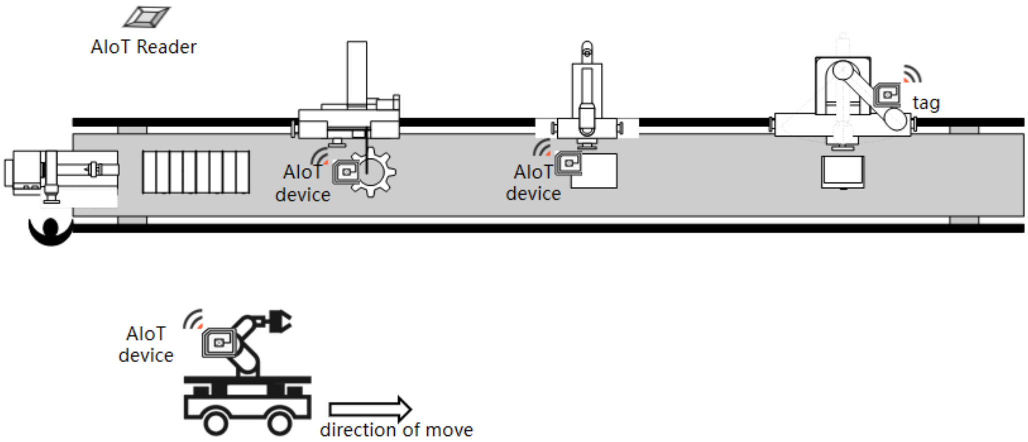


Figure 7 Positioning Deployment Schematic in Intelligent Manufacturing

- **Production Process Positioning:** AIoT AIoT readerss are deployed at key nodes along the production line to monitor the flow of materials as they pass through these checkpoints. This enables effective tracking of the assembly, movement, and inspection steps within the production process, ensuring an orderly and efficient workflow. Typically used on assembly lines, this type of application involves one-dimensional positioning, requiring an accuracy of at least sub-meter level.

- **Robot Object-Finding:** Robots equipped with AIoT devices use AIoT positioning technology to determine the relative position of the robotic arm to the target object. By leveraging wireless signals, the robotic arms can be guided to specific locations to perform various predefined manufacturing and assembly tasks [10]. This application demands a positioning accuracy of decimeter level and requires a high frequency of positioning updates for real-time control.

- **Employee Attendance Tracking:** By integrating AIoT devices with employee badges, AIoT positioning can provide real-time visibility of the location and distribution of staff. This enables automated attendance tracking, working hour statistics, and monitoring of on-duty/off-duty statuses, facilitating efficient personnel scheduling and safety management. This application places high demands on the accuracy, real-time performance, and stability of the positioning system.

6.1.4 Smart Parking

While outdoor positioning technologies have matured significantly, with solutions like GPS and cellular positioning effectively meeting the needs for navigation in everyday travel and various aspects of production and life, there remains a gap in addressing the growing demand for indoor positioning and navigation with cost-effective solutions. For instance, in underground parking lots, people often struggle to locate available parking spaces, significantly impacting their overall travel experience. As illustrated in Figure 8, AIoT positioning technology offers an efficient and low-cost solution for providing indoor positioning and navigation services, enabling smart parking and making travel more convenient.

The smart parking ecosystem is extensive, covering the entire closed-loop process, including parking information management, space sharing, space reservation, vacant space guidance, parking, vehicle retrieval, gate control, and automated payment. In parking lots of shopping malls, large exhibition centers, and stadiums, the primary positioning requirements are focused on guidance to vacant spaces, intelligent vehicle retrieval, and exit route guidance [9].

Figure 8 AIoT positioning scenario in car park

Vacant Parking Space Guidance: By integrating AIoT device reading and writing capabilities into the driver's smartphone and deploying AIoT devices at each parking space, the system can determine the relative position between the driver and available parking spaces. During entry, the driver's smartphone interacts with multiple parking space AIoT devices to identify the location of a vacant spot and generates a guided route, helping the driver quickly locate an empty parking space.

- **Intelligent Vehicle Retrieval:** Similarly, when the driver needs to find their vehicle upon exit, the smartphone interacts with surrounding parking space AIoT devices to determine the relative position between the driver and the parking spot. The system then generates a walking route to guide the driver directly to their vehicle, simplifying the process of vehicle retrieval and ensuring a swift departure.

- **Exit Route Guidance:** The complex internal layout of parking lots and unclear signage for entrances and exits often lead to confusion and increased time costs for drivers. When the driver is ready to leave, the system displays the location of the parking lot exits on the map. The user can select a preferred exit, and the smartphone, using reference AIoT devices within the parking lot, determines the current position of the vehicle. The system then plans an optimal exit route based on real-time traffic conditions and congestion at the exits, helping the user avoid delays and providing a smooth and efficient departure experience.

6.2 Government and Public Service Positioning Scenarios

6.2.1 Museums and Exhibitions

In large-scale venues such as museums and exhibition centers, where thousands of visitors may gather at any given time, there is a need to manage numerous valuable artifacts and exhibits. As visitor expectations for the exhibition experience continue to rise, the museum and exhibition sector urgently requires a low-cost, efficient, and easy-to-deploy positioning technology to ensure the safety of exhibits, optimize the visitor experience, and enhance management efficiency.

As shown in Figures 9 and 10, AIoT positioning technology can be utilized by deploying AIoT readers throughout the indoor environment. These readers interact with AIoT devices placed near the exhibits, enabling real-time tracking of valuable items, which helps prevent loss or damage. Additionally, visitors can use handheld AIoT readerss integrated withAIoT device reading and writing capabilities. By interacting with AIoT devices placed near the exhibits, the system can determine the relative position of the exhibits to the visitor, providing automated exhibit explanations and guided tours, thereby enriching the visitor experience and making the visit more engaging [8].

Figure 9 Positioning scene in museum exhibit

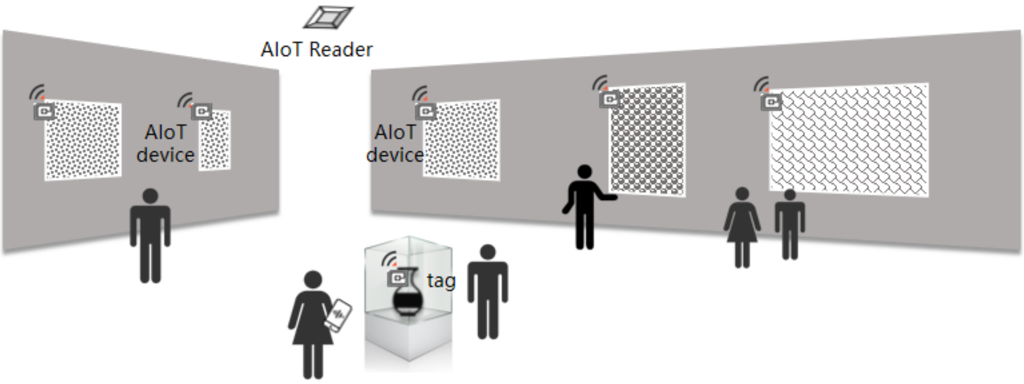


Figure 10 Schematic deployment of museum exhibition positioning

- **Exhibit Security Management:** The system provides real-time tracking and precise positioning of exhibits within the museum, effectively preventing incidents such as theft or damage and enhancing the security of valuable items. This application requires extremely high positioning accuracy, for the exact placement of exhibits, potentially down to the centimeter level. Additionally, a high frequency of positioning updates is necessary to ensure constant monitoring.

- **Personalized Visitor Guidance:** The system offers customized tour services to visitors based on their real-time location, suggesting points of interest and the best routes for exploration, thereby enhancing the overall visitor experience. This scenario requires moderate positioning accuracy, sufficient to accurately identify the visitor's current exhibition area or nearby exhibits, allowing for precise tour recommendations. The positioning update frequency should be dynamically adjusted based on the visitor's movement speed and touring needs. When a visitor is stationary and observing an exhibit, the update frequency can be reduced to save resources. Conversely, when the visitor is moving, the update frequency should be increased to ensure the guidance service remains timely and accurate.

- **Crowd Monitoring and Management:** The system tracks the real-time location of visitors within the museum, continuously monitoring crowd distribution, movement patterns, and density changes. This data supports the museum's safety management efforts. The required positioning accuracy ranges from moderate to high, depending on the need to distinguish crowd conditions in different areas of the museum. The update frequency should be flexibly adjusted based on the museum's operating hours and fluctuations in visitor traffic. During peak hours, the update frequency should be increased to allow for real-time crowd monitoring. During off-peak times, the update frequency can be lowered to conserve system resources.

6.2.2 Mining and Utility Tunnels

In underground work environments such as mines and utility tunnels, the space is confined, and the risk level is high. Additionally, there is a need for frequent inspections and maintenance involving multiple job roles and complex procedures. Key challenges for enterprise safety management include determining the location of personnel, managing workers based on job role and work area, and ensuring the safety of employees.

As illustrated in Figures 11 and 12, by integrating AIoT devices with employee ID cards and deploying AIoT readers in the work zones, the system can provide real-time tracking of personnel locations. The most critical requirements for this scenario are high positioning accuracy and real-time updates [11], with typical positioning accuracy ranging from 1 to 3 meters [8].

Figure 11 Positioning Scenarios in Urban Corridor

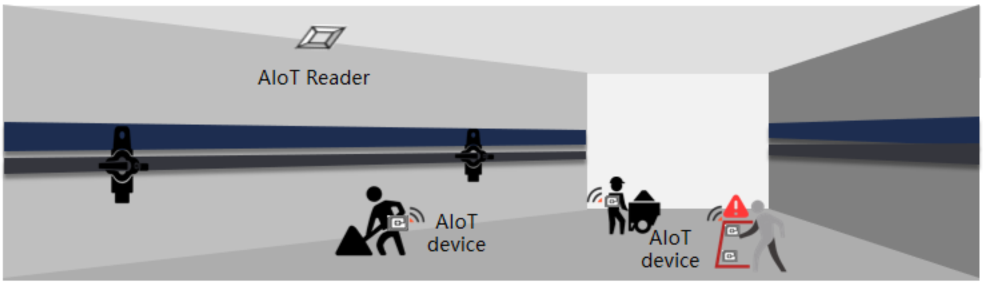


Figure 12 Schematic diagram of the positioning and deployment of the mine pipeline corridor

- **Inspection Positioning:** The system provides real-time positioning and movement tracking of inspection personnel, enabling managers to monitor the exact location and work status of inspectors at all times, ensuring comprehensive and efficient inspection operations. During inspections, the system should report the inspector's position every second, with a required positioning accuracy of 1 to 3 meters, allowing for precise real-time tracking of personnel movements.
- **Operational Management:** Real-time positioning and movement tracking of underground workers help managers monitor the activity range of personnel. The system can detect and alert for abnormal behaviors such as disappearance, leaving assigned posts, unauthorized area access, overstaffing, understaffing, and solitary work in hazardous areas, ensuring compliance with underground work protocols. The required positioning accuracy for this application is within 3 meters.
- **Electronic fence:** The system monitors personnel in critical or hazardous areas to prevent unauthorized access to restricted zones, such as mining faces or blind alleys. If someone enters or leaves these areas without authorization, the system triggers an immediate alarm to prevent major accidents. The required positioning accuracy for this scenario is region-level, and the reporting frequency must be every second to ensure timely alerts.

6.2.3 Public Prosecution and Justice

In prisons and detention centers, managing personnel presents numerous challenges, such as difficulties in tracking inmate movement and detecting unauthorized access to restricted areas. These issues not only increase the complexity of management but also elevate safety risks. As shown in Figure 13, the application of AIoT positioning technology in correctional facilities can effectively address problems like limited police resources, high work pressure, and the challenge of comprehensive monitoring, thereby enhancing the efficiency and safety of prison management.

The positioning accuracy requirements are not stringent; an indoor accuracy of less than 10 meters is generally sufficient [8]. In most scenarios, the system only needs to distinguish personnel based on their location within specific zones, meeting the needs of presence-level positioning.

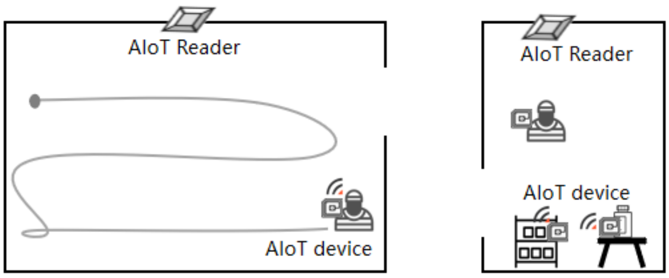


Figure 13 Schematic diagram of the positioning and deployment of prison cells

- **Security Monitoring of Key Areas:** Specific high-priority zones within the prison, such as solitary confinement cells and storage areas, require enhanced security monitoring. The system continuously tracks personnel activities in these areas to prevent unauthorized access or detect unusual behavior. In this scenario, AIoT devices are deployed within the monitoring zones to locate AIoT devices and determine the precise position of individuals, enabling continuous surveillance of critical areas. The required positioning accuracy is at the region level, and the reporting frequency must meet the needs of real-time monitoring.
- **Monitoring of Daily Activities:** The system provides real-time monitoring of inmates' daily activities within the prison, accurately tracking their location, movement paths, and dwell time. The required positioning accuracy is around 5 meters, and the update frequency must be at least once per second to promptly detect any abnormal behavior.

6.2.4 Healthcare and Elderly Care

With the acceleration of population aging and advancements in medical technology, the demand for precise positioning of personnel, equipment, and resources in the healthcare and elderly care sectors is becoming increasingly evident. The required positioning accuracy in this field is typically at the meter level [8]. As illustrated in Figure 14, AIoT positioning technology provides significant benefits in these scenarios:Personnel Management， Real-time tracking of the locations of medical staff and patients enables timely and effective treatment and care, ensuring efficient operation throughout the entire medical process. Accurate positioning helps improve response times and enhance patient safety. Equipment Management， Precise location tracking of medical equipment can greatly increase equipment utilization, reduce the time spent searching for medical devices, and help maintain high standards of medical quality and patient safety.Given these needs, AIoT positioning technology has become an emerging choice for the healthcare and elderly care sectors due to its advantages, including battery-free operation, long lifespan, and high stability.

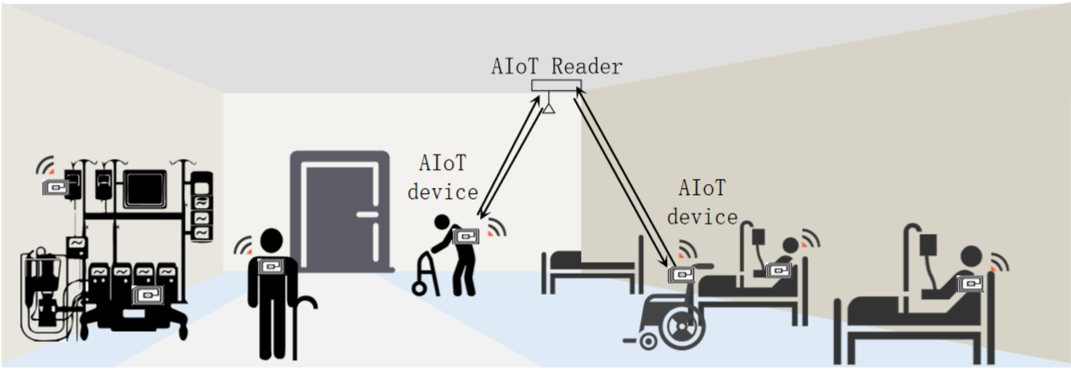


Figure 14 Schematic diagram of the positioning and deployment of medical and elderly care

- **Real-Time Patient Positioning and Monitoring:** Accurate tracking of patient locations, including in wards, hallways, and operating rooms, allows healthcare providers to respond promptly to patient needs and offer personalized care services. For patients requiring special attention, such as the elderly or those with limited mobility, real-time positioning ensures their safety and helps prevent accidents. The positioning accuracy must be sufficient to reliably identify the specific room or area where the patient is located. The positioning update frequency should meet real-time requirements so that medical staff can continuously monitor patient movements.

- **Medical Equipment Tracking and Management:** Medical equipment is an essential resource in healthcare and elderly care facilities. Real-time tracking and management of medical devices can enhance utilization efficiency and reduce the time spent searching for equipment. Additionally, for high-value or fragile devices, the system can provide theft prevention and damage alerts. The required positioning accuracy must be precise enough to determine the exact location of the equipment, while the update frequency can be flexibly adjusted based on the usage patterns and needs of the devices.

- **Rapid Response to Emergency Situations:** Quick response to emergencies is critical in the healthcare and elderly care sectors. In the event of natural disasters such as fires or earthquakes, or sudden medical emergencies, healthcare facilities need to rapidly and accurately locate personnel to assess whether evacuation or rescue operations are complete. This capability helps increase the speed of emergency response, reduces potential harm and property loss. The required positioning accuracy must be at least room-level, and the update frequency should meet real-time demands.

6.3 Personal and Family Positioning Scenarios

6.3.1 Family Care

Elderly individuals and young children represent two vulnerable groups. For the elderly, as age increases, memory and mobility gradually decline, making them more prone to accidents such as getting lost or falling. For young children, their strong curiosity combined with a lack of self-protection skills can lead to accidents such as wandering off or injuries. Additionally, pets have become an integral part of modern families, and tracking their location is increasingly important. Location tracking not only helps prevent pets from getting lost but also allows owners to monitor their pets' daily activity levels. As a result, location tracking for family members has become a pressing need for families seeking peace of mind and safety. In terms of positioning capabilities, the accuracy should be at least meter-level to ensure that family members can be quickly located in emergency situations [12].

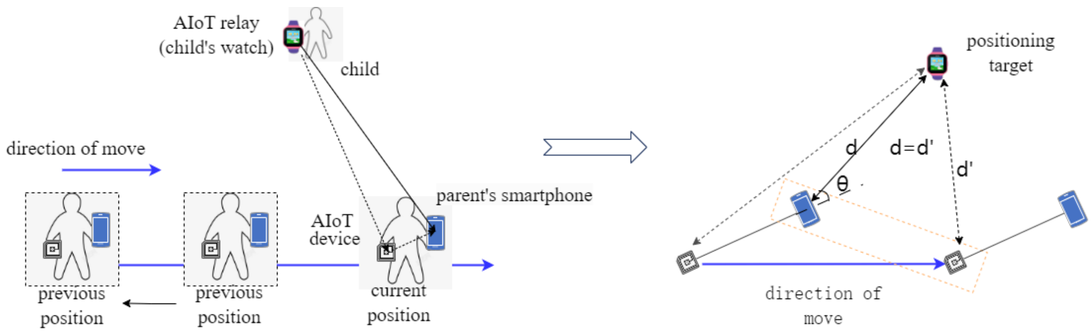


Figure 15 Schematic of the deployment of the child-finding[12]

- **Accident Prevention for the Elderly and Children:** Elderly individuals or young children can wear wearable AIoT devices, which are activated and read by nearby smartphones. As illustrated in Figure 15, the system utilizes the consistent relative distance between the smartphone and the AIoT device, along with multiple AIoT readers acting as observation points. When the receiver (smartphone) moves, the position of the AIoT device roughly coincides with the phone's location. This allows the system to track the phone's movement and use it to estimate the distance to the AIoT device, as well as to determine the speed of the child's movement relative to the receiving device. By leveraging this data, the system can accurately the location of the elderly person or child. The positioning is achieved by eliminating non-ideal factors from both the transmitter and receiver, isolating the channel state information (CSI) of the backscatter link, thus enabling high-precision AIoT positioning.
- **Pet Tracking:** Pets can wear AIoT devices, and family members can initiate a location tracking request via their smartphones. The AIoT devices are activated and read by base stations or nearby AIoT relay nodes, providing the real-time location of the pet. The required positioning accuracy is at the meter level, with a high update frequency to ensure timely tracking.

