Design and Evaluation of a Joint Optimization Algorithm for High-Precision RFID-IoT-Based Cargo Tracking Systems

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In the context of the booming modern logistics and supply chain management, cargo tracking technology has emerged as a pivotal means to enhance logistics efficiency and transparency. High-precision cargo tracking systems are particularly crucial in complex warehousing and transportation scenarios, as they can effectively address issues like positioning errors and signal attenuation. This research puts forward a high-precision cargo tracking approach grounded in a joint optimization algorithm. By integrating multiple positioning technologies, namely Received Signal Strength Indicator (RSSI), Time Difference of Arrival (TDOA), and Angle of Arrival (AOA), accurate positioning across diverse environmental conditions is attained. The experimental design encompasses a battery of evaluations, including accuracy tests, real-time performance tests, and system stability analyses, to validate the practical application efficacy of the algorithm. In the accuracy tests, compared with the traditional positioning algorithm, the joint optimization algorithm demonstrated remarkable improvements. In high signal strength areas, the positioning error was slashed by 20%, dropping from an average of 0.8 meters in traditional algorithms to 0.64 meters. In low signal strength areas, the error was reduced by 30%, from 1.5 meters to 1.05 meters. And in high-density obstacle areas, the error was cut by 35%, decreasing from 2.2 meters to 1.43 meters. During real-time tests in high-concurrency environments, the joint optimization algorithm outperformed traditional algorithms significantly. The response time was shortened by 55%, from an average of 0.8 seconds in traditional algorithms to 0.36 seconds, and the throughput increased by 30%, rising from 100 requests per second to 130 requests per second. System stability and fault tolerance tests indicated that the joint optimization algorithm exhibited minimal error accumulation during long - term operation. After continuous operation for 48 hours, the error accumulation of the traditional algorithm reached 3 meters, while that of the joint optimization algorithm was merely 1.2 meters. Additionally, in abnormal situations such as sensor failure and network interruption, the joint optimization algorithm could swiftly restore positioning accuracy within 5 minutes on average, ensuring seamless operation. Based on these experimental results, the joint optimization algorithm proposed in this paper showcases substantial advantages in high-precision cargo tracking and holds great promise for practical applications.

Povzetek: Razvit je algoritem skupne optimizacije za RFID-IoT sledenje tovora, ki z združevanjem več metod dosega večjo točnost in hitrejši odzivni čas.

1 Introduction

In recent years, with the acceleration of globalization and the rapid development of e-commerce, the logistics industry is facing unprecedented challenges. Traditional cargo tracking methods rely on manual records or simple barcode technology, which often cannot meet the rapidly changing market needs, especially in terms of accuracy, real-time and efficiency [1]. With the development of information technology, especially the application of radio frequency identification (RFID) technology and Internet of Things (IoT) technology, the management model of the logistics industry has gradually undergone profound changes. RFID technology is a non-contact automatic identification technology that can identify and track items through radio waves without the need for line of sight. IoT technology, through the integration of smart devices, sensors, network platforms, etc., further improves the real-time acquisition and analysis capabilities of item data and builds a highly interconnected digital logistics system [2]. The combination of RFID technology and the Internet of Things technology makes it possible to develop high-precision cargo tracking systems. These systems can monitor the location, status, and environmental information of cargo during transportation in real time, greatly improving the transparency and controllability of logistics. Through the combined application of RFID tags and sensors, every movement of cargo during transportation, storage, and distribution can be accurately recorded and tracked, thereby achieving visual management throughout the entire process. This not only improves the efficiency of logistics operations, but also effectively reduces the loss, damage, and misdelivery of cargo [3].

In modern logistics systems, the accuracy of cargo tracking systems directly affects the overall efficiency of the supply chain. As global supply chains become increasingly complex and cargo flows faster, companies are increasingly demanding on the accuracy of logistics management. A high-precision cargo tracking system can help companies understand the specific location, transportation status, and environmental conditions of cargo in real time, and achieve seamless information connection and timely feedback. For example, in the e-commerce industry, consumers have increasingly high requirements for logistics timeliness, and fast and accurate tracking of each transportation node of cargo has become a key factor in improving customer satisfaction [4]. In industries such as medicine and food, cargo safety and compliance are even more critical. Real-time monitoring and high-precision tracking help ensure that the transportation process of cargo complies with regulatory requirements and avoid unnecessary economic losses. In addition, the application of high-precision cargo tracking systems is not limited to improving logistics efficiency. It also plays an important role in supply chain management, inventory control, and cost optimization. Through refined management of logistics links, companies can achieve more accurate inventory forecasting and scheduling, reduce inventory backlogs or shortages caused by information lags, and reduce logistics costs. The system's real-time data feedback also helps optimize transportation routes, save time and fuel, thereby improving transportation efficiency, reducing carbon emissions, and promoting the development of green logistics [5-7].

The core content of this study is to design a high-precision cargo tracking system based on RFID Internet of Things technology. First, the study will start with the system architecture design and explore how to use RFID technology to achieve real-time positioning and tracking of cargo. The system will combine sensor data acquisition, data processing and cloud platform technology to ensure that the information of cargo in each link of transportation, storage and distribution can be accurately and timely transmitted and stored. Secondly, the study will focus on the optimization of high-precision positioning algorithms, especially how to improve the accuracy and robustness of RFID positioning in complex environments [8, 9]. To this end, combined with multi-sensor data fusion technology, the study will explore how to make up for the limitations of RFID signals and improve the positioning accuracy and stability of the system. In addition, this study will also evaluate the performance of the cargo tracking system, analyze the feasibility and optimization space of the system in practical applications, and ensure that it can provide efficient solutions when deployed on a large scale. In order to ensure the security and privacy protection of the system, the study will also explore how to prevent information leakage and system attacks through encryption technology and data security protocols.