6.3.2 Finding things in Home

In smart home scenarios, one of the key applications is locating personal belongings, which are often small items such as keys, wallets, identification documents, and medication. These items are easily misplaced, and it can be challenging to find them, especially for elderly individuals whose memory may decline over time. In such cases, AIoT devices attached to these items can be leveraged to locate them using nearby nodes such as smartphones, home gateways, or set-top boxes.

The requirements for positioning accuracy and update frequency in this scenario are relatively low. However, the system needs to convert the absolute coordinates of the item into a format that is easily understandable for the user. For example: Providing a reference object near the item: "The keys are on the table, next to the vase." Offering approximate distance and direction: "The keys are about 3 meters away, towards the northeast at an angle of approximately 30 degrees." Additionally, this coordinate translation can be facilitated by attaching reference AIoT devices to common household objects and mapping them in the software database. For instance, Reference AIoT device1 could correspond to the living room sofa, while Reference AIoT device2 might be associated with the bookshelf in the study. This mapping allows the system to provide location information relative to familiar household items, making it more intuitive for users to find their belongings.

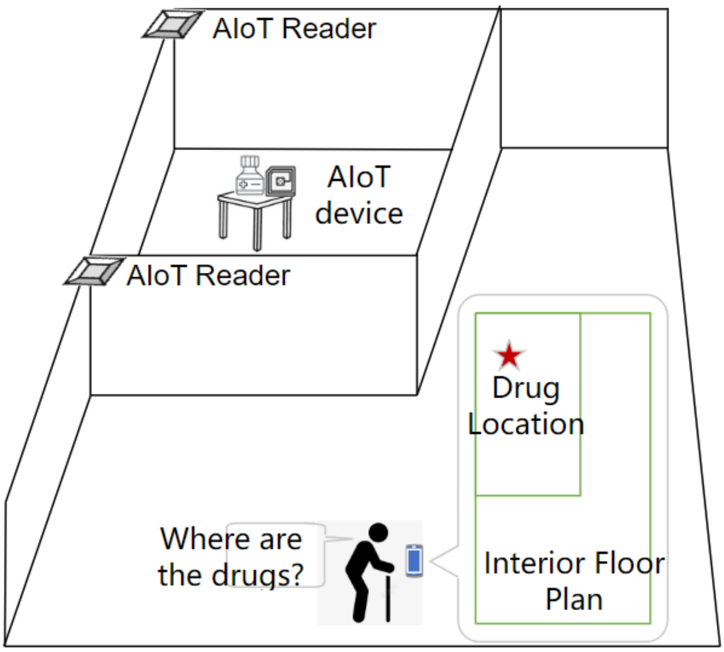


Figure 16 Schematic of positioning deployment for finding things in Home

- **Medication Tracking:** To help elderly individuals quickly locate their medication, a smartphone can assist in finding the item's location [13]. As illustrated in Figure 16, a AIoT device can be attached to the medication container. If the elderly person forgets where the medication is placed, AIoT positioning technology can be used to locate it. When there is a Line of Sight (LoS) path, the positioning accuracy can be less than 1 meter. If only a Non-Line of Sight (NLoS) path is available (as shown in Figure 16, where the medication and the elderly person are in different rooms), the positioning accuracy is typically around 1 to 2 meters. This level of accuracy can help the elderly person identify the general area where the medication is located.

- **Tracking of Valuable Items:** Some valuable items, such as passports or other important documents, are used infrequently, making it easy to forget whether they are still at home, where they are stored, or if they have been lost or stolen. To better track these items, a AIoT device can be attached, and a zero-dimensional presence detection method can be used to first confirm whether the item is still within the home. If it is confirmed to be at home, the above-mentioned positioning techniques can help the user quickly find the item. Additionally, customized notifications can be set up through a smartphone APP: if certain tagged items leave the designated home area, the user will receive an alert on their phone.

6.4 Analysis of Positioning Requirements and Performance Metrics

A summary analysis of the above scenarios reveals that AIoT positioning applications are primarily focused on indoor environments, encompassing three main categories: positioning, navigation, and tracking. **Positioning** refers to determining the precise location of a target within a defined space. The target can be either a person or an object, with applications including attendance management, electronic fence, and shelving operations. **Navigation** focuses on guiding users by planning the optimal route from a starting point to a destination. It continuously updates the user's position on the map in real time, adjusting the route guidance until the destination is reached. This capability typically uses a smartphone as both the AIoT reader and the display interface, allowing the phone to perform positioning measurements while also displaying the navigation map.**Tracking** involves the continuous, uninterrupted monitoring of a target's movements to capture its trajectory. The target can be a person or an object, with common applications including anti-lost solutions and logistics tracking.

Based on the descriptions of typical positioning scenarios in the previous sections, this chapter selects representative positioning applications and summarizes their requirements for AIoT devices and AIoT readers**,** as well as the p Performance Metrics for positioning**,** as shown in Table

Table 1 Positioning requirements and metrics analysis

for typical positioning scenarios

positio ning	positio ning	Positio ning busine ss	positio ning mode	Servic e	AIoT devic e	AIoT Reade rs deploy	Positioning indicators				
							Hori	Se	po	e	fr

	low	low	low	low	medium	medium	medium	high	high
	high	low	high	low	medium	high	high	low	low
	<5s	<1s	<3s	<5s	<5s	<5s	<1s	<5s	<5s
	99%	95%	99%	95%	90%	90%	90%	95%	95%
	＜5m	——	——	＜1m	＜5m	＜5m	＜1m	＜5m	＜5m
	AIoT base station	AIoT base station	Networked AIoT readers	Networked AIoT readers	AIoT base station and relay node	AIoT base station and relay node	Single-Point AIoT reader	AIoT base station	AIoT base station and relay node
	positioning target with the device	Reference device	positioning target with the device	positioning target with the device	Reference device	Reference device	positioning target with the device	positioning target with the device	positioning target with the device
	periodicity	periodicity	periodicity	trigger	trigger	trigger	trigger	periodicity	trigger
	Active Positioning	Passive Positioning	Active Positioning	Active Positioning	Passive Positioning	Passive Positioning	Active Positioning	Active Positioning	Active Positioning
	Employee Attendance	electronic fence	Inbound and Outbound Management	Shelf Management	Parking and finding a car	Guided Tours	Robot Finding	Patrol Positioning	Accident prevention for the young and old
	person		object		person		object	person	
	positioning				navigation			tracking	

	object	Positioning of production processes	Active Positioning	periodicity	positioning target with the device	Single-Point AIoT reader	<3m	95%	<3s	medium	high
		Pet Tracking	Active Positioning	trigger	positioning target with the device	Single-Point AIoT reader	<5m	95%	<1s	low	high

7 End-to-End AIoT Positioning Technology

End-to-end AIoT positioning technology encompasses the **terminal layer**, **network layer**, **algorithm layer**, and **application layer**. As illustrated in Figure 17:

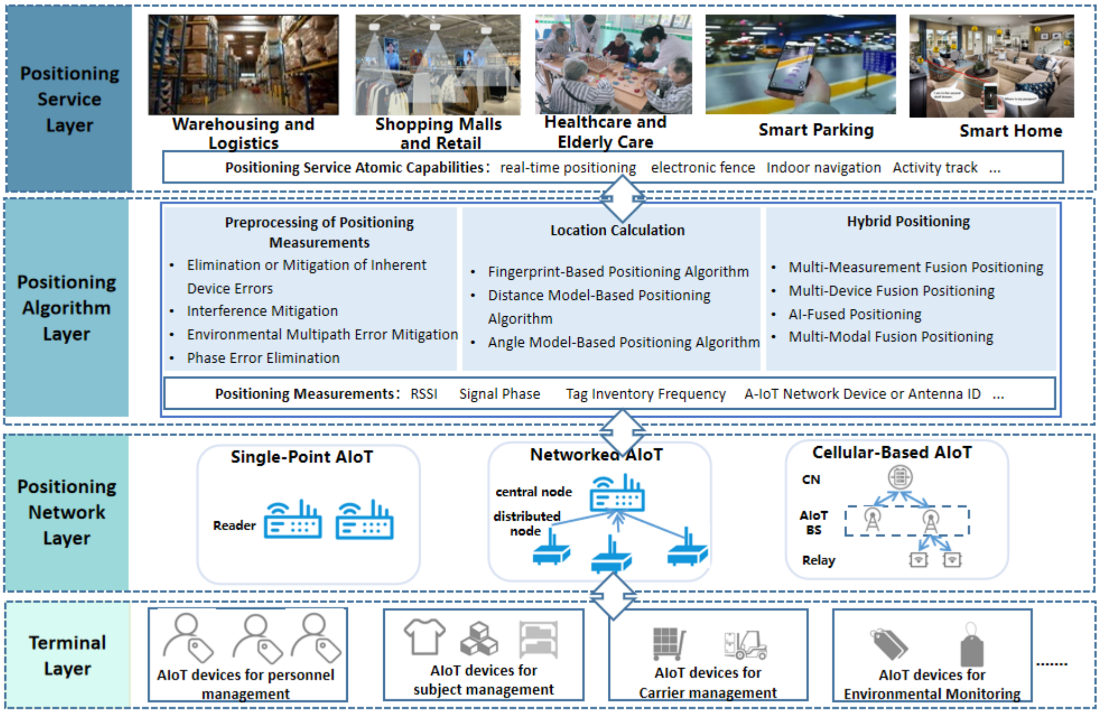


Figure 17 End-to-end technology system for AIoT positioning

- **Terminal Layer:** The terminal layer primarily consists of AIoT devices attached to positioning targets or reference devices deployed in the environment, typically in the form of electronic devices. These devices are made up of a chip and an antenna and operate without batteries, relying on energy harvesting. AIoT readers such as base stations continuously transmit RF signals to the devices, which converts the RF energy into DC power to supply the digital chip. Once the AIoT device is activated by the RF energy, it uses backscatter communication to report its ID and sensor data to the AIoT readers. The positioning function extracts measurement data from the wireless signal. These AIoT devices are classified as Type I devices by 3GPP. To enable longer transmission distances, 3GPP has further defined Type II-A devices, which have enhanced energy harvesting capabilities, and Type II-B devices, which can actively transmit signals [14]. The positioning algorithms differ based on whether they use backscatter signals or actively transmitted signals. This chapter will primarily focus on positioning algorithms based on backscatter signals.

- **Network Layer:** This layer includes the single-point architecture, networked architecture, and cellular-based architecture as discussed in Chapter 5. The choice of network architecture depends on the specific positioning scenario: single-point and networked architectures are typically used for indoor localized environments, while the cellular-based architecture is employed to extend coverage in outdoor scenarios. The selected network architecture influences both the positioning algorithms and processes, which will be analyzed in detail in Section 7.1.

- **Algorithm Layer:** This layer is responsible for preprocessing the positioning measurement data and calculating the AIoT device's location using algorithms based on fingerprinting, distance, and angle estimation. It also supports advanced methods involving multi-measurement, multi-device, multimodal, and AI-enhanced positioning. The placement of the algorithm layer may vary depending on the network architecture: in single-point and networked architectures, the algorithm layer can be co-located with the application layer on a server close to the client. In the cellular-based AIoT architecture, the algorithm layer can be implemented by the core network's positioning elements or supported by edge computing resources closer to the client. Due to the reliance on backscatter signals, AIoT positioning faces challenges such as measurement errors, signal weaknesses compared to active transmission, and increased susceptibility to environmental multipath and interference effects. However, the ultra-low cost, low power consumption, and maintenance-free nature of the AIoT devices enable unique positioning algorithms for AIoT, which will be explored in detail in Section 7.2.

- **Application Layer:** This layer provides fundamental positioning services tailored to specific applications, such as real-time positioning, electronic fence, indoor navigation, and movement tracking, as well as interfaces for positioning interaction and display.

Since the network layer determines the choice of positioning process and algorithms, and the algorithm layer is the core focus of positioning technology research, the following sections will provide a detailed analysis of each layer in the order of network layer, algorithm layer, terminal layer, and application layer.

7.1 Positioning Network Layer — Network Architecture and Air Interface Topology

Based on the connection method between AIoT devices and AIoT readers, the positioning network architecture of AIoT can be divided into three main categories: single-point AIoT architecture, networked AIoT architecture, and cellular-based AIoT architecture. The AIoT network architecture is closely related to the design of positioning algorithms and processes: **In single-point AIoT and cellular-based AIoT architectures,** the direct connection topology integrates both the transmission and reception of positioning signals, resulting in similar algorithmic approaches. However, **in networked AIoT and cellular-based AIoT architectures,** the introduction of relay nodes necessitates the consideration of separated signal transmission and reception when designing the positioning algorithms. In networked AIoT, the deployment of distributed nodes, and in cellular-based AIoT, the introduction of relay nodes, require additional considerations for the interaction between central nodes and distributed nodes, as well as between base stations and relay nodes. Furthermore, in the cellular-based AIoT architecture, the positioning process must adhere to the functional roles and workflow design of existing cellular positioning network elements. Additional functionalities need to be incorporated to support the specific requirements of AIoT positioning within the cellular framework.

7.1.1 Single-Point AIoT Positioning Architecture

Single-point AIoT refers to a direct connection between the AIoT reader and the AIoT device, similar to the traditional RFID architecture. In this setup, the AIoT devices are either attached to the objects being positioned or deployed as reference devices within the positioning area. The AIoT devices first use an energy harvesting module to convert RF energy or ambient energy into electrical power, which drives the circuitry of the AIoT device's processing and communication module. The AIoT devices then receive and demodulate the positioning command signals and use backscatter communication to transmit the positioning signal back to the AIoT reader.

The AIoT reader plays a key role in activating the AIoT device, sending downlink positioning commands, receiving uplink positioning signals, and estimating the positioning measurements. These measurements are then reported to the positioning service platform, which performs the position calculations. The positioning commands and signals mentioned in Figure 18 conform to the ISO 18000-6C standard, reusing the inventory commands sent by the AIoT reader to the AIoT devices and the signals from the AIoT devices reporting their Electronic Product Code (EPC).

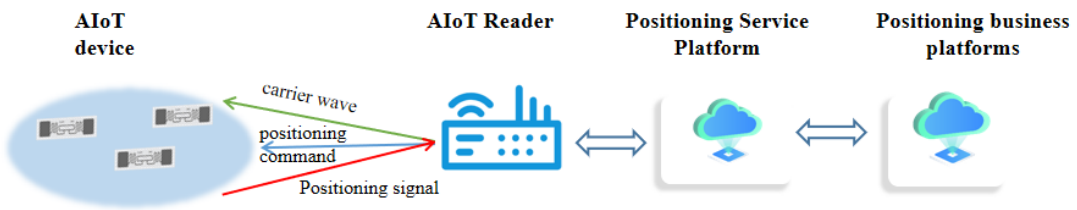


Figure 18 Single-Point AIoT Positioning Architecture

7.1.2 Networked AIoT Positioning Architecture

In the networked AIoT positioning architecture, the reading and writing of AIoT devices are jointly handled by the central node and the distributed nodes, as illustrated in Figure 19. A single central node is deployed in conjunction with multiple distributed nodes. The central node interacts with the positioning platform, managing the distributed nodes to send activation signals and positioning commands to the AIoT devices. The AIoT devices then reflect the positioning signals directly back to the central node. In this setup, the transmission of the positioning signal is handled by the distributed nodes, while the reception is handled by the central node.

When designing the positioning process, it is crucial to consider the coordination between the central node and the distributed nodes. Additionally, the design of the positioning algorithms must account for the different paths of the transmitted and received positioning signals. Currently, the networked architecture adheres to the ISO 18000-6C standard, with the positioning commands and signals reusing the inventory commands sent by the AIoT readers and the signals used when AIoT devices report their Electronic Product Code (EPC). In the future, this architecture will support the cellular-based AIoT positioning protocol.

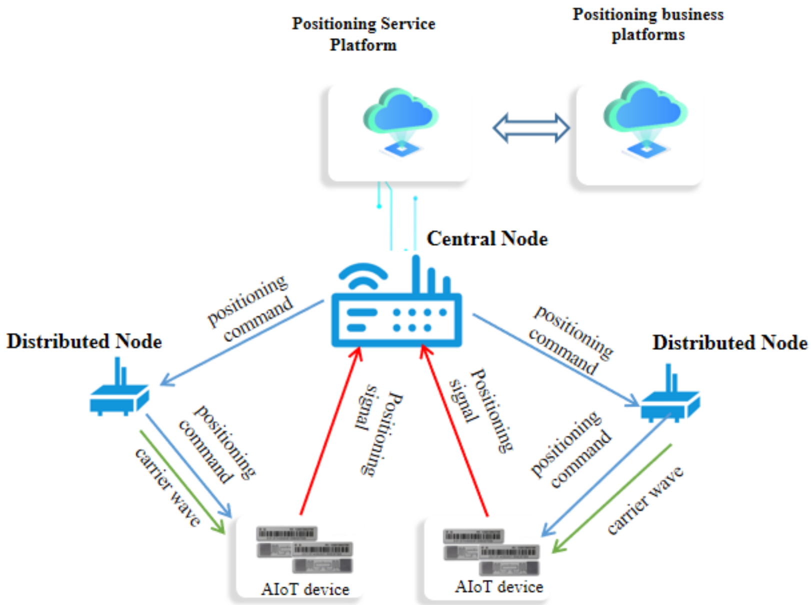


Figure 19 Networked AIoT Positioning Architecture

7.1.3 Cellular-based AIoT Positioning Architecture

In the cellular-based AIoT architecture, base stations or relay nodes are equipped with AIoT device reading and writing modules, reusing core network elements such as SMLC (Serving Mobile Location Center) and LMF (Location Management Function) as the positioning platform, which supports the functions of the algorithm layer. SMLC interacts with client positioning applications, receiving location requests from applications and returning the calculated position information. LMF receives positioning requests from the SMLC, issues positioning commands to the AIoT device reading module at the base station, receives the measurement data from the base station, performs position calculation, and then sends the position information back to the SMLC.

To ensure secure positioning, the UDM (Unified Data Management) network element is involved in managing the AIoT device subscription and location permissions of the AIoT devices. Regarding the positioning signals, 3GPP has not yet finalized the detailed specifications. However, the preliminary conclusion is that due to the AIoT devices' low power consumption and limited computational capabilities, the physical layer and link layer protocols should be kept simple.

As shown in Figure 20, the air interface topology between the AIoT devices and base stations can be divided into three scenarios [14]:

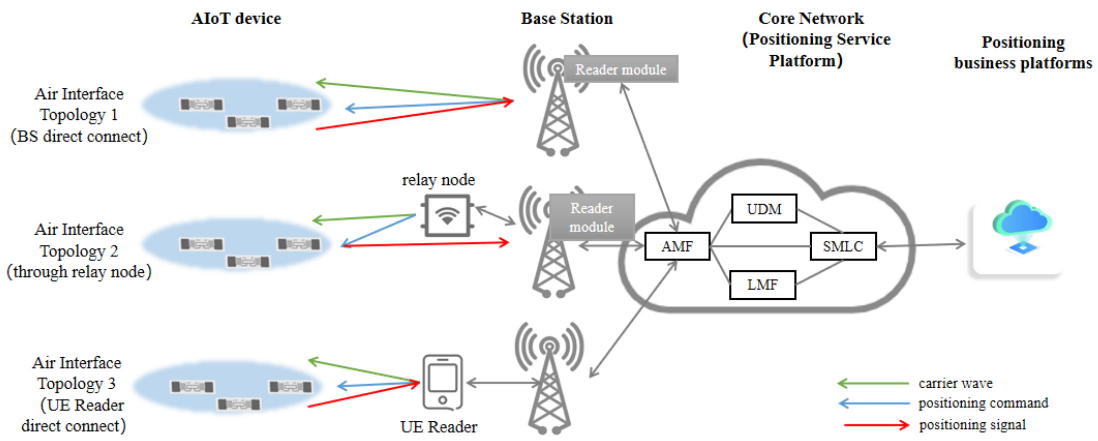


Figure 20 Cellular-based AIoT Positioning Architecture

- **Air Interface Topology 1:** The base station integrates the AIoT device reading module and directly connects to the AIoT device, sending activation signals and positioning commands. The AIoT device backscatters the positioning signal to the base station, where the AIoT device reading module estimates the measurement data and sends it to the core network for position calculation. This configuration follows an integrated transmission and reception architecture.