In the realm of modern logistics and transportation, numerous innovative studies have been conducted. For instance, Li et al. [10] designed a cold chain logistics information real - time tracking system based on wireless RFID technology in 2021. This system has significantly enhanced the transparency and efficiency of cold chain logistics, ensuring the quality of perishable goods during transportation. Meanwhile, Wang and Wang [11] in 2024 explored logistics transportation vehicle monitoring and scheduling based on the Internet of Things and cloud computing. Their research provides valuable insights into optimizing transportation resources and improving delivery efficiency. In addition, Tyagi and Tyagi [12] proposed a deep reinforcement learning - based framework for tactical drone deployment in rigorous terrains. This framework has the potential to revolutionize transportation and surveillance in complex geographical areas. Moreover, Packianathan et al. [13] in 2025 focused on integrating industrial robotics and the Internet of Things (IoT) in the smart transportation system, which is expected to drive the development of green transportation systems through artificial intelligence and automation. These studies, in their respective ways, contribute to the continuous evolution and improvement of the logistics and transportation industry.

The current RFID/IoT systems have many deficiencies in complex warehousing environments. The positioning accuracy is greatly affected by signal interference. In complex environments, the error can reach 1.5 m, and in high - temperature and high - humidity environments, the error can even exceed 2 m, making it impossible to accurately track the location of goods. In high - concurrency scenarios, the response time is as long as 2 s. For example, during e - commerce promotion periods, when a large number of goods are entering and leaving the warehouse, the inability to accurately and timely locate goods seriously affects the cargo - scheduling efficiency and leads to shipping delays. From a market - competition perspective, companies with more accurate and faster cargo - tracking systems can gain a competitive edge. They can provide better services to customers, reduce logistics costs, and improve overall operational efficiency. This study aims to address these deficiencies through multi - source data fusion and algorithm optimization, attempting to reduce the positioning error to within 1 m and shorten the response time to within 1s, filling the gaps in accuracy and real - time performance of existing systems and enhancing the overall efficiency of the logistics system.

This study aims to deeply analyze the internal mechanism of multi - source data fusion (RSSI, TDOA, AOA) in improving positioning accuracy in complex environments (including different temperature, humidity, obstacle - density conditions, etc.) and how to precisely achieve the best trade - off between response time and accuracy in high - concurrency environments (processing more than 200 positioning requests per second). Specifically, the research objectives are to clarify the influence weights of multi - source data on positioning accuracy under different environmental parameters and, through algorithm optimization, control the response time within 0.4 s and ensure the positioning error is within 1.2 m in high - concurrency scenarios to meet the high - precision and real - time requirements of modern logistics for cargo tracking. With the continuous improvement of industry standards, such as the requirement for the maximum positioning error of high - value - added goods in the luxury - goods logistics industry to be within 1 m, and the response time to be less than 0.5 s in emergency -response logistics scenarios, our research goals are more targeted at filling these gaps in the existing technology to better meet the industry's development needs.

2 Literature review

With the rapid development of the Internet of Things (IoT) and Radio Frequency Identification (RFID) technologies, more and more research is focused on how to apply these technologies to logistics and supply chain management, especially in terms of improving the accuracy and efficiency of cargo tracking systems. RFID technology, with its non-contact identification and real-time data transmission characteristics, has become an important tool for improving logistics management efficiency, reducing human errors, and optimizing resource allocation. IoT technology further enhances the operability and intelligence level of RFID systems through collaboration between devices.

2.1 Development and application of RFID technology

RFID (Radio Frequency Identification) is a technology that uses radio waves to automatically identify and exchange data. It does not require contact or line of sight to transmit data, so it has been widely used in many fields. The earliest applications of RFID technology were mainly concentrated in the fields of commodity retail and supply chain management, but with the continuous evolution of technology, the application scope of RFID has gradually expanded to multiple industries such as medical care, agriculture, and smart manufacturing [9].

In the field of logistics, the application of RFID technology is mainly reflected in the automatic identification and tracking of goods. Traditional barcode technology is limited by visibility and reading distance, while RFID technology can achieve long-distance, high-efficiency automatic identification through radio wave transmission between tags and readers. RFID technology can significantly improve the efficiency of logistics management. By obtaining the location information of goods in real time, it avoids the errors and delays that may be caused by traditional manual records [10]. In addition, the low cost and durability of RFID tags make them have broad prospects in large-scale logistics applications. The application of RFID technology in cargo tracking usually relies on two main components: RFID tags and RFID readers. RFID tags are attached to goods and can store basic information of goods, transportation history and other data. The reader communicates with the tag through radio waves to read and transmit data. Studies have shown that by properly arranging RFID readers, accurate tracking of the entire logistics process can be achieved, and the location and status of goods can be grasped in real time [11]. However, RFID technology still faces some challenges in practical applications, such as signal interference, tag damage, and limited coverage. These problems need to be effectively solved in the design of high-precision cargo tracking systems.