- **Air Interface Topology 2:** A relay node is deployed near the AIoT device to send activation signals and positioning commands. The AIoT device backscatters the positioning signal to the base station, where the base station’s reading module estimates the measurement data. This configuration adopts a separated transmission and reception architecture.

- **Air Interface Topology 3:** UE Readers such as smartphones integrate the AIoT reading module and interact with the AIoT device. The UE Readers receives the positioning request from the core network, activates the AIoT device, and sends the positioning command. The AIoT device backscatters the positioning signal, and the UE Readers estimates the measurement data before reporting it to the core network. In this scenario, the UE Readers acts as a relay node, and the entire architecture follows an integrated transmission and reception architecture.

7.2 Positioning Algorithm Layer — Estimation of Positioning Measurements and Position Calculation

7.2.1 Estimation of Positioning Measurements

Positioning measurements refer to the parameters used to determine the location of the target object. In AIoT systems, these measurements include not only common wireless channel metrics like signal phase and signal strength (RSSI) but also additional auxiliary information such as the inventory frequency of the AIoT device and the ID of the AIoT reader or antenna.

However, several factors can significantly impact the accuracy of these measurements, including the inherent errors of the AIoT devices and AIoT readers, signal interference, and multipath environments. This section will first define the key measurements used in AIoT positioning and outline the methods for estimating these measurements. The focus will then shift to techniques for preprocessing the measurements to enhance accuracy.

7.2.1.1 Analysis of Positioning Measurements

1. Signal Phase

In AIoT communication, the signal propagation process is illustrated in Figure 21. The AIoT reader first transmits a carrier signal S_{send} at a specified frequency band to activate the AIoT device. The carrier signal also carries inventory commands, which are sent to the AIoT device. The AIoT device demodulates the information received from the AIoT reader and modulates this information onto the carrier signal, which is then backscattered.

The AIoT reader receives the backscattered signal S_{revs} from the AIoT device, demodulates the information carried on the signal, and completes the entire communication process.

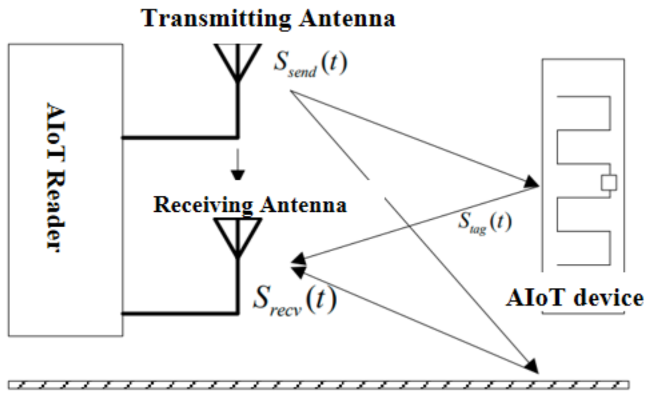


Figure 21 wireless signal propagation for AIoT

At the initial stage of the communication process, the signal transmitted by the AIoT reader is denoted as S_{send} .

$$S_{sent}(t) = A\cos(2\pi f_c t + \varphi_0 + \varphi_T) \qquad (7-1)$$

Among these parameters:

- A : the amplitude of the signal,
- f_c : the carrier frequency of the signal,
- ϕ_0 : the initial phase of the signal,
- ϕ_T : the phase shift caused by the transmission path of the AIoT device.

Once the signal reaches the AIoT device, it activates the device. The device then modulates its own information onto the carrier signal and backscatters it. The signal received by the AIoT reaer is denoted as S_{revs} .

$$S_{recv}(t) = \alpha\delta A\cos(2\pi f_c(t - \tau_T - \tau_R) + \varphi_0 + \varphi_T + \varphi_{tag} + \varphi_R) \qquad (7-2)$$

In this context:

- δ is the **attenuation factor** introduced during the signal transmission process,

- τ_T and τ_R are the **time delays** for the forward and backward transmission of the signal, respectively,
- ϕ_R is the **phase shift** introduced by the receiving path of the AIoT reader,
- ϕ_{tag} is the **phase shift** introduced by the AIoT device itself during the modulation process, α representing the AIoT device's modulation information.

As illustrated in Figure 22, the phase changes introduced at each stage are shown. Among all these phase variations, only the changes caused by signal propagation (τ_T and τ_R) are relevant to ranging calculations. The other phase shifts are considered errors in the measurement process.

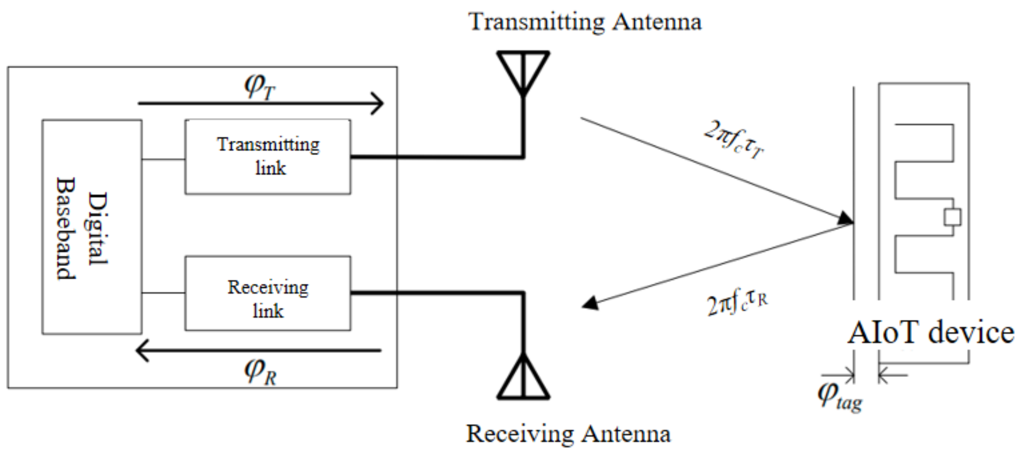


Figure 22 phase change during signal propagation

The commonly used method is to obtain the signal phase information through I/Q demodulation, as illustrated in Figure 23.

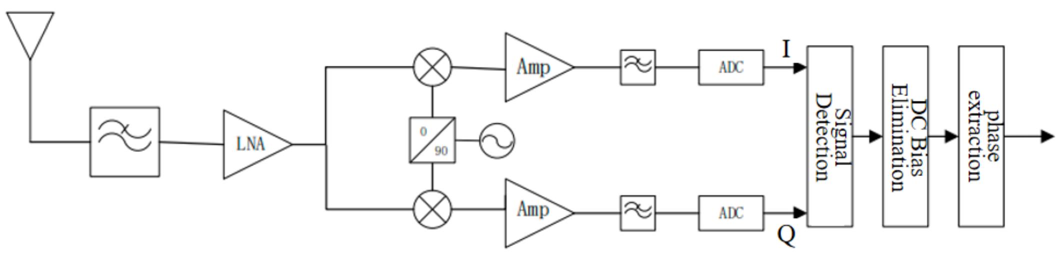


Figure 23 I/Q Demodulation Schematic

Upon receiving the signal, the AIoT reader splits the received signal into two paths. Each path is then mixed with two **orthogonal signals** generated by the local oscillator (LO). The resulting mixed signals are passed through a **low-pass filter** to obtain the **I/Q baseband signals**. The phase information of the received signal can then be extracted based on the I/Q baseband signals.

The signal generated by the local oscillator, denoted as S_{LO} is:

$$S_{LO}(t) = A_{LO}\cos(2\pi f_c t + \varphi_{LO}) \quad (7-3)$$

$$I(t) = \frac{1}{2}A_{LO}\left[\alpha\delta A\cos(2\pi f_c(\tau_T + \tau_R) + \varphi_n\right] \quad (7-4)$$

$$Q(t) = \frac{1}{2}A_{LO}\left[\alpha\delta A\sin(2\pi f_c(\tau_T + \tau_R) + \varphi_n\right] \quad (7-5)$$

In this context, $\varphi_n = \varphi_0 + \varphi_T + \varphi_{tag} + \varphi_R - \varphi_{LO}$.

The phase information of the signal can be calculated as shown in the following equation:

$$\varphi = \arctan(\frac{Q(t)}{I(t)}) \quad (7-6)$$

$$d = \frac{1}{2}\frac{\varphi_c + 2\mathrm{n}\pi}{2\pi f} \quad (7-7)$$

2. Signal Strength (RSSI)

The AIoT device receives a continuous wave transmitted by the antenna of the AIoT reader and modulates its data onto the return signal. By modeling the signal separately for the forward and backward paths, the electromagnetic wave energy received by the AIoT device from the transmitting antenna of the activator can be expressed as:

$$P_{tag-Rx} = P_{reader-Tx}G_{reader-Tx}G_{tag}L(\frac{\lambda}{4\pi d_1})^2 \quad (7-8)$$

In this context:

- P_{tag-Rx}: the energy received by the AIoT device,
- $P_{reader-Tx}$: the signal energy transmitted by the antenna of the AIoT reader,

- $G_{reader-Tx}$ and G_{tag} : the signal gains of the AIoT reader antenna and the AIoT device antenna, respectively,
- L : the channel attenuation factor,
- d_1 : the forward communication distance.

Similarly, the energy of the signal received by the receiving antenna of the AIoT reader can be expressed as:

$$P_{reader-Rx} = P_{tag-Tx} G_{reader-Rx} G_{tag} L (\frac{\lambda}{4\pi d_2})^2 \qquad (7-9)$$

In this context:

- $P_{reader-Rx}$: the energy received by the antenna of the AIoT reader,
- P_{tag-Tx} : the signal energy reflected by the AIoT device,
- d_2 : the backward communication distance,

β is the energy utilization efficiency of the AIoT device, indicating that $P_{tag-Rx} = \beta P_{tag-Tx}$.

By combining the above equations, we can derive:

$$P_{reader-Rx} = \beta P_{reader-Tx} G_{reader-Tx} G_{reader-Rx} G_{tag}^2 L^2 (\frac{\lambda}{4\pi})^4 (\frac{1}{d_1 d_2})^2 \qquad (7-10)$$

By analyzing the energy equations, the RSSI (Received Signal Strength Indicator) can be calculated as follows:

$$RSSI = 10\log_{10}(P) \qquad (7-11)$$

When the AIoT reader operates as an integrated transceiver, meaning d_1 and d_2 are equal, the formula for RSSI can be expressed as follows:

$$RSSI = RSSI_0 - 10n\log_{10}(\frac{d}{d_0}) \qquad \textbf{(7–12)}$$

- $RSSI_0$: the RSSI value at reference distance d_0 ,
- n : the path loss exponent (a typical recommended value for n is 2).

From this formula, it is evident that as the distance d decreases (i.e., the AIoT device gets closer to the AIoT reader), the RSSI value increases.

3. Inventory Frequency of AIoT Device

Each time the AIoT device completes an inventory process with the AIoT reader, it is considered to have been successfully read once. When the AIoT device is located within a close range of the AIoT reader antenna, the number of reads per unit time is high and relatively stable. This metric can be used as a rough indicator of the relative distance between the AIoT device and the AIoT reader antenna.

4. AIoT reader or Antenna ID

When a AIoT device is identified by an AIoT reader, it can be assumed that the AIoT device is within the activation and identification range of the corresponding antenna. For integrated transceiver readers, the antenna ID can help define the approximate area covered by the activation and identification range of the AIoT reader's antenna. For AIoT readers with separated transmitter and receiver functions, the antenna ID can be used to constrain the area to the intersection of the activation range of the transmitter antenna and the identification range of the receiver antenna.

7.2.1.2 Preprocessing of Positioning Measurements

The accuracy of positioning measurements greatly affects the overall positioning accuracy. However, factors such as inherent device errors, signal interference, and environmental multipath effects can significantly impact the accuracy of these measurements. This section will discuss methods to mitigate or compensate for these adverse effects, focusing on:

- Elimination of inherent errors from AIoT device and AIoT readers,
- Interference suppression,
- Multipath error mitigation,

- Phase Error Elimination.

7.2.1.2.1 Elimination or Mitigation of Inherent Device Errors

1. **Elimination of AIoT device SFO or CFO**

To reduce the impact of Sampling Frequency Offset (SFO) from the AIoT device on the positioning measurements, the SFO can be preprocessed to eliminate its effects. Assume that the carrier signal frequency is f_0 and the AIoT device modulation frequency is f_1. If the SFO introduces a frequency error of Δf (assumed to be positive), the received signal frequencies at the receiver will be $f_0 + f_1 + \Delta f$ and $f_0 - f_1 + \Delta f$. By performing frequency-domain correlation between the received signal and the carrier signal, the resulting frequency component is $f_1 + \Delta f$.

Since the AIoT reader knows the value of f_1, the frequency error Δf caused by the AIoT device's SFO can be determined. Using this value, the AIoT reader can preprocess or compensate the phase of the positioning measurements accordingly.

In addition, based on the AIoT device's modulation method (e.g., On-Off Keying (OOK)), a specific sequence of the AIoT device's backscatter signal can be designed. This sequence can help the receiver estimate the AIoT device's SFO or Carrier Frequency Offset (CFO) through correlation operations.

2. **Elimination of Carrier Phase Variation Caused by AIoT Device Backscatter**

In AIoT positioning systems, the carrier phase variation caused by AIoT device backscatter (referred to as φ_{tag}) can introduce measurement errors in the phase of the reflected carrier signal. This variation is influenced by factors such as AIoT device type, the object the AIoT device is attached to, attachment method, and periodic environmental changes.

During phase measurement, it is typically assumed that the carrier phase variation due to AIoT device backscatter remains relatively stable over short time periods. By performing multiple measurements and applying differential processing, this fixed component of the phase variation

(φ_{tag}) can be eliminated, reducing the impact of AIoT device backscatter phase changes on the accuracy of the positioning measurements.

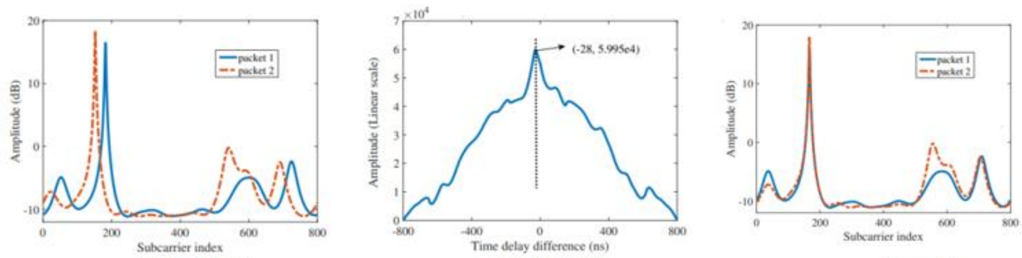
3. Improved Phase Acquisition Based on Elimination of AIoT reader SFO or STO

In an AIoT positioning system with a separated transmitter and receiver architecture, it is also necessary to address the impact of Sampling Frequency Offset (SFO) or Sampling Time Offset (STO) between the transmitter and receiver, which can cause synchronization issues and affect the accuracy of positioning measurements.

Within the coherence time, a multi-packet configuration is employed. The transmitter sends packet 1 to the receiver at time T1 and sends packet 2 at time T2. The receiver then performs correlation between the signals received at these two different times to estimate the synchronization error within the coherence time.

As shown in Figure 24:

- The receiver correlates the received signals from packet 1 and packet 2 (Figure ①).
- The synchronization error is obtained (Figure ②).
- The synchronization error is then used for compensation, achieving signal synchronization between the transmitter and receiver (Figure ③).



Figure① Figure② Figure③

Figure 24 Transceiver-side Irrationality Elimination in Transceiver-Separation Architecture

4. Configuration of Encoding Scheme in Positioning Systems

In an AIoT system, the AIoT devices can be configured to use different encoding schemes and

Backscatter Link Frequency (BLF) bandwidths, which affect the sensitivity of the AIoT reader. The sensitivity of the device, in turn, determines the minimum detectable RSSI (Received Signal Strength Indicator) value of the AIoT device, thereby influencing the maximum distance over which the AIoT device can be detected.

Although higher sensitivity of the AIoT reader allows for a wider range of measurable RSSI values, lower RSSI measurements are more susceptible to self-interference and noise, leading to increased measurement errors and reduced positioning accuracy. Therefore, during the positioning process, it is essential to consider the trade-off between measurement accuracy and the device's sensitivity. The encoding scheme and BLF bandwidth of the AIoT device should be configured accordingly, balancing the needs for accurate positioning and optimal system performance.

7.2.1.2.2 Interference Mitigation

The presence of interference components reduces the sensitivity of the receiver and affects the amplitude and phase of the measured signals, ultimately degrading the positioning accuracy of the AIoT system.

In the integrated transceiver architecture, if the AIoT device lacks significant frequency-shifting capability, it uses the same spectrum for backscatter signals. Consequently, when the AIoT reader receives the backscattered signal, it may also pick up the carrier leakage signal from the transmitter. This interference, known as self-interference, affects the demodulation and measurement of the backscattered signal. Additionally, due to obstructions in the environment (e.g., walls), the transmitted carrier signal may be reflected back to the receiver, causing clutter interference or reflection interference, which further disrupts the demodulation and measurement of the backscattered signal.

In the separated transmitter-receiver architecture, the distributed node or relay node transmits the carrier signal, while the receiver captures the backscattered signal. During this process, the receiver may also receive the carrier signal from the relay node. Since the carrier signal and backscattered signal have similar frequencies, the carrier signal can interfere with the demodulation and measurement of the backscattered signal, resulting in cross-link interference.

Regardless of the type of interference, the sensitivity of the receiver is negatively impacted.

Interference complicates the measurement of the backscattered signal and reduces the positioning accuracy. For example, if self-interference is not suppressed, the signal entering the receiver's Low Noise Amplifier (LNA) may produce intermodulation distortion, and the Analog-to-Digital Converter (ADC) may become saturated, leading to significant errors in phase measurement [21].

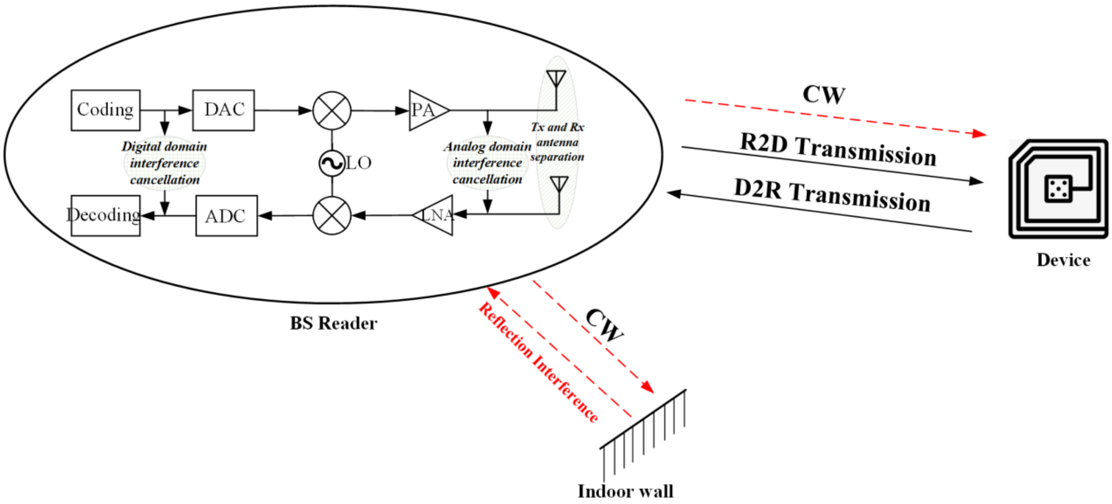


Figure 25 interference suppression in AIoT system

The following methods are proposed to mitigate or suppress interference in both integrated transceiver and separated transceiver architectures:

- **Interference Suppression at the AIoT reader Side [15]:** As illustrated in Figure 25, there are three main approaches: 1)**Spatial Interference Isolation:** When the base station transmits the carrier signal for positioning, interference can be reduced by physically isolating the transmitting and receiving antennas and adding a physical shield between them. For example, physical isolation between transmitting and receiving antennas can achieve 30 dB isolation, while a shield can provide an additional 47 dB isolation, resulting in a total of 77 dB suppression in the antenna domain. 2) **Analog Domain Circuit Suppression:** This method constructs a signal that is equal in amplitude but opposite in phase to the self-interference signal, effectively cancelling it out in the analog domain (e.g., achieving 45 dB suppression). 3) **Digital Domain Interference Suppression:** After the self-interference signal passes through the Analog-to-Digital Converter (ADC), channel estimation is used to create a signal that is equal in amplitude but opposite in phase, cancelling the interference in the digital domain (e.g., achieving 10 dB suppression).

- **High-Rate Modulation for AIoT Devices:** In the future design of AIoT devices for cellular-based AIoT, high-rate modulation can be used to increase the frequency separation between the backscatter signal and the carrier signal (e.g., 20 MHz). This frequency separation allows the receiver to use an analog filter to suppress self-interference or cross-link interference. However, this approach places higher demands on the AIoT device's capabilities, requiring the AIoT device to have significant frequency-shifting capability, such as the Type II-A devices discussed in Section 7.3.

7.2.1.2.3 Environmental Multipath Error Mitigation

To address multipath errors in the environment, multiple signal phase measurements can be collected across different frequency points. By reconstructing the Channel Frequency Response (CFR) and applying the Inverse Fast Fourier Transform (IFFT), a rough estimate of the signal propagation time can be obtained. This estimation can then be used for multipath suppression, reducing the impact of multipath reflections on the positioning accuracy.

After eliminating the inherent device errors, if there are k frequency points, the phase for each frequency point can be obtained as follows:

$$\varphi = [\varphi_1, \varphi_2 .. \varphi_k] \quad (7-13)$$

The **CRF** can then be reconstructed based on these phase measurements for each frequency point:

$$C = [C_1, C_2 ... C_k] \quad (7-14)$$

$$C_i = a_i e^{-j\varphi_i} \quad (7-15)$$

Let c_i be the **CFR** at frequency point f_i for the receiving antenna. The attenuation coefficient of the signal at frequency point i, denoted as a_i, can be estimated based on the AIoT device's preamble sequence Q_k , where $k = 0,1,2,3,\cdots,L-1, L$ represents the length of the preamble sequence. The received preamble sequence at the receiver is denoted as R_k .

The frequency-domain channel attenuation coefficient a_i can be expressed as:

$$a_i = \frac{1}{L}\sum_{k=0}^{L-1}(Q_k^* \times R_k) \quad (7-16)$$

The signal propagation time function can then be obtained by applying the **Inverse Fast Fourier** Transform (IFFT) as follows:

$$f(t) = IFFT(C) \quad (7-17)$$

The peak value of the time-domain waveform corresponds to the time τ , which is the flight time of the shortest propagation path. Based on this flight time, a rough estimate of the relative distance to the target can be calculated as:

$$d_0 = c\tau \quad (7-18)$$

Assuming there are M multipath components, the CFR at frequency f_i for the receiving antenna can be expressed as:

$$C_i = \mathrm{a}_0 e^{-j\frac{2\pi}{c}f_i d} + \sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{a}_1 e^{-j\frac{2\pi}{c}f_i d_{\mathrm{m}}} \quad (7-19)$$

In this context:

- a_0 :the signal amplitude of the LoS (Line of Sight) path,
- a_m :the signal amplitude of the $m-th$ NLoS (Non-Line of Sight) path,
- d :the true distance of the LoS path,
- d_m :the true distance of the $m-th$ NLoS path.

By using the rough distance estimation to process the phase measurements at each frequency point, the influence of multipath effects on the LoS signal can be mitigated. The resulting phase measurement value after multipath suppression is:

$$\varphi_i^{'} = \angle \sum_{i=1}^{k} C_i e^{-j\frac{2\pi}{c}(f_i - f_k)d_0} \qquad (7-20)$$

7.2.1.2.4 Phase Error Elimination

1. Phase Center Correction [16]

The phase center is the reference point from which the AIoT reader transmits and receives electromagnetic waves. In most cases, the geometric center of the AIoT reader antenna is approximated as the phase center, even though they may not be perfectly aligned. This approximation can lead to small measurement errors. While eliminating inherent reader errors is sufficient for most practical scenarios, achieving higher positioning accuracy requires phase center correction, which can further reduce errors and improve the precision of position calculation.

To perform phase center correction, the AIoT device is moved along a known trajectory in a plane. During this process, the AIoT reader continuously polls the AIoT device using the antenna that requires calibration. A series of phase measurements is collected. Let n be the window length; the collected phase vector list can then be transformed into an $m*n$ phase matrix S, where m is the number of sampled points and n is the window size.

$$\mathbf{S} = \begin{bmatrix} phase_1^1 & \cdots & Phase_1^n \\ \vdots & \ddots & \vdots \\ phase_m^1 & \cdots & phase_m^n \end{bmatrix} \qquad (7-21)$$

Since the movement trajectory of the AIoT device is known, a position matrix T can be constructed for each phase measurement.

$$\mathbf{T} = \begin{bmatrix} (x_1^1, y_1^1, z_1^1) & \cdots & (x_1^n, y_1^n, z_1^n) \\ \vdots & \ddots & \vdots \\ (x_m^1, y_m^1, z_m^1) & \cdots & (x_m^n, y_m^n, z_m^n) \end{bmatrix} \qquad (7-22)$$

Due to the impact of NLoS effects in the measurements, it is necessary to perform LoS extraction. The phase direction of NLoS signals is inconsistent across different locations. Therefore, the first phase within each window is selected as an anchor point. The subsequent phases are adjusted based on the distance differences, converting them into the theoretical phase at the anchor position. By aggregating multiple adjusted phase measurements, the influence of NLoS signals can be effectively suppressed, resulting in a cleaner LoS phase signal, as illustrated in Figure 26.

$$Phase_m^{'} = \sum_{i=1}^{n} Phase_m^{i} \cdot e^{-j(\frac{4\pi f(d_i - d_1)}{c})} \qquad (7-23)$$

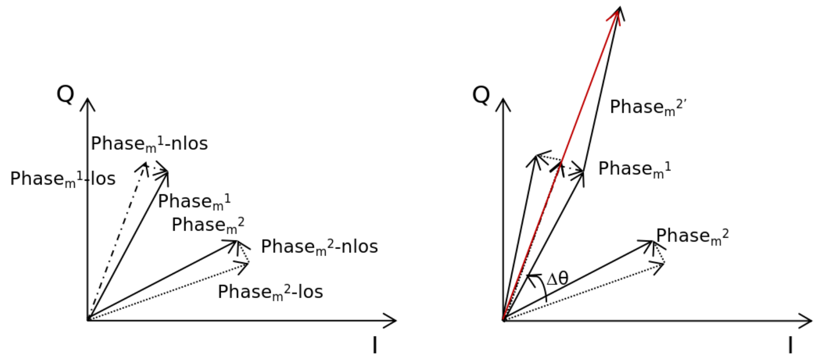


Figure 26 multiple phase superposition to suppress NLoS signals

Based on the calculated LoS phase signal**,** a hologram can be constructed. If a certain location is designated as the phase center, the inherent phase error can be expressed as:

$$\varphi_m = (Phase_m^{'} - \frac{4\pi f d_m}{c}) \bmod (2\pi) \qquad (7-24)$$

If the selected location is indeed the phase center, the calculated inherent phase errors will be relatively consistent. By combining the inherent errors obtained from each window into an array POPOPO, the likelihood function used to determine whether a position is the phase center can be expressed as:

$$PO = [\varphi_1, \cdots \varphi_m] \qquad (7-25)$$

$$P = \frac{1}{std(PO)} \qquad (7-26)$$

By scanning through the likelihood values for each point in the hologram, the position with the maximum likelihood value is identified as the phase center.

2. Phase Unwrapping

Due to the inherent ambiguity of phase measurements, directly using raw phase data for positioning can complicate the algorithm and reduce efficiency. In continuous data acquisition tasks, phase unwrapping can be employed to resolve the integer or partial cycle ambiguity in the phase measurements.

The phase unwrapping algorithm compares the phase at the current timestamp with the phase at the previous timestamp. If the absolute phase change is greater than or equal to 180 degrees, an integer multiple of 360 degrees is added or subtracted to correct the phase, restoring continuity.

However, this method requires compliance with the spatial sampling theorem. If the gap between consecutive phase measurements exceeds a quarter of the wavelength, the unwrapping process may fail. To address this, Kalman filtering or other smoothing techniques can be applied to remove outlier points and smooth the phase variation curve, achieving more effective phase unwrapping [17].

3. Elimination of Phase Errors Due to Separated Transceiver Architecture

In a networked AIoT system with separated transmitter and receiver, the receiver uses a frequency-difference-based method for error elimination. While the distributed node transmits the activation signal to the AIoT device, the central node simultaneously receives the activation signal S_i from the distributed node via the air interface.

The central node can then use the following calculation formula to track the frequency offset between the transmitter (distributed node) and the receiver (central node). By estimating this frequency offset, the transmitter can apply a pre-compensation value for the frequency, effectively reducing the impact on the phase measurements.

The specific phase compensation value is given as follows:

$$\theta = angle[(\sum_{i=0}^{L} S_i \times S_{i+N}^{*})/L] \qquad (7-27)$$

$$\varphi = \frac{\theta}{N}\frac{F_s}{2\pi} \tag{7-28}$$

In this context:

- L :represents the number of measured sample points,
- N :indicates the sample interval corresponding to the frequency difference,
- F_s :the sampling rate of the system.

7.2.2 Location Calculation

AIoT positioning technology is a type of wireless communication-based localization, utilizing passive RF waves as the information carrier for position estimation. The choice of positioning algorithms is closely tied to the characteristics of the signal. This section provides a detailed analysis of three key positioning methods based on the ISO18000-6C communication protocol:

- Fingerprint-based positioning,
- Distance model-based positioning
- Angle model-based positioning.

These methods are applicable to both single-point and networked AIoT positioning architectures. In practical applications, the selection of the positioning algorithm depends on the required accuracy, network architecture, and antenna deployment.

For cellular-based AIoT, due to differences in AIoT devices, network architecture, and communication protocols, the positioning algorithms discussed in this section can still be applied. However, the implementation details may require adaptation to account for these changes. Further research and development on these adaptations will be conducted in the future.

7.2.2.1 Fingerprint-Based Positioning Algorithm

A fingerprint refers to the signal characteristics of a AIoT device at a target location, which are typically associated with the location through a matching algorithm. Any distinctive feature or combination of features can serve as a location fingerprint. In AIoT positioning scenarios, RSSIand phase can be used as fingerprint features. Classic fingerprint-based positioning algorithms in AIoT include the Landmarc algorithm [18] and the VIRE (Virtual Reference Elimination) algorithm [19].

1. Landmarc Algorithm

The core idea of the Landmarc positioning algorithm is a centroid-based weighting method built on RSSI values. By using the real-time RSSI values of reference AIoT devices, the algorithm aims to mitigate the common environmental interference affecting signal propagation at nearby locations. This approach enhances the accuracy of object positioning by leveraging the RSSI values as a reference.

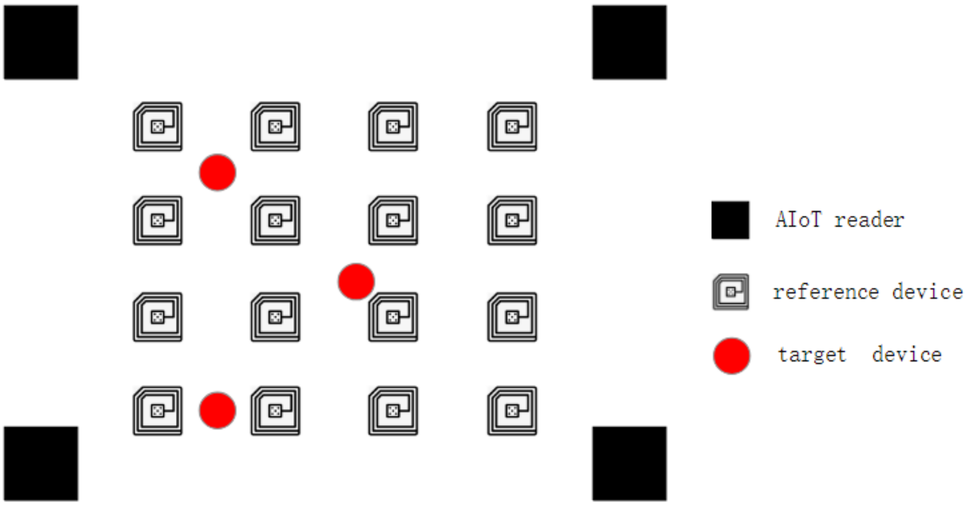


Figure 27 Schematic diagram of the Landmarc positioning algorithm

As shown in Figure 27, let's assume there are:

- N : AIoT readers,
- M : reference devices,
- L : target AIoT devices to be positioned.

Define the signal strength vector of the reference AIoT devices for each AIoT reader as:

$$S = \begin{bmatrix} S_1^1 & S_2^1 & \cdots & S_N^1 \\ S_1^2 & S_2^2 & \cdots & S_N^2 \\ \cdots & \cdots & \cdots & \cdots \\ S_1^M & S_2^M & \cdots & S_N^M \end{bmatrix} \tag{7–29}$$

In this context, S_n^m represents the RSSI value of the reference AIoT device m received by the AIoT reader n.

Let E be the signal strength vector received by the AIoT readers when reading the target AIoT devices, defined as:

$$E = \begin{bmatrix} E_1^1 & E_2^1 & \cdots & E_N^1 \\ E_1^2 & E_2^2 & \cdots & E_N^2 \\ \cdots & \cdots & \cdots & \cdots \\ E_1^T & E_2^T & \cdots & E_N^T \end{bmatrix} \quad \textbf{(7–30)}$$

In this context, E_n^l represents the RSSI value of the target AIoT device l received by the AIoT reader n.

According to the K-Nearest Neighbor (KNN) algorithm, the Euclidean distance between the target AIoT device and each reference AIoT device needs to be calculated. The k reference AIoT devices that are closest to the target AIoT device are then selected. This results in the distance vector matrix D, defined as:

$$D = \begin{bmatrix} D_1^1 & D_2^1 & \cdots & D_m^1 \\ D_1^2 & D_2^2 & \cdots & D_m^2 \\ \cdots & \cdots & \cdots & \cdots \\ D_1^T & D_2^T & \cdots & D_m^T \end{bmatrix}, m \le M \quad \textbf{(7–31)}$$

In this context, D_m^l represents the Euclidean distance between the reference AIoT device m and the target AIoT device t. Since there are N AIoT readers, an additional summation step is required to reduce the potential errors caused by individual AIoT readers.

The aggregated Euclidean distance can be expressed as:

$$D_m^1 = \sqrt{\sum_{i=1}^{N} \left(S_i^m - E_i^1\right)^2} \quad \textbf{(7–32)}$$

As the distance D_m^l decreases, it indicates that the target AIoT device t is closer to the reference device m. By sorting the distances for a given target AIoT device, the top k smallest values are selected, corresponding to the k nearest reference AIoT devices. Using the KNN algorithm, the coordinates of the target AIoT device can be estimated based on the coordinates and weights of these k nearest reference AIoT devices.

$$\left(x^t, y^t\right) = \sum_{i=1}^{k} w_i \left(x^i, y^i\right) \quad \textbf{(7–33)}$$

In this context, $w_i = \left(\frac{1}{D_i^t}\right) / \left(\sum_{i-1}^{k} \frac{1}{D_i^t}\right)$, w_i represents the weight value of the $i-th$ nearest reference device's coordinates. The weight is assigned based on the principle that $i-th$ AIoT devices closer to the target AIoT device are more valuable and should have a greater influence on the position estimation.

The performance of the algorithm is evaluated using the Root Mean Square Error (RMSE) between the calculated position and the actual position of the target AIoT devices. The RMSE is defined as:

$$RMSE = \sum_{j=1}^{t} \sqrt{\left(x^j - x_0^j\right)^2 + \left(y^j - y_0^j\right)^2} \quad \textbf{(7–34)}$$

In this context:

- (x_0^j, y_0^j) epresents the actual position of the target AIoT device j ,
- (x^j, y^j) is the calculated position of the target AIoT device j using the Landmarc algorithm.

The Landmarc positioning algorithm deviates from the traditional approach of relying solely on information from the AIoT readers and the target AIoT devices for positioning. Its key innovation is the introduction of reference AIoT devices**,** which are significantly less expensive compared to AIoT readers. This reduces the overall cost of the AIoT positioning system and helps to avoid excessive interference that could arise from deploying too many AIoT readers. At the same time, it enhances the accuracy of the positioning system, as illustrated in Figure 28.

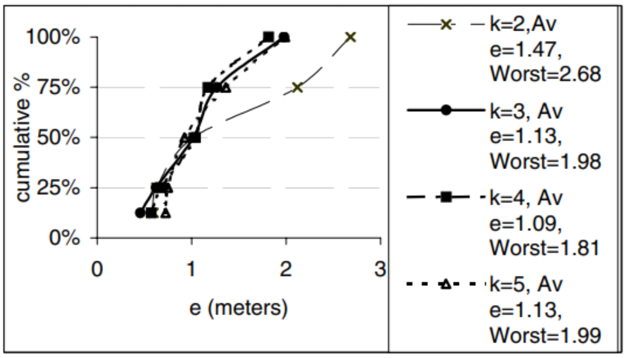


Figure 28 Localisation accuracy of Landmarc's algorithm for different values of k

2. VIRE Algorithm

The positioning accuracy of the Landmarc algorithm is highly dependent on the number of reference AIoT devices. When the number of reference devices reaches a certain threshold, the positioning accuracy stabilizes at a high level. However, excessively increasing the number of reference devices can lead to higher costs and increased signal interference between the AIoT devices, which may degrade the positioning performance.

To address the issue of interference from high AIoT device density, the VIRE (Virtual Reference Elimination) algorithm introduces virtual reference devices. This method aims to maintain high positioning accuracy while reducing the cost associated with physical reference AIoT devices. The use of virtual reference AIoT devices provides additional auxiliary positioning points without causing interference to other AIoT devices, thus avoiding an increase in hardware costs.