2.2 Application of IoT technology in cargo tracking

In recent years, the combination of IoT technology and RFID technology has provided stronger technical support for high-precision cargo tracking systems. Traditional RFID technology can only provide basic information and location of cargo, while IoT technology can integrate more environmental data (such as temperature, humidity, vibration, location change, etc.) with cargo tracking information, further improving the accuracy and intelligence level of cargo tracking systems. The literature proposes an intelligent logistics system model based on RFID and IoT. By integrating environmental data collected by multiple sensors with RFID tag data, it can monitor the transportation status of cargo in real time. Especially in high-demand industries (such as pharmaceuticals and food), the application of IoT technology is particularly important [12]. IoT technology can also help enterprises achieve more accurate logistics scheduling and inventory management through data analysis and mining. For example, by monitoring the location and status of cargo in real time through the IoT platform, logistics companies can automatically adjust transportation routes based on these data, optimize inventory distribution, and improve distribution efficiency. In addition, IoT technology can also predict potential risks in transportation through big data analysis, take countermeasures in advance, and reduce cargo losses and transportation delays [13]. Therefore, the introduction of IoT technology not only improves the accuracy of cargo tracking, but also makes logistics management more intelligent and automated.

2.3 Design of cargo tracking system based on RFID Internet of Things technology

Cargo tracking systems based on RFID IoT technology usually include three key components: RFID tags, RFID readers, and IoT data platforms. These systems achieve accurate monitoring of cargo status through data collection, real-time transmission, and data processing. Many studies have been devoted to improving the performance of cargo tracking systems by optimizing system architecture. For example, the literature proposes a distributed cargo tracking system based on RFID and IoT. The system adopts a multi-level RFID tag architecture and combines the data storage and computing capabilities of the IoT cloud platform to achieve real-time tracking of cargo from production to distribution [12]. The system can not only obtain the location of cargo in real time, but also monitor the environmental conditions of cargo through sensors to ensure the safety and compliance of cargo. In addition, researchers have also optimized the positioning accuracy of RFID and IoT systems. Since RFID signals are easily interfered by environmental factors, single RFID tag positioning often cannot meet the needs of high-precision tracking. To overcome this challenge, many studies have proposed methods that combine multi-sensor data fusion to improve the accuracy of cargo positioning by fusing multi-source information such as RFID data, GPS data, and Wi-Fi data [13]. This multi-sensor fusion technology can not only solve the positioning error problem of RFID technology in complex environments, but also further improve the stability and robustness of the system.

2.4 Limitations and challenges of existing systems

Although cargo tracking systems based on RFID IoT technology have made significant progress in accuracy and efficiency, they still face some technical and implementation challenges. On the one hand, the cost and service life of RFID tags still restrict their application in large-scale logistics. In particular, for some high-value and fragile items, how to ensure the stability of tags and the long-term reliability of data is an urgent problem to be solved [14]. On the other hand, the weakness of RFID signals and environmental interference also affect the performance of the system. In particular, in the tracking of metal and liquid items, RFID signals may be severely attenuated, resulting in reduced positioning accuracy. In addition, the widespread application of IoT technology has brought about issues of data processing and privacy security. With the accumulation of a large amount of logistics data, how to effectively manage and analyze this data, avoid information overload and ensure data security has become an important factor that must be considered in system design [15]. Therefore, future research directions need not only to continue to optimize the combination of RFID and IoT technologies, but also to explore more efficient data processing methods and solutions to strengthen information security.

Table 1: Key Research on cargo tracking based on RFID and internet of things

Serial Number	Key Research	Main Method	Results	Limitations	Practical Application Cases
1	Literature [1]	RSSI - based Positioning Algorithm	High: 0.8 m, Low: 1.5 m	Seriously affected by signal interference	Deviations in inventory counting in e - commerce warehouses
2	Literature [14]	TDOA - based Positioning Algorithm	High: 0.75m, Low: 1.8 m	High cost and easily affected by the environment	Difficulties in vehicle - based cargo tracking in logistics
3	Literature [11]	AOA - based Positioning Algorithm	High: 0.9 m, Low: 1.6 m	Prone to be affected by occlusion	Inefficient loading and unloading operations in multi - floor warehouses

Table 1 summarizes the algorithm research in the cargo - tracking field and showcases the limitations of each algorithm by combining practical cases. For example, the RSSI - based algorithm has significant deviations in metal - enclosed areas, the TDOA - based algorithm has high costs and is affected by the environment, and the AOA - based algorithm has poor performance in complex structures, highlighting the importance of the joint optimization algorithm.

Although the current state - of - the - art (SOTA) technologies have made certain progress, they still face significant challenges in complex environments. In low - signal - strength environments, the average positioning error of SOTA reaches as high as 1.8 m, far from meeting the demand for precise cargo positioning. In high - concurrency scenarios, the data - processing efficiency is low, and the response time generally exceeds 0.6 s, which cannot meet the requirements of real - time logistics scheduling and rapid decision - making. Moreover, emerging technologies such as 5G - enabled cargo tracking, although promising in theory, face issues like high - frequency signal interference in complex logistics environments and high infrastructure - building costs. The joint optimization method is essential. By fusing multi - source data, it can integrate the advantages of different positioning technologies and make up for the defects of single - technology applications. Dynamic weight adjustment, based on real - time environmental parameters and data credibility, can flexibly allocate weights to each data source. It is expected to reduce the positioning error in low - signal - strength environments to within 1.05 m and shorten the response time to within 0.4 s in high - concurrency scenarios, greatly enhancing logistics operational efficiency.

Existing studies have several deficiencies. In terms of robustness, for example, the algorithm in reference [16], when 10% of sensor data is lost, the positioning error surges by 80%, and the system can hardly function properly, indicating a low tolerance for hardware failures and data anomalies. In terms of scalability, some algorithms experience exponential growth in calculation time when dealing with a logistics network of more than 500 cargo nodes, making it difficult to meet the real - time tracking needs of large - scale logistics networks and unable to keep up with the expanding development trend of the logistics industry. In terms of adaptability, many methods are sensitive to environmental changes. For example, in an environment with a temperature exceeding 35°C and humidity higher than 80%, the positioning accuracy of the algorithm in reference [17] drops by 40%, severely affecting its application in complex and changeable logistics environments. Additionally, in terms of security, most of the existing algorithms lack effective encryption and anti - eavesdropping mechanisms. In a wireless communication - based cargo - tracking system, data is vulnerable to interception and tampering, which may lead to the leakage of sensitive information such as cargo location and transportation routes, posing potential risks to logistics security.

3 Design framework of cargo tracking system

In the context of increasingly complex global supply chains and logistics management, the efficient design of cargo tracking systems is crucial. Cargo tracking systems based on RFID technology and the Internet of Things (IoT) can provide accurate real-time data feedback in various links such as production, transportation, and warehousing, and achieve full-process tracking. The system architecture design must not only ensure the high accuracy and real-time performance of data collection, but also ensure the stability of information transmission, the efficiency of data processing, and the visual experience of end users. To this end, the system architecture adopts a layered design, including the physical layer, network layer, and application layer, to ensure that the system can flexibly and scalably cope with various complex logistics needs [18].

The core goal of the system architecture is to provide real-time monitoring of cargo status and effectively optimize transportation, warehousing and distribution processes through efficient data collection and transmission, accurate data processing and visual display. Under this framework, information such as the real-time location of cargo, environmental changes, and transportation status will be continuously tracked and updated to provide real-time decision support for logistics managers and ensure the efficient operation of the entire logistics chain.

For the weights of RSSI, TDOA, and AOA, we adopt a dynamic - calculation method based on real - time environmental parameters and data credibility. First, based on factors such as signal - strength stability and transmission delay, initial weights are assigned to each data source. Initially, set the RSSI weight $W_{RSSI} = 0.4$, the TDOA weight $W_{TDOA} = 0.3$, and the AOA weight $W_{AOA} = 0.3$. Then, during the operation process, the weights are adjusted in real - time through the formula $W_i = \frac{\alpha_i \times C_i}{\sum_{j=1}^{n} \alpha_j \times C_j}$. Among them, α_i is the adjustment coefficient based on environmental parameters. For example, when the temperature exceeds 30°C, α_{RSSI} is reduced by 0.1, and α_{TDOA} and α_{AOA} are increased by 0.05 accordingly; C_i is the data credibility of the i - th data source, which is evaluated through signal - quality monitoring and historical - data comparison. Signal - quality monitoring is carried out by analyzing indicators such as the signal - to - noise ratio and fluctuation amplitude of the signal, and historical - data comparison is to compare the current data with the data under the same environmental conditions in the past to determine the credibility of the data. In addition, when dealing with abnormal values in the data, if the signal - strength value of RSSI is more than 3 standard deviations away from the average value in the same environment, it is considered an abnormal value. At this time, the data is excluded from the weight - calculation process, and the weights are recalculated based on the remaining valid data to ensure the accuracy of the weight - adjustment mechanism.