As illustrated in Figure 29:

- Q is the number of real reference devices,
- M is the number of AIoT readers,
- L is the number of target devices,
- N is the number of virtual reference AIoT devices.

The virtual reference AIoT devices are evenly distributed within the small areas covered by every four real reference AIoT devices. This approach enhances the positioning granularity and accuracy while minimizing the need for additional hardware and reducing costs.

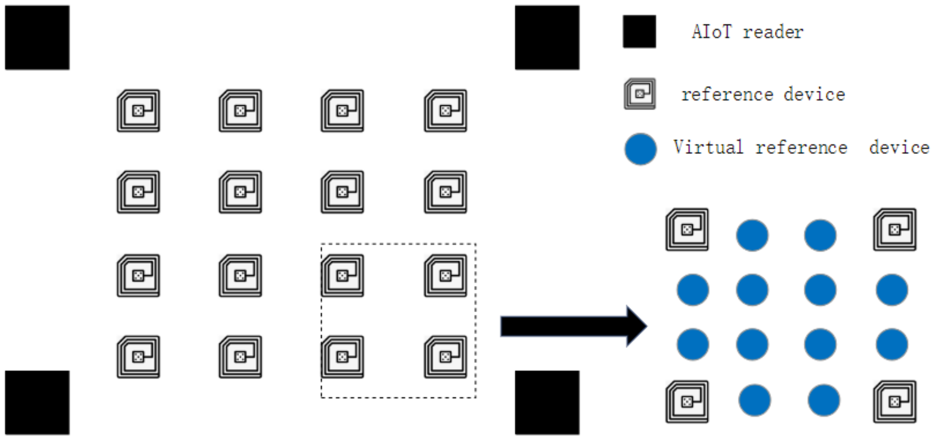


Figure 29 the VIRE positioning algorithm

The AIoT reader calculates the RSSI values of each virtual reference AIoT device using an interpolation algorithm based on the known RSSI values of the real reference AIoT devices. Once the RSSI values for all reference AIoT devices (both real and virtual) are obtained, the VIRE algorithm selects the relevant reference AIoT devices for each reader by comparing the difference between the RSSI values of the reference AIoT devices and the target AIoT devices against a predefined threshold**.**

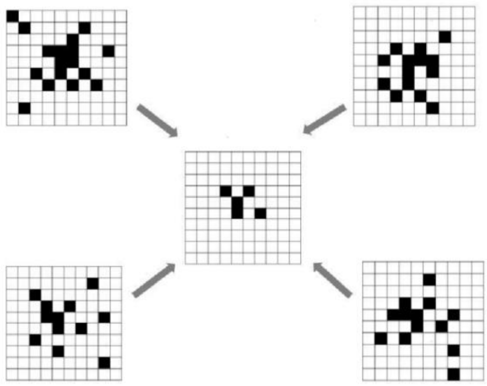


Figure 30 the screening of virtual reference labels

Next, the "Fuzzy Map" method is used to filter reference AIoT devices:

- The entire positioning area is divided into equal-sized grid cells, with the center of each grid cell representing a virtual reference AIoT device. The AIoT reader scans the area sequentially, collecting the signal strength values of the reference AIoT devices and the target AIoT devices.

- As shown in Figure 29, the AIoT reader calculates the Euclidean distance based on the measured RSSI values. It then compares this distance with a predefined threshold. If the distance is smaller than the threshold, the virtual reference AIoT device is marked in black; if it is greater, the virtual reference AIoT device is left unchanged. By adjusting the threshold N times (e.g., 4 times as depicted in the figure), the AIoT reader identifies a set of virtual reference devices. These virtual reference devices are those closest to the target point in the actual environment, forming a "fuzzy map".
- As illustrated in Figure 30, the intersection of the 4 fuzzy maps is taken to retain the area with the highest likelihood, resulting in the final fuzzy map. This region is the area where the target device is most likely to be located.

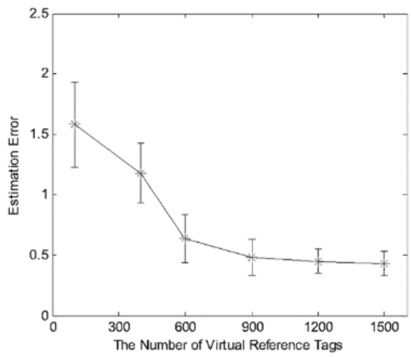


Figure 31 Positioning accuracy of VIRE algorithm with different number of virtual tags

Based on the "fuzzy map", the weighted coefficient method is used to determine the coordinates of the actual target AIoT device. When applying the VIRE positioning algorithm, it is important to note that the relationship between the RSSI value of reference devices and distance is not strictly linear. If linear interpolation is used to estimate the RSSI values of virtual reference AIoT devices instead of using real measured values, significant deviations may occur, as shown in Figure 31.

Although increasing the number of virtual reference AIoT devices can improve positioning accuracy, this improvement has a limit due to the quality of the data. As a result, the ultimate accuracy of the positioning may remain suboptimal. This method is generally suitable for achieving meter-level accuracy in relatively stable positioning environments.

7.2.2.2 Distance Model-Based Positioning Algorithm

1. RSSI-Based Distance Model Positioning

In RF signal propagation, the relationship between signal strength and distance can be modeled using the RSSI-distance model. This model describes how signal strength attenuates as distance increases, and can be expressed as follows:

$$RSSI = RSSI_0 - 10n\log_{10}(\frac{d}{d_0}) + X \qquad (7-35)$$

where:

- $RSSI_0$ is the RSSI value at a reference distance d_0,
- n is the path loss exponent,
- d is the distance between the AIoT device and the AIoT reader,
- X is the noise factor.

Using this formula, the distance can be estimated based on the strength of the RSSI signal. However, in practice, RSSI is easily affected by hardware and environmental factors, making direct distance estimation less accurate. Therefore, this method is often used as part of antenna-level positioning algorithms, as illustrated in Figure 32.

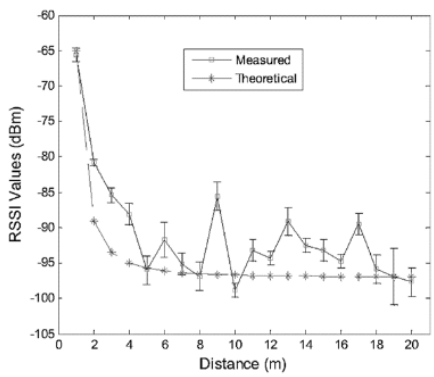


Figure 32 Theoretical versus actual change curve of RSSI with increasing distance[19]

In Figure 32, the theoretical RSSI curve is shown alongside the actual measured RSSI curve, demonstrating discrepancies due to environmental factors.

The theoretical foundation of the antenna-level positioning algorithm is based on which AIoT reader antenna can read the AIoT device. The positioning terminal is assumed to be near the corresponding AIoT antenna. Given that the coverage range of an AIoT antenna can span tens to hundreds of meters, and that the signal coverage of adjacent AIoT antennas may overlap, a AIoT device might be read by multiple antennas simultaneously.

Simply using the AIoT antenna ID may not be sufficient to determine the precise location of the AIoT device. To enhance the positioning accuracy, the RSSI-distance model can be integrated as auxiliary information, allowing for a more precise device-to-region mapping. This approach leverages both the antenna ID and the RSSI-distance estimation to refine the positioning result.

2. Phase-Based Distance Model Positioning

If the distance between the AIoT device and the AIoT reader antenna is d , the phase-distance model can be expressed as:

$$\varphi = \left(\frac{4\pi f d}{c} + \varphi_{Tag} + \varphi_{Antenna}\right) \bmod (2\pi) \qquad (7-36)$$

where:

- f is the signal frequency,
- φ_{Tag} and $\varphi_{Antenna}$ are the phase offsets of the AIoT device and the AIoT reader antenna, respectively,
- c is the speed of light.

In phase-based positioning, the AIoT reader can only measure the phase value within a single cycle. Due to the periodic nature of the phase information, the phase ambiguity issue must be resolved to ensure unique positioning results. This can be addressed by using multiple frequency points, spatial points, or time points, allowing for multiple phase measurements to be used in the position calculation.

(1) Position Calculation Based on Multi-Frequency Phase

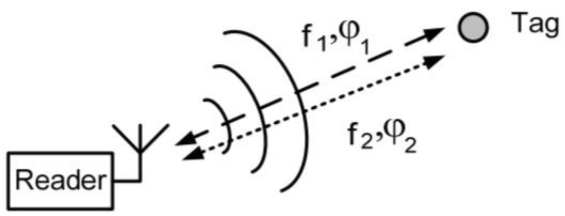


Figure 33 the positioning method based on phase difference measurements in the frequency domain[20]

As illustrated in Figure 33, the FD-PDOA (Frequency-Difference of Arrival - Phase-Difference of Arrival) method involves the AIoT reader transmitting carrier signals at two different frequencies, f_1 and f_2. The backscattered signal phases at f_1 and f_2 are measured, and the distance information can be calculated as follows:

$$d = \mathrm{abs}\left(\frac{c}{4\pi}\frac{\varphi_1 - \varphi_2}{f_1 - f_2}\right) \tag{7-37}$$

The maximum measurable distance is affected by the frequency difference of the backscattered signal and can be expressed as:

$$R_{\max} = \mathrm{abs}\left(\frac{c}{2(f_1 - f_2)}\right) \tag{7-38}$$

The multi-frequency phase-based positioning method addresses the phase ambiguity problem effectively. An averaging technique can be employed to mitigate phase noise and obtain a more stable phase difference, as illustrated in Figure 34.

From Figure 34, it can be observed that due to phase noise interference, there are significant variations at a few sampling points within the operational frequency band. However, after data averaging, a more stable phase difference is obtained across the frequency range, enhancing the robustness of the positioning method.

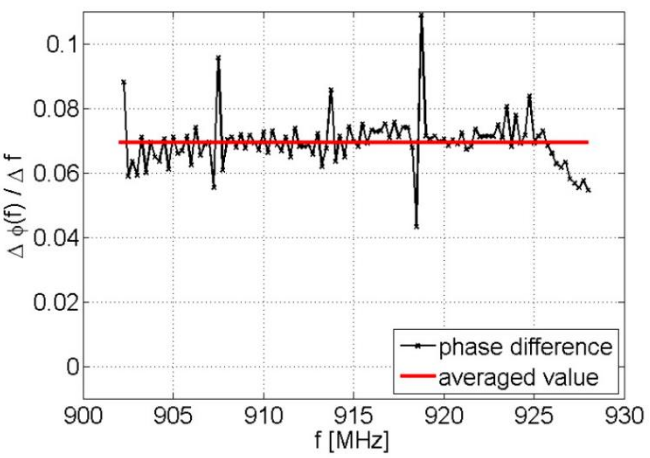


Figure 34 Phase Measurement Results of the Frequency-Difference Phase Measurement Method[27]

(2) Position Calculation Based on Multi-Spatial Phase Points

SD-PDOA (Space-Difference of Arrival - Phase-Difference of Arrival) includes two methods: the hyperbolic positioning method based on actual antennas and the synthetic aperture method using a moving antenna.

a) Hyperbolic Positioning Algorithm

The hyperbolic positioning algorithm uses the phase difference between two antennas and substitutes it into the distance model to obtain the distance difference between the AIoT device and the two antennas. According to the properties of a hyperbola, the possible position of the AIoT device can be determined. Assume the coordinates of antenna 1 are (x_1, y_1), and the coordinates of antenna 2 are (x_1, y_1). Based on the phase difference measured by the two antennas, the distance difference between the AIoT device and the two antennas is:

$$\Delta d = \frac{c}{4\pi f}\Delta\varphi \qquad (7-39)$$

From this, a hyperbola can be constructed to determine the possible location of the AIoT device:

$$\frac{x^2}{a^2} - \frac{y^2}{b^2} = 1 \qquad (7-40)$$

$$\begin{cases} a = \Delta d \\ b = \sqrt{c^2 - a^2} \\ c = \frac{1}{2}\sqrt{(x_1 - x_2)^2 - (y_1 - y_2)^2} \end{cases} \qquad (7-41)$$

Using multiple distance differences, multiple hyperbolas can be formed. The intersection of these hyperbolas gives the position of the AIoT device.

According to the formula, constructing a unique hyperbola based on the distance difference requires the phase difference between the two antennas to be less than one phase cycle. This means the distance difference between the AIoT device and the two antennas must be less than half the wavelength. When the distance between the two antennas is less than half the wavelength, by triangle constraints, the difference between the two sides is less than the third side, so the distance difference naturally lies within half a wavelength. As shown in Figure 35, when the distance between the two antennas is greater than half the wavelength, a feasible region can be constructed where the points within this region have a distance difference to the two antennas of less than half a wavelength, allowing for position calculation. This feasible region defines the positioning range [22]. The positioning accuracy is shown in Figure 36.

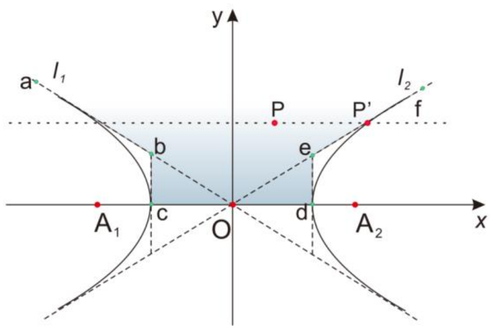


Figure 35 Illustration of Hyperbolic Phase-Based Positioning Method

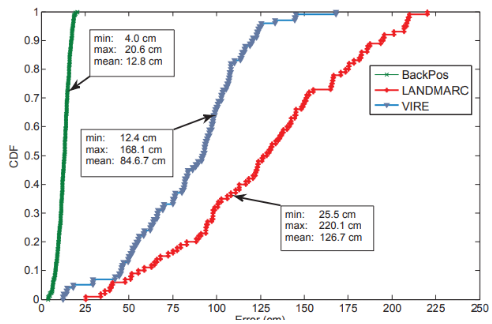


Figure 36 Positioning Accuracy Based on Feasible Region Using Hyperbolic Method

b) Synthetic Aperture Positioning Algorithm

The synthetic aperture positioning algorithm presupposes a monitoring area that may encompass the AIoT device's location. Based on the known antenna positions and the measured phase values, every point in the monitoring area is scanned, and the likelihood of the AIoT device being at each point is calculated [23]. The theoretical phase value of the AIoT device can be determined for each point in the monitoring area. A similarity likelihood function is used to evaluate the difference between the theoretical and measured phase values, ultimately constructing a hologram that reflects the likelihood of the AIoT device's presence across the entire area. The final result is obtained using algorithms such as maximum likelihood estimation.

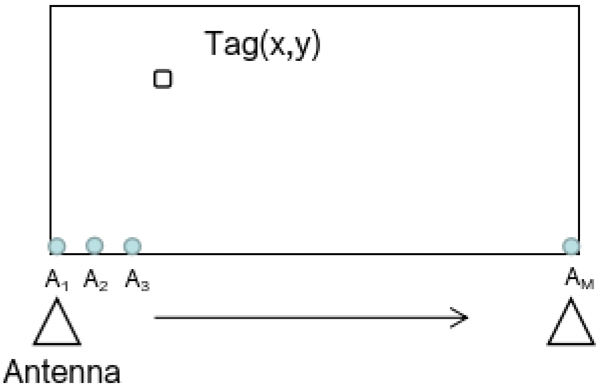


Figure 37 Illustration of Phase-Based Synthetic Aperture Positioning Method

In AIoT positioning, phase-based spatial probability distribution methods use the synthetic aperture algorithm, as shown in Figure 37. A moving antenna is used to simulate multiple antennas scanning the AIoT device. If the AIoT device follows a known trajectory and speed while the antenna remains stationary, the algorithm is equivalent. The implementation steps are as follows:

Assume the monitoring area S is represented as a matrix of size $P*Q$. During the movement of the antenna, $A_1, A_2, \dots A_m$ phase measurement points are obtained. For any position $Z(p,q)$ in the monitoring area, the theoretical phase value measured by the antenna can be calculated if the AIoT device is at that position:

$$\varphi_{m,p,q} = \frac{4\pi}{\lambda} d(A_m, Z_{p,q}) \bmod 2\pi \quad (7-42)$$

Where d is the Euclidean distance between two points. A likelihood function (e.g., cosine similarity function) can be designed to measure the similarity between the theoretical phase value and the actual measured phase value φ_0, constructing a hologram H:

$$L = \frac{1}{M} \sum\nolimits_M \frac{\varphi_{m,p,q} \cdot \varphi_0}{\left\| \varphi_{m,p,q} \right\| \left\| \varphi_0 \right\|} \quad (7-43)$$

$$h_{p,q} = L(\varphi_{p,q}, \varphi_0) \quad (7-44)$$

$$\mathbf{H} = \begin{bmatrix} h_{1,1} & \cdots & h_{1,Q} \\ \vdots & \ddots & \vdots \\ h_{p,1} & \cdots & h_{P,Q} \end{bmatrix} \quad (7-45)$$

The coordinates of the target AIoT device can be determined from the hologram H :

$$(x, y) = \arg\max(h_{x,y}) \tag{7-46}$$

The experimental results are shown in Figure 38.

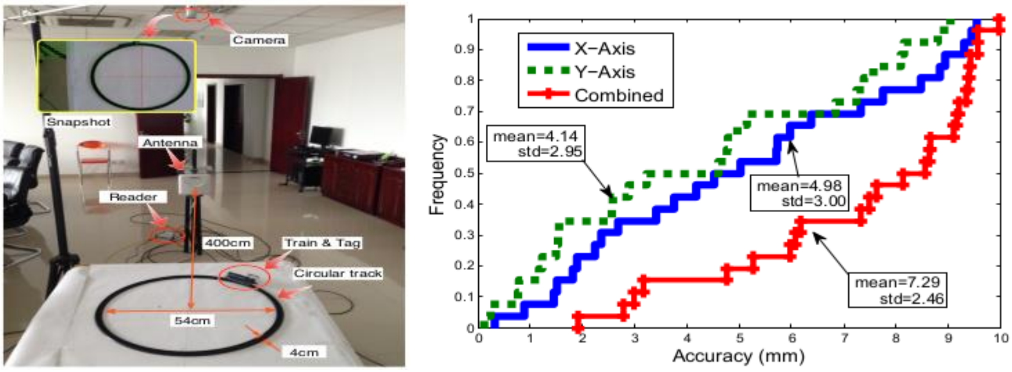


Figure 38 Positioning Accuracy of the Synthetic Aperture Algorithm with Uniform Circular Motion of the Tag [23]

(3) Position/Speed Calculation Based on Multi-Temporal Phase Points

TD-PDOA (Time-Difference of Arrival - Phase-Difference of Arrival) is a method for measuring the radial velocity of a AIoT device using phase differences over time. This technique leverages the phase difference of the LoS (Line of Sight) path at two different time points to calculate the radial speed of the AIoT device relative to the reader. This method is well-suited for navigation and tracking applications in AIoT systems.

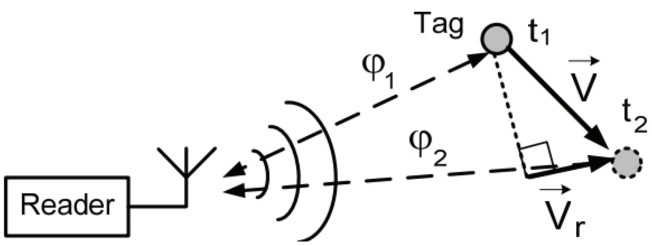


Figure 39 Illustration of Phase-Based Positioning Method Using Temporal Phase Difference

As shown in Figure 39, assume the AIoT device moves at a constant speed over a certain period. The phase difference of the backscattered signal is measured at two distinct time points. The radial velocity projection of the AIoT device relative to the reader can be calculated as follows:

$$V_r = -\frac{c}{4\pi f}\frac{\partial \phi}{\partial t} \qquad (7-47)$$

- f is the carrier frequency,

- V_r is the radial velocity projection of the AIoT device relative to the reader,the **n**egative sign indicates theAIoT device is moving away from the reader, while the positive sign indicates the AIoT device is moving closer, as determined by the direction of the phase change.

Additionally, when performing speed measurement, the following conditions must be met:

- The phase should be read continuously during the time interval.
- The phase difference should not exceed π , as this may cause phase wrapping errors or errors during unwrapping.

Based on this, the maximum and minimum measurable speed ranges can be determined.

Besides speed calculation, analyzing the continuous phase values of the AIoT device over a long time window can provide a spatio-temporal dynamic profile of the AIoT device, enabling estimation of the AIoT device's position relative to the antenna [24].

In a conveyor belt scenario, as shown in Figure 40, when a tagged item moves along the conveyor belt, the distance between the AIoT device and the antenna initially decreases and then increases. The phase profile forms a V-shaped region. The greater the distance between the antenna and the AIoT device, the slower the V-shaped change. The order in which the AIoT device passes by the antenna corresponds to the order in which the V-shaped region reaches its lowest point.

To address factors such as unstable polling speeds and phase jitter, algorithms like DTW (Dynamic Time Warping) can be used to identify the V-shaped region. This positioning technique is commonly employed in scenarios where determining the order of items is important.

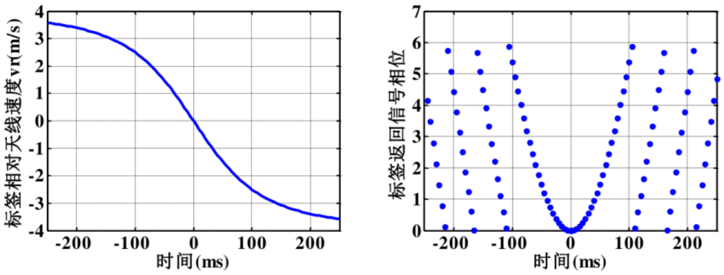


Figure 40 Illustration of the V-Shaped Region of Phase Changes Over Time [25]

7.2.2.3 Angle Model-Based Positioning Algorithm

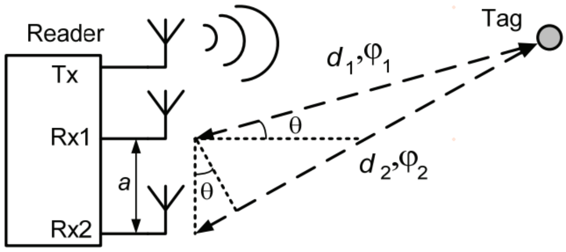


Figure 41 Illustration of Phase Difference Measurement Method in Spatial Domain

AOA (Angle of Arrival) refers to the relative angle at which a wireless signal arrives at the antenna. In the context of AIoT systems, since AIoT devices lack data processing capabilities, the AOA is determined by the AIoT reader's antenna. As shown in Figure 41, assume the phase difference between the backscattered signals received by two adjacent antennas is $\varphi_2 - \varphi_1$, and the distance between the antennas is a. The path difference between the signals arriving at different antennas is $d_2 - d_1$, and the AOA can be expressed as:

$$\theta \approx \arcsin\left[-\frac{c}{2\pi f}\frac{(\varphi_2-\varphi_1)}{a}\right] \qquad (7-48)$$

From Figure 42, it can be seen that as the AIoT device moves from -0.5m to 0.5m relative to the AIoT reader, the AOA changes from -15 degrees to 15 degrees.

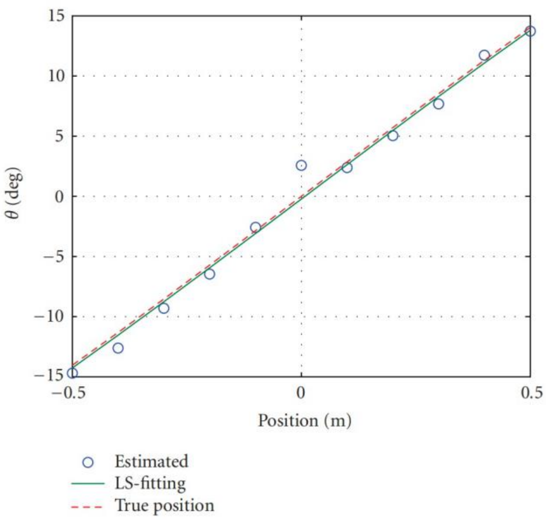


Figure 42 Simulation Results of AOA Variation with Distance Between Tag and Reader [28]

Due to the phase ambiguity, when the distance between two antennas is greater than half the wavelength, multiple beams may exist. If the distance between the two antennas is less than half the wavelength, the AOA has a unique solution [26]. In this case, as the distance between the AIoT device and the antenna group increases, the hyperbola gradually approaches its asymptote, enabling position calculation using the asymptote.

The optimal way to obtain the AOA is through an antenna array or by constructing a virtual antenna array (VAA) using a moving antenna to gather phase information. With multiple AOA measurements obtained from an antenna array, the position of the AIoT device can be determined by finding the intersection of these angles. The time difference during phase measurement depends on the measurement capability and configuration of the AIoT reader. During time-division measurement, the AIoT reader needs to inventory the AIoT device multiple times within a fixed time interval to capture backscattered signals at different times. Consistency in initial phase measurement must be maintained to avoid positioning errors due to phase measurement discrepancies.

The basic principle of the Virtual Antenna Array (VAA) is that the AIoT reader moves along a certain trajectory, constructing a virtual antenna array. Using this virtual array, the AIoT reader calculates the AOA of the AIoT device, as shown in Figure 43.

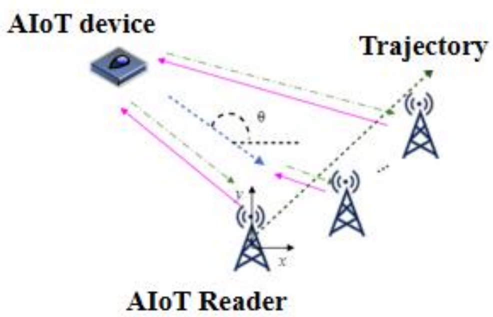


Figure 43 Angle Measurement Principle Using Virtual Antenna Array

Assume the reference signal or data frame transmitted by the AIoT device for positioning $s[m](m=1,2,3,...,M)$. The baseband sampling point of the $n-th$ data packet received by the AIoT reader is represented as:

$$r[n,m] = h[n,m] * s[m] \cdot e^{j(\varphi_0 + 2\pi f_0 (t_n + m T_s))} + w[n,m] \qquad (7-49)$$

where:

- $h[n,m]$ is the channel impulse response,
- φ_0 is the phase of the initial data packet,
- f_0 is the frequency offset between the AIoT device and the AIoT reader,
- t_n is the time interval between the initial data packet and the $n-th$ data packet,
- T_s is the sampling time,
- $w[n,m]$ is the received noise.

The channel can be simplified as:

$$\boldsymbol{h}[\boldsymbol{n}, \boldsymbol{m}] = \boldsymbol{\alpha} \cdot \boldsymbol{e}^{j\vec{\boldsymbol{\beta}} \cdot \vec{\boldsymbol{r}}[\boldsymbol{n}]} \qquad (7-50)$$

where:

- α is the channel gain,
- $\vec{\beta}$ is the wave vector,
- $\vec{r}[n]$ represent the relative coordinates of the $n-th$ data packet.

For a 2D array structure in the $x-y$ plane, this simplifies to:

$$\vec{\boldsymbol{\beta}} \cdot \vec{\boldsymbol{r}}[\boldsymbol{n}] = \frac{2\pi}{\lambda}(\boldsymbol{x}[\boldsymbol{n}] \cos(\boldsymbol{\theta}) + \boldsymbol{y}[\boldsymbol{n}] \sin(\boldsymbol{\theta})) \qquad (7-51)$$

where:

- θ is the Angle of Arrival (AOA) of the AIoT device,
- λ is the wavelength of the signal,
- $x[n]$ and $y[n]$ are the coordinates of the $n-th$ received data packet in the $x-y$ coordinate system (the original coordinates are those of the first received data packet).

Thus, the received signal can be expressed as:

$$r[n,m]=\alpha s[m]e^{j(\varphi_0+2\pi f_0(t_n+mT_s)+\frac{2\pi}{\lambda}(x[n]\cos(\theta)+y[n]\sin(\theta)))}+w[n,m] \quad (7-52)$$

To estimate the AOA, it is necessary to construct the corresponding equations and apply algorithms such as MUSIC (Multiple Signal Classification) and ESPRIT (Estimating Signal Parameters via Rotational Invariance Techniques). These algorithms are used to estimate the angle θ.

Compared with traditional multi-antenna AOA estimation, the main difference in VAA estimation is the presence of the polynomial term $2\pi f_0 t_n$. Additionally, the position of the AIoT reader $(x[n], y[n])$, depends on the movement trajectory and time of the AIoT reader. In traditional multi-antenna AOA estimation, the positions of the antennas in the array are fixed.

The position of the AIoT reader $(x[n], y[n])$ can be estimated using an IMU (Inertial Measurement Unit) or similar methods. Below, we use the extended MUSIC algorithm as an example to briefly describe the principle of VAA angle estimation.

Assume that the AIoT reader transforms the N data packets into a column vector, represented as:

$$\mathbf{y}[m]=\mathbf{a}(f_0,\theta)u[m]+\mathbf{w}[m] \quad (7-53)$$

The steering vector $a(f_0,\theta)$ is expressed as:

$$\mathbf{a}(f_0,\theta)=\begin{bmatrix} e^{j\left(2\pi f_0 t_1+\frac{2\pi}{\lambda}(x[1]\cos(\theta)+y[1]\sin(\theta))\right)} \\ e^{j\left(2\pi f_0 t_2+\frac{2\pi}{\lambda}(x[2]\cos(\theta)+y[2]\sin(\theta))\right)} \\ \vdots \\ e^{j\left(2\pi f_0 t_N+\frac{2\pi}{\lambda}(x[N]\cos(\theta)+y[N]\sin(\theta))\right)} \end{bmatrix} \quad (7-54)$$

The signal vector $u[m]$, which is fixed for all virtual antennas, is represented as:

$$u[m]=\alpha s[m]e^{j(\varphi_0+2\pi f_0 m T_s)} \quad (7-55)$$

Additionally, $\mathrm{w}[\mathrm{m}]=[\mathrm{w}[1,\mathrm{n}],\mathrm{w}[2,\mathrm{n}],\cdots,\mathrm{w}[\mathrm{N},\mathrm{m}]]^T$ is an $N\times 1$ Gaussian noise vector, with a covariance matrix given by:

The covariance matrix is defined as: $\mathbf{S}=\mathbb{E}\{\mathbf{y}\mathbf{y}^*\}$, where:

- S has dimensions $N \times M$,
- $\mathbb{E}\{\cdot\}$: the expectation operator,
- $(\cdot)^*$ represents the conjugate transpose.

In the MUSIC algorithm, the AOA can be estimated by searching for K signal subspace components. Further, let E_w be the eigenvector matrix of dimension $N \times (N-K)$ corresponding to the smallest $(N-K)$ eigenvalues of S . The MUSIC spectrum is then expressed as:

$$P_{MU}(f_0,\theta) = \frac{1}{a^*(f_0,\theta)\mathbf{E}_\mathbf{w}\mathbf{E}_\mathbf{w}^* a(f_{0,}\theta)} \quad (7-56)$$

Furthermore, by using a two-dimensional search algorithm and finding the maximum peak of the MUSIC spectrum, the AOA angle θ can be estimated:

$$(\hat{f}_0,\hat{\theta}) = \arg\max_{(f_0,\theta)}\{p_{MU}(f_0,\theta)\} \quad (7-57)$$

In the above virtual antenna array angle estimation or positioning algorithm, the movement speed of the positioning device must be limited to ensure the algorithm's effectiveness. To satisfy the spatial Nyquist criterion, the movement distance of the AIoT reader between two consecutive data packet receptions must not exceed $\lambda / 2$. Therefore, the condition is:

$$v_r \le \frac{\lambda}{2T_0} \quad (7-58)$$

Where:

- v_r is the movement speed of the receiver,
- T_0 is the time interval between periodic signals or data packets sent by the transmitter.

According to the actual test results, as shown in Figure 44, within a range of 5 meters:

- The AOA estimation error using the virtual antenna array is less than 25° with a 95% confidence level,

- The distance estimation error is less than 1 meter with a 95% confidence level.

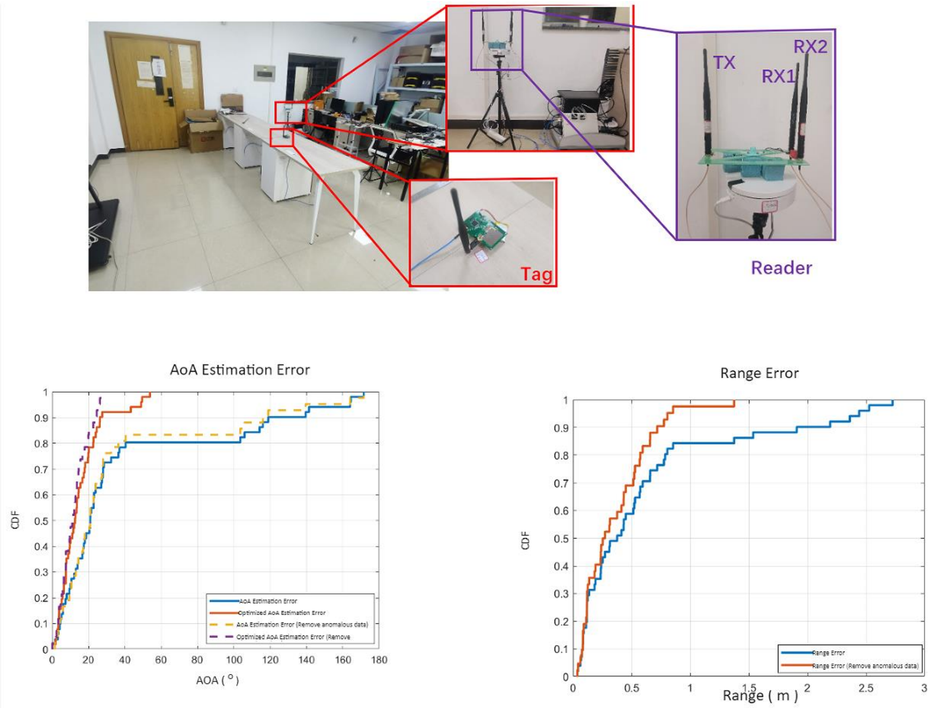


Figure 44 Experimental Platform for AOA and Distance Estimation Using Virtual Antenna Array

(Source: Vivo Communications Research Institute)

7.2.3 Hybrid Positioning

The AIoT positioning technology offers advantages such as no need for built-in power, easy deployment, and low cost. However, the working characteristics of AIoT device backscatter communication often lead to challenges in achieving high positioning accuracy and reliability, due to factors such as signal interference and environmental multipath effects. To address these challenges, we introduce hybrid positioning techniques, which enhance the performance of AIoT systems by integrating multiple measurements, multi-device data, multi-modal information, and AI algorithms.

7.2.3.1 Multi-Measurement Fusion Positioning

In AIoT positioning, available measurements include phase, RSSI, reading count, and antenna ID. Relying solely on a single measurement often leads to limited data availability and inherent constraints, making it difficult to accurately determine the target's position. For example, if positioning is based only on antenna ID, the accuracy will be restricted by the antenna deployment density and coverage range.

Furthermore, different measurements are suitable for different scenarios, and positioning models based on a single measurement have significant limitations. For instance: Carrier Phase requires calculating the phase difference to resolve phase ambiguity, making it suitable for scenarios with antenna arrays or AIoT device arrays. In a multipath environment, the measured value is an aggregate of both Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) signals, achieving good positioning accuracy only in open, clear LoS scenarios.

To enhance the accuracy of AIoT positioning, it is generally necessary to comprehensively consider multiple measurements and apply advanced data processing techniques and positioning algorithms to reduce errors and improve stability. By fusing multiple measurements, the positional characteristics of the target can be more fully described, thereby effectively improving positioning accuracy and reliability.

For example, in a warehouse storage scenario, traditional RSSI-based positioning methods are highly susceptible to environmental interference, resulting in low positioning accuracy. AIoT devices rely on backscatter communication; during the same inventory period, AIoT devices closer to the antenna beam's center receive more energy and have a higher probability of being read, leading to a higher reading count. As shown in Figure 45, leveraging this characteristic of the AIoT device, a multi-measurement fusion positioning method combining RSSI and reading count is proposed. By weighting the RSSI based on the number of times a AIoT device is read per second, extracting features such as the variance of the RSSI, and jointly analyzing the weighted RSSI and original reading count, the current location of the AIoT device can be determined.

Field tests demonstrate that by jointly analyzing RSSI and reading count, the positioning accuracy can be improved to 1-3 meters with a 90% confidence level, validating the effectiveness of multi-measurement fusion positioning.

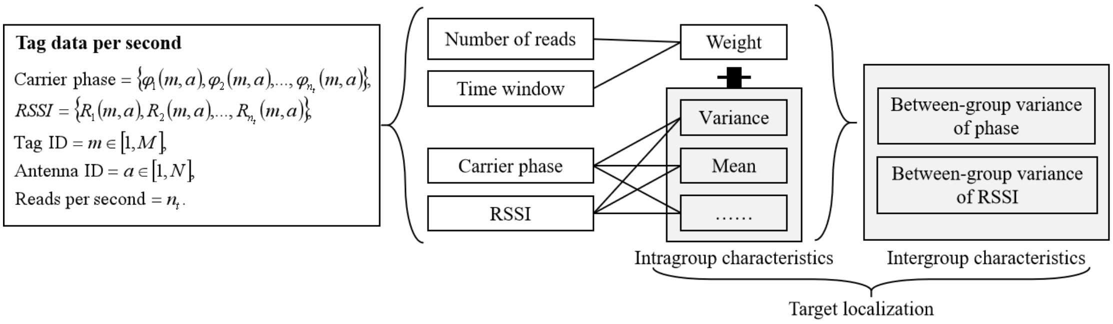


Figure 45 Multi-Measurement Fusion Positioning

7.2.3.2 Multi-Device Fusion Positioning

In general, increasing the number of antennas can enhance positioning accuracy. Similarly, by forming a device array using multiple AIoT devices, the stable topology of the AIoT device array and the signal differences among AIoT devices can be leveraged to more accurately estimate the position of the array [29]. Based on the deployment location of the AIoT device array, multi-device fusion positioning can be categorized into bound multi-device fusion positioning and unbound multi-device fusion positioning, as illustrated in Figure 46.

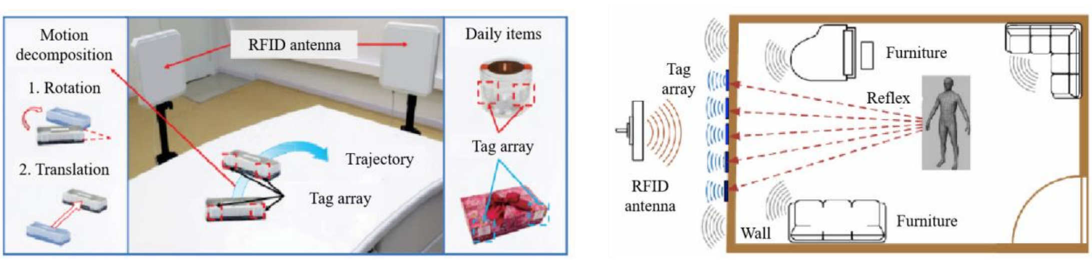


Figure 46 Illustration of Multi-Device Fusion Positioning

Bound multi-device fusion positioning uses a AIoT device array attached to the target. The antenna continuously scans the AIoT device array, and the target's location is determined based on the changes in signals as the target moves. When multiple AIoT devices are organized into an array with a specific topology, the differences in signals among AIoT devices and the changes in the array's topology can be analyzed to identify the relationship between the signal variations of individual AIoT devices and the positional changes of the AIoT device array. This enables precise tracking of the target's movement [30].