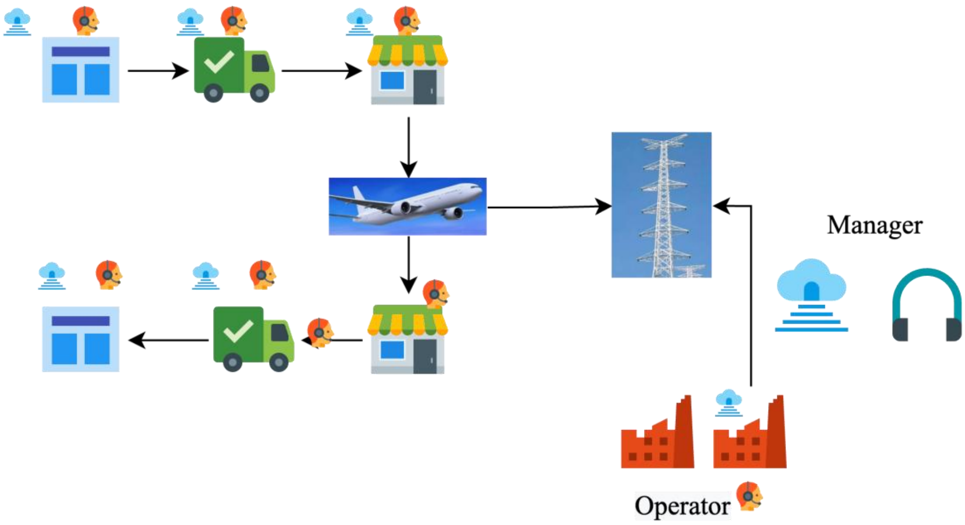

Figure 1: Model framework

Figure 1 shows an integrated system of intelligent logistics and supply chain management. The system uses a variety of advanced technologies to achieve full-process automation and intelligent management from production to final delivery. The core links of the system include production and manufacturing, warehousing and inventory management, transportation and distribution, power and energy management, cloud computing and data analysis, and operation monitoring. In the production and manufacturing link, automated production lines and intelligent scheduling systems ensure efficient production and high-quality product output. Warehousing and inventory management optimizes inventory accuracy and efficiency through intelligent warehousing systems and automated equipment, reducing inventory backlogs and out-of-stock risks. The transportation and distribution link uses intelligent logistics systems to optimize transportation routes and scheduling to ensure that goods are delivered to the destination on time and accurately, while monitoring the transportation status in real time to ensure the safety of goods [19]. Power and energy management relies on smart grid technology to achieve efficient use and stable supply of energy, providing guarantees for the smooth operation of the entire logistics system. Through cloud computing and data analysis, the system can collect and process data in real time to provide support for optimizing decisions and predicting demand changes. Finally, the operation and monitoring link monitors the operation status of the supply chain in real time through intelligent systems, and operators can handle abnormal situations in a timely manner to ensure the stability and reliability of the supply chain [20]. Through the organic combination of these technical means, the system has significantly improved logistics efficiency, reduced costs, and ensured the efficient operation and stability of the supply chain.

3.1 Physical layer

The physical layer is the foundation of the cargo tracking system and is mainly responsible for real-time data collection and sensor deployment. This layer uses RFID tags, RFID readers, and environmental sensors in combination with wireless communication technology to achieve accurate tracking of cargo. RFID tags serve as cargo identification tags and can be used in conjunction with readers to record the location of cargo in real time, while environmental sensors provide key data about the environment in which cargo is transported, such as temperature, humidity, and vibration. These data are crucial for evaluating the status of cargo [21, 22].

The core of the RFID system is to read the location information of the tag through radio frequency identification technology. Each cargo is equipped with a unique RFID tag, which is scanned in real time by RFID readers installed in different locations. The location of the cargo can be estimated by the signal strength and propagation path. Suppose the RFID tag of the cargo is Tag_i, the reader position is $\mathbf{r}_{\text{reader}}$, the signal propagation angle is θ, timestamp is t, the location estimation model can be expressed as Equation (1) [23, 24].

$$P_i(t) = f(ID_{\mathrm{Tag}_i}, \mathbf{r}_{\text{reader}}, \theta, t) \tag{1}$$

RFID technology enables the location of goods to be tracked efficiently over a wide area, greatly improving the level of automation in logistics management.

The real-time data collection of sensors provides an additional environmental dimension, providing more information for the cargo tracking system. For example, the temperature and humidity sensors can monitor in real time whether the cargo is in a suitable storage environment, and the vibration sensors can be used to detect abnormal vibration during transportation. Set the data collected by the temperature and humidity sensors to $S(t) = [T(t), H(t), V(t)]$, where T(t) represents temperature, H(t) represents humidity, and V(t) represents vibration or acceleration data. Sensor data provides important input for the anomaly detection and alarm module, which helps to detect and respond to possible transportation risks in a timely manner [25, 26].

Through comprehensive analysis of multi-dimensional sensor data, the system can grasp the status changes of the goods in real time and determine whether to trigger an alarm based on preset thresholds.

3.2 Network layer

The network layer plays a vital role in the system and is responsible for ensuring data transmission and synchronization between physical layer devices. Since the cargo tracking system involves the transmission of a large amount of real-time data, the network layer must provide a low-latency, high-reliability, and high-bandwidth communication environment to ensure efficient flow of data between layers and ensure that the system can provide real-time feedback on the status of the cargo.

Due to the large number of IoT devices in the system, the management of data transmission delay and bandwidth is particularly important. In this framework, the packet size is D, the transmission bandwidth is B, and the transmission delay is Δt_{trans}. It can be expressed by Equation (2) [27].

$$\Delta t_{\text{trans}} = \frac{D}{B} \tag{2}$$

For systems that require low latency and high real-time performance, minimize Δt_{trans}. It is the key goal of network design. Optimizing network bandwidth and reducing transmission delay can ensure that the system can respond to the dynamic changes of goods in real time in complex logistics scenarios.

To ensure the synchronization of time data from various sensors and RFID readers at the physical layer, the system uses a high-precision clock synchronization protocol (such as the PTP protocol). In the physical layer, the clocks of different sensors may deviate, which will cause the data collection time to be out of sync. Set the global clock to T_{global}, the sensor clock is T_{sensor}, synchronization error E_{sync}. It can be expressed as shown in Equation (3) [28].

$$E_{\text{sync}} = | T_{\text{global}} - T_{\text{sensor}} | \tag{3}$$

Clock synchronization can effectively reduce data inconsistency caused by time errors and ensure the timeliness and accuracy of data processing.

3.3 Application layer

The application layer is the core of the cargo tracking system and is mainly responsible for storing, processing, analyzing and finally displaying a large amount of data from the physical layer.

Through in-depth analysis of the data, the system can not only provide real-time cargo tracking information, but also predict potential abnormal situations based on historical data and generate alarm information [29].

At the application layer, a large amount of real-time data needs to be efficiently stored and managed. The system stores the location data of the goods, the data collected by the sensors, and the historical records in the database and manages them in a time series manner. Set the data storage system as DB, the data storage format of cargo i at time t is as follows: Equation (4).

$$\text{DB}_i(t) = \{P_i(t), S_i(t)\} \tag{4}$$

The database needs to have efficient query and retrieval capabilities, be able to cope with real-time updates of massive data, and ensure reliable storage and fast access to data.