Unbound multi-device fusion positioning utilizes an array of AIoT devices placed in the environment to detect signals reflected by moving objects, such as people, in front of the array.

The first step is to remove strong reflections from walls and direct signals transmitted from the antenna to the AIoT devices. By applying the principle of signal superposition, the reflected signals from people can be extracted. The person's movement can then be modeled as a Hidden Markov Chain, where the observable states are the preprocessed signal strengths from the AIoT device array, and the hidden states represent the person's position in the room. By constructing a Hidden Markov Model and observing the changes in signal states within the AIoT device array, the movement path of the person in the room can be estimated [31].

Compared to antennas, AIoT devices are smaller, cheaper, and easier to deploy, giving multi-device fusion positioning high application value. For example, in warehouse logistics, integrating positioning data from multiple AIoT devices allows managers to quickly and accurately track the real-time location of goods, significantly improving the efficiency and accuracy of inventory management.

7.2.3.3 AI-Fused Positioning

The AI-fused positioning framework for AIoT can be broadly divided into three processing modules: signal preprocessing, feature extraction, and position estimation, as shown in Figure 47. Based on the purpose of AI integration, AIoT AI-fused positioning can be classified into two types: pre-fusion and post-fusion.

- **Pre-Fusion:** This occurs primarily in the feature extraction module, with the main goal of using AI fusion for noise reduction, assessing environmental interference, and removing outliers, thereby enhancing the generalization and robustness of the positioning system.
- **Post-Fusion:** This takes place mainly in the feature extraction and position estimation modules. It focuses on using AI fusion to extract features and establish nonlinear mappings, ultimately improving positioning accuracy.

In AIoT positioning, the estimated position of the target object is often affected by noise, leading to drift. By employing pre-fusion AI algorithms, these noise data points can be effectively and directly removed. For instance, RF-finger [32] computes a likelihood feature map of the AIoT device array based on phase and RSSI features, and then applies an AI clustering algorithm to filter out noise in the finger movement trajectory, enabling accurate tracking and restoration of the finger's movement path.

To determine the target position, a physical signal model must first be constructed, and features must be extracted to compute the final target position. Specifically, AIoT signals can provide channel parameter information such as RSSI, phase, reading rate, and activation energy. These parameters contain information related to the target's position. By leveraging AI algorithms for fusion, the nonlinear relationship between these parameters and the target position can be better established, thereby improving positioning accuracy. For example, Tagoram [33] constructs a signal model and computes a holographic map of the position to achieve high-precision target positioning.

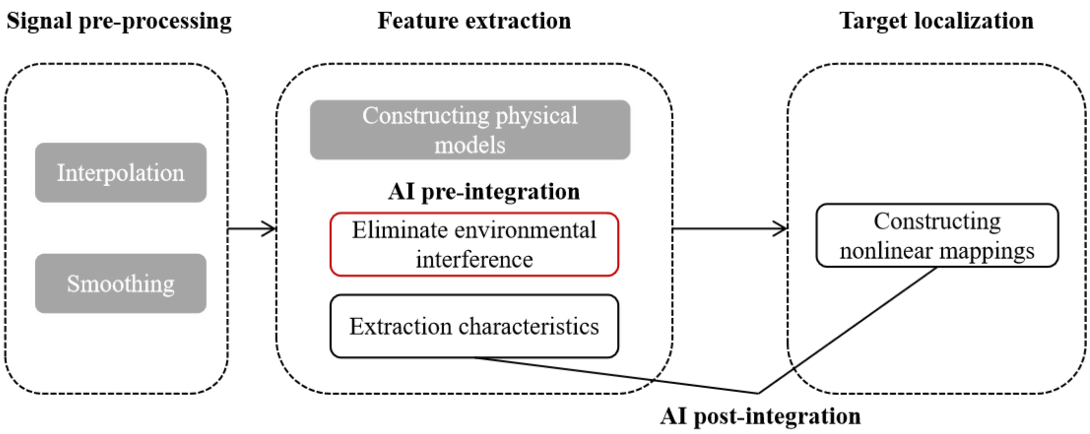


Figure 47 AI-Fused Positioning Framework

This framework illustrates the flow of data through the preprocessing, feature extraction, and position estimation modules, demonstrating how AI techniques can be integrated to enhance positioning performance.

7.2.3.4 Multi-Modal Fusion Positioning

By integrating information from multiple modalities, the inherent limitations of AIoT can be addressed, thereby further enhancing the system’s positioning accuracy. As shown in Figure 48, AIoT can work collaboratively with other wireless technologies or sensors, such as WiFi, Bluetooth, 5G, cameras, millimeter-wave radar, infrared sensors, and IMU (Inertial Measurement Unit).

Different wireless technologies and sensors complement AIoT. Preprocessing is firstly applied to eliminate discrepancies in measurement data from various devices.

Features relevant to positioning are extracted from each modality, such as signal strength, image features, and timestamps.

Through feature fusion, accurate positioning of the target is achieved. Collaborative use of multiple technologies compensates for the limitations of individual techniques in certain environments, offering a more comprehensive and intelligent solution. For example: In smart warehousing, cameras can monitor the movement and status of goods, while passive AIoT devices provide unique identification and related information about the items.

The future evolution of AIoT readers will surpass the current capabilities of traditional RFID systems.Nodes like Bluetooth Beacons, WiFi gateways, and even smartphone terminals could serve as AIoT readers, activating AIoT devices or receiving backscattered signals.

Depending on the specific application scenarios and requirements, existing nodes can be flexibly chosen as AIoT reader, making the implementation of positioning functions more convenient.

This approach enables precise positioning and tracking of various targets, whether it be goods in a warehouse, customers in a shopping mall, or pets in a household.

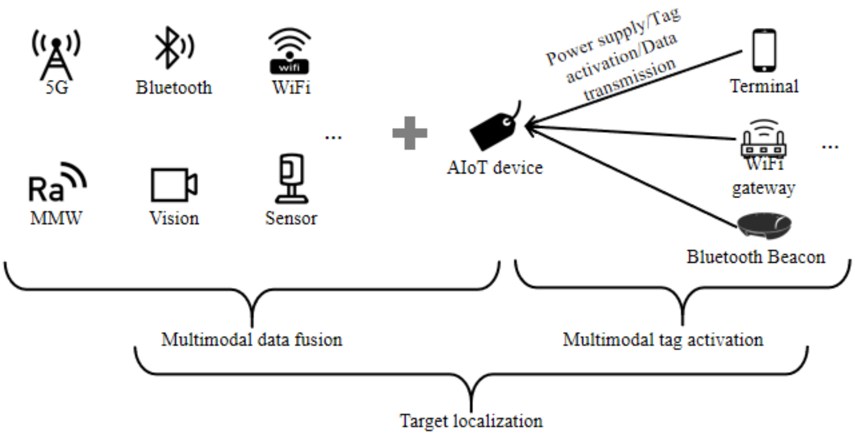


Figure 48 Multi-Modal Fusion Positioning

7.3 Terminal Layer — AIoT Device Technology

The terminal layer of AIoT includes passive, semi-passive, and active AIoT devices. Both passive and semi-passive AIoT devices do not have the capability to actively transmit signals or estimate measurements. Throughout the positioning process, AIoT devices interact with AIoT readers via backscattered signals. The AIoT reader receives the AIoT device’s echo signals, estimates the positioning measurements, and sends these measurements to the positioning platform for location calculation.

Current RFID AIoT devices face several issues, such as low clock precision, weak echo signals, and susceptibility to multipath effects and interference. These problems limit the communication range of the AIoT devices and hinder improvements in positioning accuracy. To address these challenges, the 3GPP standard defines three types of AIoT devices for cellular-based AIoT based on their power supply methods and their ability to autonomously generate signals:

- I devices:

The capabilities and architecture of I devices are similar to traditional RFID tags, with a peak power consumption of only around 1 μW.

They lack the ability to amplify uplink and downlink signals, supporting only passive communication by backscattering information to AIoT readers.

Compared to the immediate power usage of RFID tags, I devices can accumulate energy through RF harvesting before starting to operate, making them suitable for positioning scenarios with communication distances of up to 30 meters.

I-Class devices are the most cost-effective for large-scale deployments.

- II-A device:

II-A devices support only passive communication but have a peak power consumption of up to several hundred μW. Either the uplink or downlink signal (or both) can be amplified to extend coverage.

Unlike traditional amplification mechanisms, the uplink amplification in II-A Class devices is achieved through a reflective amplifier.

These AIoT devices can harvest environmental energy, such as ambient light or vibration energy, in addition to RF harvesting, making them suitable for positioning scenarios with communication distances of 100 to 200 meters, offering higher positioning accuracy than I-Class devices.

- II-B device:

II-B AIoT devices have a peak power consumption that can reach several hundred μW to even mW levels. These AIoT devices can autonomously generate carrier signals for uplink modulation and use traditional amplifiers to boost both uplink and downlink signals.

II-B AIoT devices may support unconventional power sources like paper batteries or supercapacitors.

They are suitable for positioning scenarios with communication distances ranging from several hundred meters to kilometer-level distances. By actively generating carrier signals, II-B AIoT devices can potentially transmit positioning reference signals, providing greater flexibility.

Overall, these 3GPP-defined AIoT devices expand the coverage range and improve the positioning accuracy of AIoT systems, addressing many of the limitations of traditional RFID tags.

7.4 Positioning Service Layer — Core Positioning Capabilities

To meet the diverse positioning needs of customers, the final solutions are often delivered via mobile apps or web interfaces. In order to facilitate the rapid implementation of positioning applications, the positioning service platform provides a range of core positioning capabilities, including real-time positioning, electronic fencing, indoor navigation, and trajectory analysis.

- **Real-Time Positioning:** This feature processes user-initiated positioning requests and provides real-time feedback on the location of the target object. It is integrated with a map or surrounding environment to display the object's position instantaneously.
- **Electronic fencing:** This feature allows users to define specific zones on a map that require close monitoring or areas for commercial push notifications. The zone can be circular, rectangular, or any custom polygon shape. When a monitored AIoT device approaches the defined zone, the system automatically triggers a condition check, generating an alert or pushing relevant information.
- **Indoor Navigation:** This feature provides route planning and navigation assistance based on indoor maps. It offers real-time positioning of AIoT devices to guide individuals or vehicles along the planned route, with the navigation information displayed through a mobile app interface.

- **Trajectory Analysis:** Trajectory analysis leverages positioning data to track the movement patterns of people or objects over a specific time period. Using an indoor geographic information system (GIS), the service analyzes spatial and temporal data, rendering the movement paths on a map. The analysis results include visualized user position distribution maps, such as heat maps, dot density maps, and other thematic maps, providing comprehensive insights into user behavior.

These core capabilities enable AIoT systems to meet various application scenarios, enhancing user experience and delivering valuable insights through precise and efficient positioning services.

8 AIoT Positioning Application Case

8.1 High-Bay Warehouse Positioning Solution

A high-bay warehouse (referred to as "high-bay") utilizes shelving systems for storing goods. The storage and retrieval methods differ for high-level and low-level shelves:

- High-level shelves: Each shelf level has a height that accommodates at least one pallet. Palletized goods are placed directly on the shelves using forklifts, eliminating the need for manual handling.
- Low-level shelves: With heights less than 2 meters, these are typically accessed manually for storage and retrieval.

Traditional methods of marking and recording goods locations rely on manual record-keeping, which is inefficient and prone to errors. For high-level shelves, the coordination between forklift operators and warehouse clerks increases the error rate, making it difficult to meet the demands of efficient warehouse operations.

The AIoT positioning solution leverages a multi-measurement fusion algorithm that combines RSSI, antenna ID, and report frequency for joint analysis. This approach effectively mitigates issues like missed reads or misreads caused by interference from metal shelving. When placing goods on the shelves, the system can automatically determine the exact shelf position and generate accurate inventory records, significantly reducing the time required for storage and retrieval compared to manual recording methods.

In a practical deployment at a manufacturing company, the solution was implemented across multiple raw material and finished goods warehouses. The total warehouse area is extensive, with the finished goods warehouse alone covering 1,000 square meters and housing over 1,000 storage locations. Due to the high turnover of items entering and leaving the warehouse, the traditional manual recording method could not keep up with the demand.

As shown in Figure 49, the application of the multi-measurement fusion AIoT positioning technology automates the recording and updating of item locations during storage and retrieval operations. The automated system replaces manual data entry, saving approximately 1-2 person-years of per warehouse.

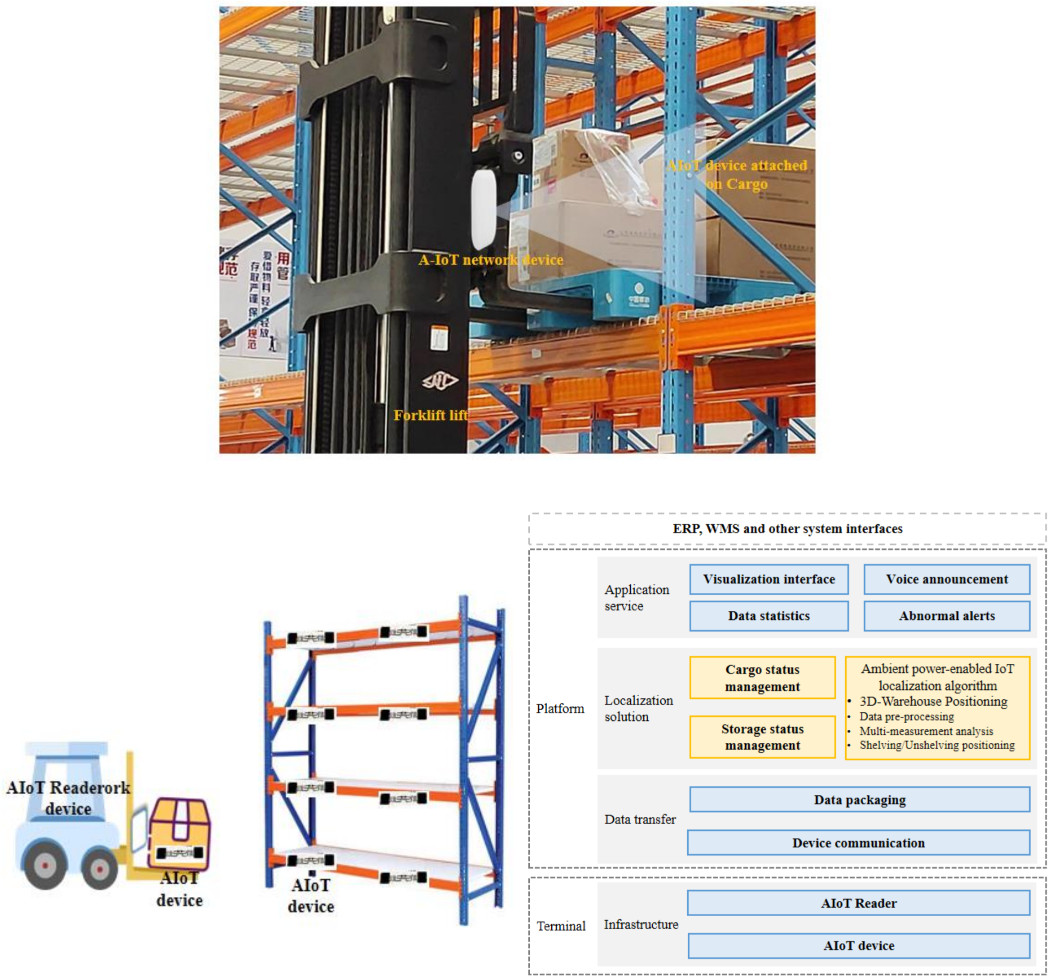


Figure 49 High-Bay Warehouse Pallet Positioning Solution

This solution demonstrates the efficiency and accuracy improvements achieved by integrating AIoT technology in high-bay warehouse management, ensuring real-time inventory updates and reducing operational costs.

8.2 Flat Warehouse Positioning Solution

A flat warehouse (referred to as "flat warehouse") utilizes a flat layout with designated storage locations for orderly placement of goods. Typically, flat warehouses store material carts, which require manual handling using forklifts or tow trucks for loading and unloading. Due to the complex on-site environment, single-device solutions often face issues such as signal blind spots, obstructions, interference from the passing objects, signal fluctuations, signal spillover, and multi-antenna signal jumps. The AIoT positioning solution leverages a multi-device fusion positioning algorithm, analyzing the variations in signals when AIoT devices are stationary versus in motion. This method extracts weighted feature values, effectively distinguishing stored AIoT devices among multiple targets, achieving 100% accuracy at the area level and positioning error of less than 1 meter at the storage location level. This solution delivers high accuracy and real-time performance, significantly improving inventory management efficiency and reducing the time spent searching for materials.

In comparison with other positioning technologies like Bluetooth or UWB, AIoT positioning offers advantages such as lower costs, no need for charging, and easier maintenance. This makes it especially suitable for warehouse environments with a large volume of goods.

In a practical application at a metal workshop of a home appliance factory, there are 30,000 types of metal sheet materials managed across 1,000+ material carts, each carrying multiple types of materials. A Material Order (MO) ticket is attached to each type of material using cable ties. Although the warehouse floor is divided into designated storage locations with corresponding IDs, in daily operations, the storage of material carts often does not follow these assignments. As a result, locating specific materials heavily relies on manual searching. If the warehouse manager is unavailable, it becomes challenging to find the materials for dispatch, leading to low warehouse management efficiency.

As shown in Figure 50, the multi-device fusion AIoT positioning solution provides automatic positioning capabilities, accurately locating the materials within the storage area. It allows for real-time online queries of material locations, enabling transport staff to quickly access the required materials. The time required for material retrieval has been reduced from approximately 5 minutes to under 1 minute, resulting in a more than 80% increase in efficiency.