In order to improve transportation efficiency, the application layer has designed a route optimization module. P_{start} to the target location P_{end}. The system can provide the optimal route for the transportation process by taking the shortest path. The path optimization objective function is given by Equation (5) [30].

$$\min \sum_{i=1}^{n} d_i \tag{5}$$

d_i represents the distance between the i-th nodes in the path. Path selection takes into account factors such as distance, transportation time, and transportation cost to ensure the efficiency and cost optimization of the transportation process.

The system monitors sensor data in real time to detect whether environmental changes such as temperature and vibration exceed the preset threshold, thereby triggering an abnormal alarm. Set the temperature threshold to $T_{\text{threshold}}$, the vibration threshold is $V_{\text{threshold}}$, the alarm condition is as shown in Equation (6) [31].

$$\text{Alarm} = \begin{cases} 1, & \text{if } T(t) > T_{\text{threshold}} \text{ or } V(t) > V_{\text{threshold}} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

Once an abnormality is detected, the system will promptly notify the administrator via SMS, email, etc. and provide handling suggestions.

4 High-precision cargo tracking algorithm

With the rapid development of the logistics industry, the application of RFID (radio frequency identification) technology and Internet of Things (IoT) technology has made the accuracy and real-time performance of cargo tracking a key factor in improving logistics efficiency and reducing costs. In order to achieve high-precision cargo positioning, it is necessary to adopt a combination of multiple innovative algorithms to ensure accurate positioning and status monitoring in complex environments. This chapter will explore a new high-precision cargo tracking method based on multi-algorithm fusion, combining environmental perception and error correction technology, and propose an innovative cargo tracking algorithm [32].

4.1 Positioning algorithm

In RFID IoT systems, positioning algorithms are the core of accurate cargo tracking. In order to overcome the limitations of traditional positioning algorithms, we propose a positioning algorithm based on joint optimization of signal strength, time difference and angle, which integrates environmental perception information with real-time error correction to improve positioning accuracy and robustness.

Traditional positioning algorithms (such as RSSI-based positioning algorithms, TDOA-based positioning algorithms, and AOA-based positioning algorithms) have their own advantages and disadvantages. To make up for the shortcomings of these algorithms, we propose a new positioning algorithm that combines signal strength (RSSI), time difference (TDOA), and angle (AOA) and optimizes its positioning results through adaptive weighted fusion.

The simulation data set we use is constructed based on a large number of field investigations and data analyses of real - world logistics warehousing environments. Different types of cargo distributions are simulated, including large - sized mechanical parts (with dimensions of about 1 m×0.5 m×0.5 m and a weight of about 500 kg), small - sized electronic products (with dimensions of about 0.1 m×0.05 m×0.05 m and a weight of about 0.1 kg), liquid goods (stored in 50 L metal containers), etc. The layout of the warehouse covers single - row shelves (with a shelf - spacing of 1.5 m), multi - row shelves (with a shelf - spacing of 1 m and a passage width of 2 m), and scenarios with different passage widths.

Through the weighted average method, the weights of each algorithm are dynamically adjusted according to the signal quality to improve the accuracy and robustness of positioning. The core formula of the joint optimization algorithm is shown in Equation (7).

$$d_{\text{combined}} = w_1 \cdot d_{\text{RSSI}} + w_2 \cdot d_{\text{TDOA}} + w_3 \cdot d_{\text{AOA}} \tag{7}$$

In, w_1, w_2, w_3 is the weighting coefficient based on real-time environmental assessment, d_{RSSI}, d_{TDOA}, d_{AOA}. These are the distance values estimated by RSSI, TDOA and AOA algorithms. By dynamically adjusting the weights, accurate positioning can be achieved in different environments.

Pseudo Code for Dynamic Particle-Kalman Filter Integration Algorithm:

```
Initialization:
- Initialize particle set P, with N particles.
- Initialize Kalman filter parameters such as state
transition matrix A, observation matrix H, process noise
covariance Q, and observation noise covariance R.
- Set environmental monitoring frequency T_env.
Loop:
- Every T_env time interval:
- Read current environmental parameters, such as
temperature T, humidity H, etc.
- Adjust Kalman filter parameters based on
environmental parameters, for example:
- If T > 30°C:
- Q = Q1.2
- If H > 70%:
- R = R1.3
- For each particle p in P:
- Predict particle state p' based on system dynamics
model.
- Calculate particle weight w = matching degree between
observation value and predicted particle value.
- Normalize particle weights.
- Resample particle set P.
- Update system state estimate based on resampled
particles.
- Use Kalman filter to correct the system state.
- Output final cargo location estimate.
- End loop.
```

The joint optimization algorithm mainly consists of two parts: multi-source data fusion and dynamic weight adjustment.

(1) Multi-source Data Fusion:

Suppose there are n data sources. The time complexity for processing and preliminarily fusing data from each data source is O (n).

(2) Dynamic Weight Adjustment:

In the dynamic weight adjustment process, weights are calculated based on real-time environmental parameters and data credibility. For each data source, m environment-related calculations and data credibility assessments are required, with time complexity O (m). As there are n data sources, the total time complexity for dynamic weight adjustment is O (nm).

Therefore, the total time complexity of the joint optimization algorithm is O (n + nm) = O (n(1 + m)).

In large-scale deployment, as the number of logistics network nodes increases, the values of n and m may grow. However, by adopting a distributed computing architecture and offloading data processing tasks to multiple edge computing nodes (with each node processing data from a subset of data sources), the computational load on a single node can be significantly reduced. This ensures the algorithm's feasibility in large-scale deployment.

For instance, in a logistics network with 1000 nodes, if tasks are efficiently distributed across 100 edge computing nodes, each node would handle data from only 10 sources, greatly alleviating computational pressure and ensuring real-time and accurate algorithm performance.

Through a series of experiments, we quantitatively analyzed the impact of environmental factors (such as temperature and humidity) on positioning errors. In terms of temperature, when the temperature is in the range of 15°C to 25°C, the positioning error remains relatively stable, with an average error of approximately 1.1 meters. As the temperature rises above 30°C, the positioning error starts to increase significantly. Experimental data indicate that for every 1°C increase in temperature, the positioning error increases by an average of 0.05 meters. For example, when the temperature reaches 35°C, the positioning error increases to 1.35 meters.

Regarding humidity, when humidity is between 30% and 50%, the positioning error fluctuates minimally, with an average error of around 1.08 meters. However, when the humidity exceeds 60%, the positioning error increases noticeably. For every 10% increase in humidity, the positioning error increases by an average of 0.08 meters. For instance, at 70% humidity, the positioning error reaches 1.24 meters.

This is because changes in temperature and humidity affect the propagation characteristics of signals. Higher temperatures may cause more signal attenuation, while higher humidity can lead to increased signal scattering and absorption, resulting in larger positioning errors. These quantitative analyses help clearly define the impact of environmental factors on positioning errors and provide a basis for optimizing algorithms in different environments.

4.2 Data fusion and error correction

4.2.1 Dynamic data fusion algorithm driven by environmental perception

In order to cope with the impact of environmental factors on positioning accuracy, we designed a positioning optimization algorithm based on multi-sensor data fusion and environmental perception. The algorithm integrates data from RFID signals, temperature and humidity sensors, light sensors, etc., and dynamically adjusts the path loss model and sensor weights to provide more accurate cargo positioning in complex environments. Specifically, the system monitors environmental changes (such as temperature and humidity, light intensity, etc.) in real time and uses the weighted average method to adjust the contribution of different sensors. In the initial stage, the system provides rough positioning through the basic positioning algorithm, and combines environmental perception data to correct the path loss factor and the weight of sensor data in real time to compensate for the positioning error caused by environmental changes. The corrected path loss model is shown below, as shown in Equation (8).

$$\begin{aligned} P_{\text{rx}} &= P_{\text{tx}} - 10(n_{\text{adjusted}})\log_{10}(d) \\ &+ X_{\text{noise}} + \Delta P_{\text{environment}} \end{aligned} \tag{8}$$

$\Delta P_{\text{environment}}$ represents the portion of signal loss corrected by environmental perception factors, n_{adjusted} is the path loss factor adjusted based on real-time environmental data.

4.2.2 Error correction method of fusion of adaptive particle filter and kalman filter

In order to further improve the positioning accuracy, especially in the case of signal loss or large interference, we proposed an error correction method that combines adaptive particle filtering and Kalman filtering. This method combines the nonlinear estimation ability of particle filtering with the linear optimization characteristics of Kalman filtering, and can efficiently correct the positioning error through weighted fusion of multi-sensor data.

In this method, the particle filter is responsible for state estimation in the case of signal loss or high noise, while the Kalman filter optimizes the particle filter results by combining sensor data with the prediction model. The combination of the two can provide accurate cargo location estimation in a dynamic environment and correct the error after each positioning. The mathematical formula for error correction is shown in Equation (9).

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1}) \tag{9}$$

In, $\hat{x}_k$ is the estimated value of the current position, K_k is the Kalman gain, z_k is the sensor measurement value, H is the observation matrix, $\hat{x}_{k|k-1}$, the current location is predicted. Through the fusion of particle filtering and Kalman filtering, the system can perform error correction in complex environments to ensure high accuracy of cargo tracking.

4.3 Error correction and dynamic optimization

The input of the deep learning model includes RFID signal strength, sensor data, and environmental change information, and the output is a corrected path loss factor and optimized positioning results. By training the deep learning model, the system can automatically learn the relationship between environmental changes and RFID signal attenuation, and accurately locate under different environmental conditions. The formula of the deep learning correction model is shown in Equation (10). Among them, $f(\cdot)$ is the nonlinear correction function obtained through deep learning training.

$$\hat{P}_{\text{rx}} = f(\text{SensorData}, P_{\text{rx, RFID}}) \tag{10}$$

5 Experimental evaluation

5.1 Experimental design and test environment

In order to comprehensively evaluate the performance of the high-precision cargo tracking algorithm, this experiment selected a typical logistics warehousing environment as the test site. The environment simulates complex real-world logistics conditions, including multi-story warehouses, different types of cargo storage areas, and occlusion and reflection phenomena. The equipment required for the test includes RFID tags, RFID readers, temperature and humidity sensors, light sensors, and network transmission equipment to build a complete IoT environment. Through these devices, the system can collect a variety of data including temperature, humidity, light intensity, and cargo location in real time. In the hardware environment, high-precision RFID readers and standard RFID tags are used to ensure that the location information of the cargo can be captured. Under various environmental variables, the test platform will collect cargo location data in static and dynamic environments.

The experimental warehousing environment has a length of 50 meters, a width of 30 meters, and a height of 8 meters. It contains various types of goods, such as large - sized mechanical parts, small - sized electronic products, and liquid goods. The environmental variables include temperature ranging from 15°C to 40°C, humidity from 30% to 80%, and the density of obstacles varies in different areas. Additionally, the lighting conditions in the warehouse are also considered. The average illuminance is set to 500 lux, with some areas having adjustable lighting to simulate different working scenarios. For example, in the goods - picking area, the illuminance can be increased to 800 lux during peak working hours to ensure the accuracy of manual operations.