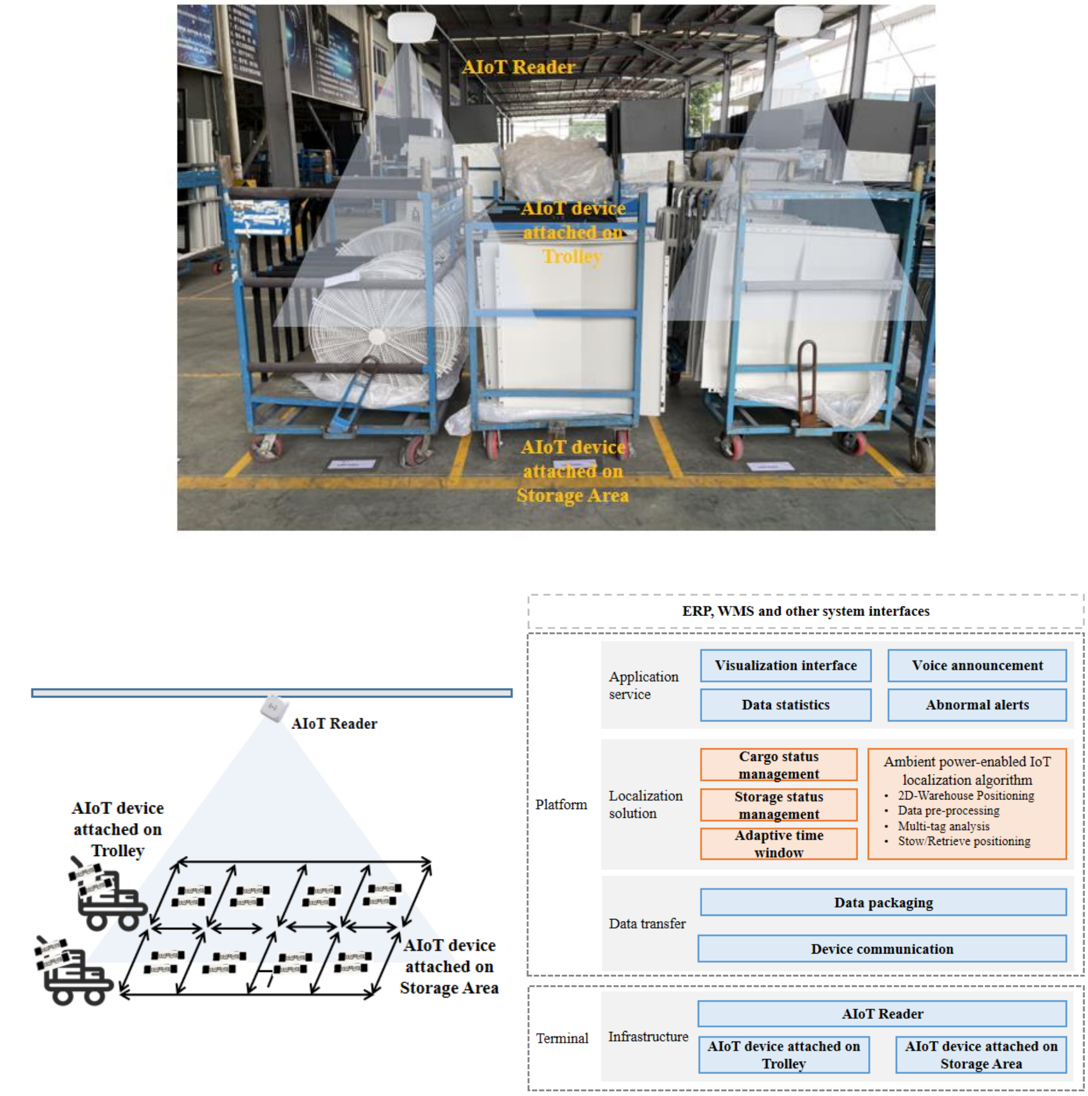


Figure 50 Material Positioning Solution for Flat Warehouse

This case highlights the efficiency gains and streamlined operations achieved through the integration of AIoT positioning technology in flat warehouse environments, offering significant improvements in accuracy and time savings for inventory management.

8.3 Cargo positioning solutions at access points

Entrance and exit checkpoint positioning is a common requirement across various industries. For manufacturing enterprises, these checkpoints are typically located at raw material warehouses, finished goods warehouses, and entrances/exits of production workshops. The assets requiring positioning include raw materials, finished products, personnel, instruments, equipment, and production tools. A single AIoT positioning solution often faces issues like multi-read errors, missed reads, and poor real-time performance in multi-door coordination.

By using a multi-modal fusion positioning algorithm, this solution integrates and analyzes data from AIoT devices and sensors. Combined with a Adevice deduplication algorithm, it effectively eliminates noise interference caused by a cluttered environment at the checkpoint, as well as interference from passing personnel or moving objects. This approach enables automatic identification of the direction of asset movement and automatically generates accurate inbound or outbound data reports. Furthermore, in scenarios with multiple checkpoints, the solution can dynamically adjust the priority of each checkpoint based on data from AIoT devices and sensors, resolving issues of silent checkpoints and missed device reads caused by traditional polling methods. This results in improved real-time coordination across multiple checkpoints.

In a practical application at a logistics warehouse of a telecommunications company, a large volume of materials waiting to be shelved or dispatched is frequently stacked near the warehouse checkpoint. During material handling, these items often pass near the checkpoint, causing signal interference with AIoT devices that are undergoing inbound or outbound operations. This interference often leads to misjudgment of the movement direction using traditional antenna ID-based positioning methods. As shown in Figure 51, the multi-modal fusion AIoT positioning solution effectively addresses these challenges, achieving 100% accuracy in entrance and exit checkpoint positioning with a delay of less than 5 seconds. This solution helps the enterprise achieve precise, efficient, and automated management of entrance and exit checkpoints.

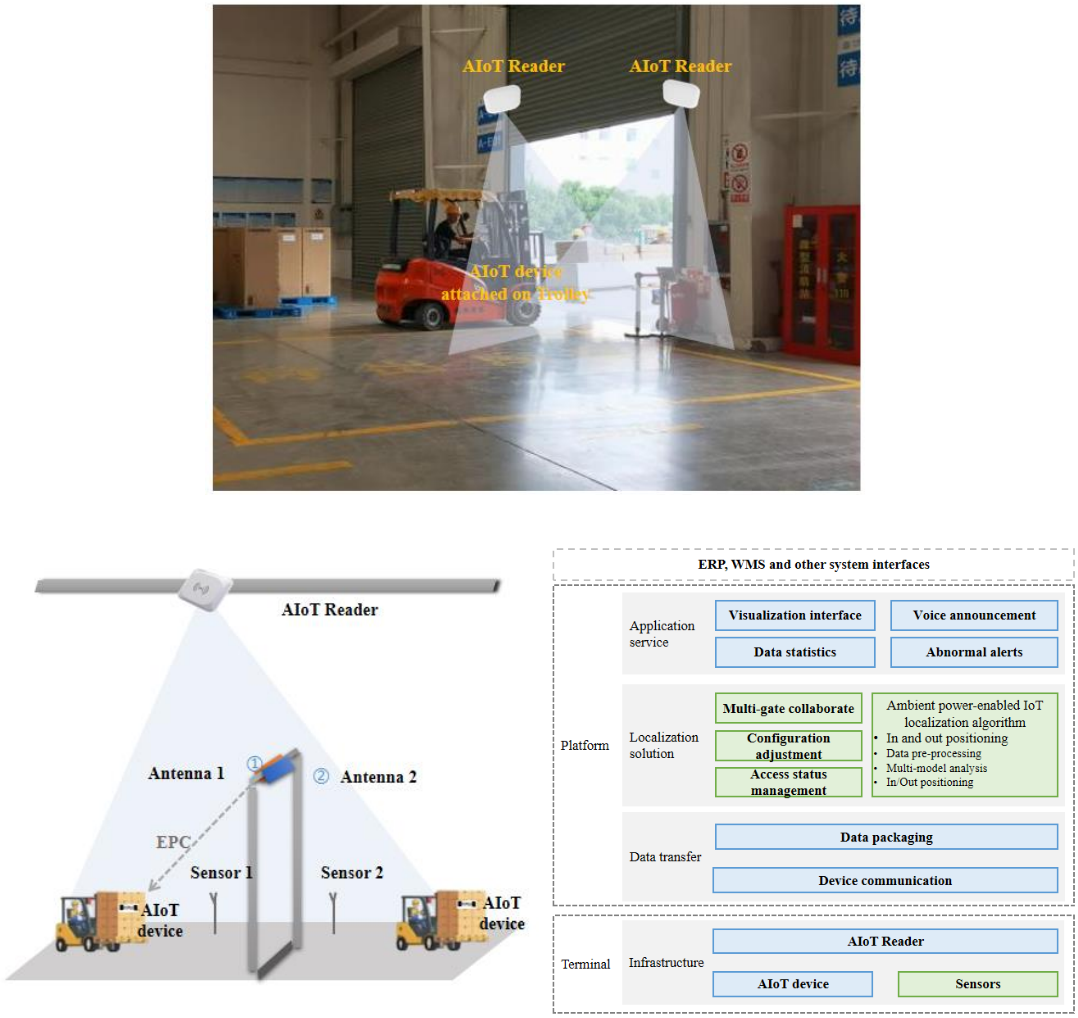


Figure 51 Cargo Positioning Solution for Entrance and Exit Checkpoints

This case demonstrates the efficiency improvements and enhanced accuracy provided by the multi-modal fusion AIoT positioning solution in managing warehouse entrance and exit checkpoints, enabling seamless automation and real-time monitoring of asset movements.

8.4 Utility Tunnel Personnel Positioning Solution

Urban utility tunnels are a crucial part of a city's infrastructure, carrying power, telecommunications, gas, heating, and other essential utilities. Effective management and maintenance of these tunnels are vital for ensuring their safe operation. To guarantee the safety and thoroughness of inspection tasks, it is necessary to monitor the real-time location and movement trajectory of personnel conducting inspections. Traditional positioning methods require the simultaneous deployment of 2 to 3 antennas to jointly determine the target's location.

However, this approach can lead to significantly increased system costs and complicated deployment when scaled across a large area.

The AIoT positioning solution leverages a large number of AIoT devices to create a array and integrates AI algorithms for precise personnel positioning. Specifically, a array is deployed alongside an AIoT antenna in the areas where inspection personnel pass through. The antenna continuously inventories the array and analyzes the variations in wireless signals from the AIoT devices. By treating the reflective characteristics of multiple targets as a whole, these variations are transformed into corresponding feature images. A deep learning convolutional neural network is then employed to automatically extract key features from these images, enabling fine-grained tracking of personnel movement trajectories.

Due to the low cost and ease of deployment of AIoT devices, and the fact that the entire area can be covered by just one antenna, the system is simple to deploy, and the overall cost is significantly reduced.

In a practical application for an urban construction company, the underground utility tunnel spans more than 67 kilometers, including compartments for water utilities and power lines. Previously, the company used WiFi-based positioning to monitor inspection personnel. However, the strong signal penetration capability of WiFi, combined with the complex multi-path interference caused by the dense network of utility lines within the tunnel, often resulted in drift in the positioning results, with measured errors sometimes reaching up to 50 meters.

As shown in Figure 52, the AIoT positioning solution based on a AIoT device array and AI fusion effectively addresses challenges such as missed reads, signal noise, and multi-target tracking. The solution incorporates data calibration and reflection model construction techniques, achieving a positioning accuracy of less than 5 meters and a positioning delay of less than 5 seconds, providing a cost-effective remote monitoring system for personnel in urban utility tunnels.

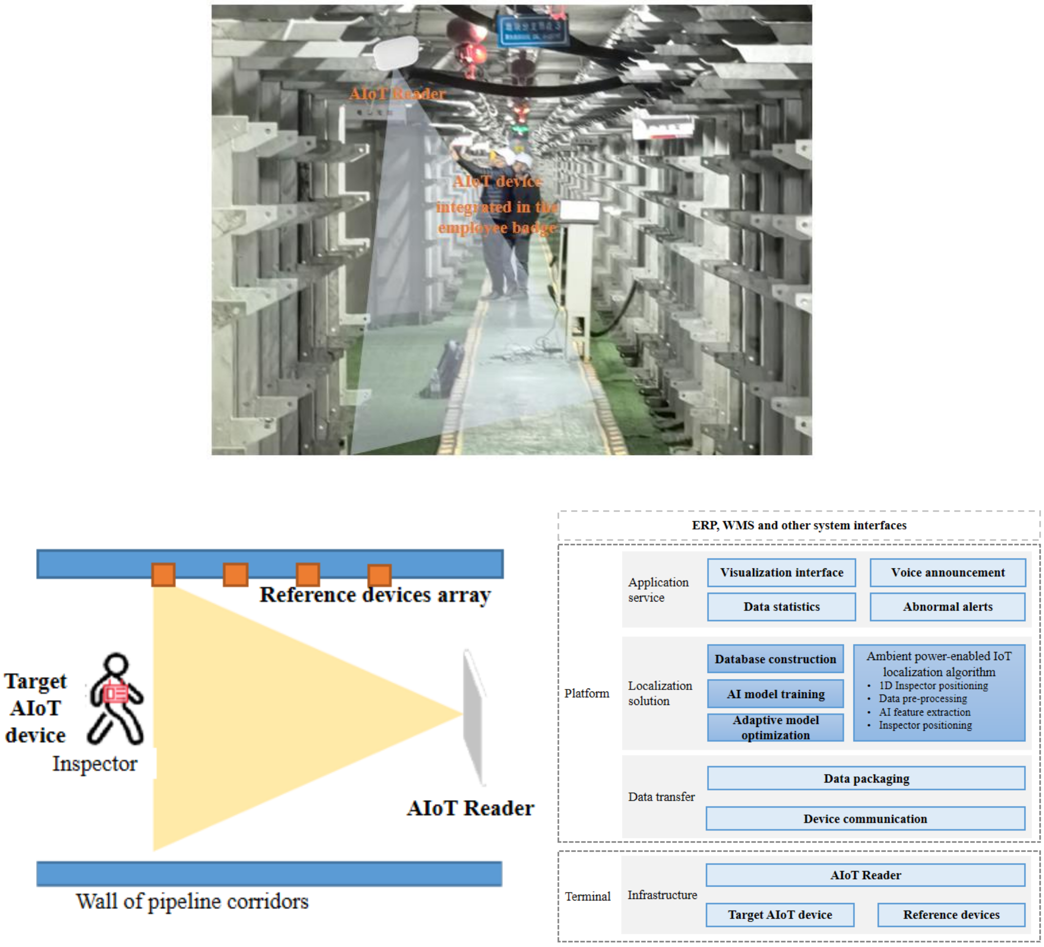


Figure 52 Utility Tunnel Personnel Positioning Solution

This case highlights the successful application of AIoT technology in enhancing the safety and efficiency of utility tunnel inspections, reducing deployment complexity, and providing reliable, real-time monitoring of personnel movements.

8.5 Apparel Retail Store Display Verification Solution

Retail stores often manage a large variety of displayed products, sourced from different suppliers. Store management requires specific placement areas for merchandise from different suppliers. Currently, display verification mainly relies on manual "spot checks," which are inefficient, costly, and lack timeliness, making real-time display verification challenging.

By equipping merchandise with AIoT devices and utilizing the abundant real-time channel data from AIoT (e.g., RSSI, phase, frequency points, and timestamps), combined with AI technologies such as machine learning, deep learning, and pattern recognition, the solution can effectively account for environmental factors like obstacles, reflective surfaces, and multi-path effects that influence signal propagation. It then deeply analyzes and learns the channel data characteristics of different shelf items, enabling automatic product positioning and display verification.

Additionally, by deploying AIoT devices in fitting rooms, changes in signal characteristics caused by customer actions (e.g., trying on clothes) can be detected. When garments are tried on, the resulting changes in wireless signal transmission can help identify the specific clothing item being worn. This allows retailers to precisely monitor consumer preferences, adjust marketing strategies promptly, and enhance conversion rates.

In a flagship store project for a leading fashion brand, a networked AIoT system was deployed, providing extensive data collection through low-cost, real-time connections. As shown in Figure 53, two AI models were developed: the "Display Verification AI Model" and the "Smart Fitting Room AI Model." These models offer real-time, visual, and accurate data on product displays and fitting room activities, meeting various intelligent management needs, such as:

- Automatic Display Verification: Ensures that merchandise is correctly displayed according to the store's plan.
- Try-On Automatic Recognition: Identifies which clothing items are being tried on by customers.
- Smart Detection of Try-On Frequency: Tracks how often specific items are tried on, providing insights into popular products.
- Intelligent Analysis of Best-Selling Styles: Helps store managers identify top-selling items and optimize product iterations.

This solution supports enhanced operational tasks, such as optimizing marketing strategies and refining product designs based on consumer behavior analysis.

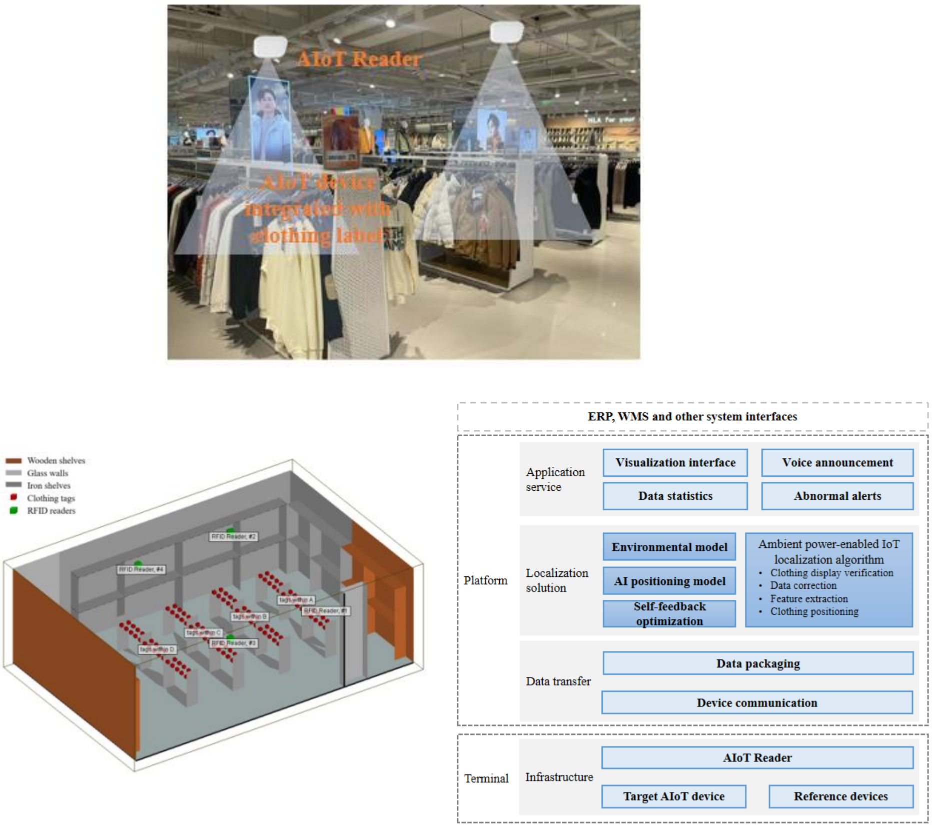


Figure 53 Apparel Retail Store Display Verification Solution

The solution demonstrates the application of AIoT in retail environments, improving store management efficiency, reducing manual effort, and providing valuable insights for data-driven decision-making in merchandising and marketing.

9 Conclusion

With its advantages of low power consumption, low cost, easy deployment, and maintenance-free operation, AIoT positioning capabilities have already seen initial applications in scenarios like warehouse logistics, store management, object finding at home, and unauthorized intrusion detection. As traditional UHF RFID technology rapidly evolves towards networked and cellular-based AIoT, system capabilities such as flexible networking, air interface communication performance, and AIoT device capabilities are expected to further improve. This will lead to enhanced positioning protocols, expanded coverage, and increased positioning accuracy. Additionally, further exploration into fusion positioning technologies, including multi-device, multi-modal, and AI algorithm integration, will help support the growing demand for positioning as a core application of 5G-A AIoT, enabling the evolution towards a multi-functional network system.

This white paper has provided an in-depth analysis of AIoT positioning scenarios, end-to-end technical solutions, and real-world application cases, showcasing the research and insights of communication companies and industry stakeholders on AIoT positioning technology. Moving forward, China Mobile will collaborate with various industry partners, universities, and joint laboratories to continue innovation in 6G AIoT positioning technologies, product development, and application expansion. The aim is to explore cutting-edge 6G AIoT positioning technologies, facilitating the deep integration of AIoT into enterprise production, social governance, and personal life. This cross-domain collaborative innovation in positioning technology is expected to foster new business models and service paradigms, ushering in a new era of intelligent connectivity for all things.