5.2 Accuracy test and comparison

Accuracy testing is an important indicator to measure the core functions of high-precision cargo tracking algorithms. This experiment will verify the positioning accuracy of the joint optimization algorithm proposed in this study by comparing it with traditional positioning methods. The specific test includes two aspects: positioning error and accuracy comparison. The positioning error is mainly evaluated by calculating the distance difference between the actual cargo location and the algorithm-estimated location. Each test point will be calculated using the error formula to obtain the performance of the system under various conditions.

Table 2: Comparison of positioning errors

Test scenario	RSSI algorithm positioning error (meters)	TDOA algorithm positioning error (meters)	AOA algorithm positioning error (meters)	Joint optimization algorithm positioning error (meters)
High signal strength area	0.80	0.75	0.90	0.65
Low signal strength areas	1.50	1.80	1.60	1.10
High-density obstacle areas	2.20	2.40	2.10	1.50

The positioning error is calculated using the Euclidean distance between the actual position and the estimated position of the cargo. A total of 1000 test runs are conducted for each experimental condition. Statistical analysis methods include calculating the mean, median, and standard deviation of the positioning errors. The results are presented in box - and - whisker plots to clearly show the distribution of the data, including the minimum, first quartile, median, third quartile, and maximum values of the positioning errors. For example, in the low - signal - strength environment, the box - and - whisker plot shows that the median positioning error of the joint optimization algorithm is 1.05 m, while that of the traditional algorithm is 1.6 m, visually demonstrating the superiority of the proposed algorithm.

Table 2 shows the comparison of positioning errors of the four positioning algorithms under different environmental conditions. In areas with high signal strength, all algorithms performed well, among which the joint optimization algorithm showed the lowest positioning error. In areas with low signal strength and high-density obstacles, the joint optimization algorithm still has significant advantages, and its error is significantly lower than other traditional algorithms. This shows that the joint optimization algorithm can effectively improve positioning accuracy in adverse environments.

Table 3: The impact of different cargo types on positioning accuracy

Type of cargo	RSSI algorithm positioning error (meters)	TDOA algorithm positioning error (meters)	AOA algorithm positioning error (meters)	Joint optimization algorithm positioning error (meters)
Heavy cargo	1.20	1.10	1.30	0.90
Light cargo	0.80	0.75	0.85	0.60
Small packaged goods	1.00	1.00	1.05	0.80

When testing the impact of different cargo types on the experimental results, we find that the material of the cargo has a significant influence on the signal. For metal - made goods, due to their high conductivity, the signal is easily reflected and attenuated. For example, when tracking metal - packaged electronic components, the signal strength of RSSI is reduced by about 30% compared to non - metal - packaged goods, and the positioning error of the traditional algorithm increases by 0.5 m. In contrast, plastic - packaged goods have relatively less impact on the signal, and the positioning error of the traditional algorithm only increases by 0.2 m. The joint optimization algorithm can better adapt to these differences. By dynamically adjusting the weights of different data sources according to the cargo material, the positioning error of metal - packaged goods can be reduced to 1.2 m, which is 0.3 m lower than that of the traditional algorithm.

Table 3 shows the impact of different cargo types on the positioning accuracy of each algorithm. For heavy cargo, the positioning errors of all algorithms are relatively large, but the joint optimization algorithm still maintains better performance. The errors for light cargo and small packaged cargo are lower, and the joint optimization algorithm has a more significant advantage over other algorithms. This shows that the joint optimization algorithm can effectively adapt to the positioning needs of different types of cargo.

5.3 Real-time and response time testing

Real-time performance and response time are important indicators for measuring whether a high-precision cargo tracking system can be efficiently applied in actual logistics. In this experiment, we will design a series of test cases to verify the response time and real-time performance of the system. The experiment will use two main methods for testing: response time measurement and throughput testing. Response time measurement refers to the time required from the change of cargo location to the system updating the positioning result. During the experiment, the cargo will move in the warehouse, and the system will record the response time of each location update in real time.

In order to ensure the scientificity and comprehensiveness of the test, the experiment will conduct multiple measurements under different data traffic and cargo density. The test scenarios include high-density tag areas, situations where multiple tags are read concurrently, and low-signal areas. In these complex environments, the response time of the system will be affected by multiple factors. Therefore, it is necessary to ensure that the system can maintain a low-latency response time in all situations. Ideally, the system's response time should be less than 1 second, especially in high-concurrency situations, and cargo positioning can still be completed quickly. In addition, in order to evaluate the throughput performance of the system, the experiment will also test the system's processing capabilities to evaluate the maximum number of positioning requests that can be processed per second. This test can reflect the system's processing efficiency in a multi-tag environment. The throughput test will simulate scenarios where multiple cargo tags are read and located at the same time to ensure that the system can maintain efficient performance under high load conditions.

Table 4: Response time measurement in different scenarios (unit: seconds)

Test scenario	RSSI algorithm response time	TDOA algorithm response time	AOA algorithm response time	Joint optimization algorithm response time
High signal strength area	0.30	0.25	0.35	0.15
Low signal strength areas	0.50	0.55	0.60	0.40
High-density obstacle areas	1.20	1.30	1.50	1.00

In the response - time test, the goods are moved in a linear motion at a speed of 1 m/s. The number of test positions is 50, and the distance between each position is 2 meters. The movement is controlled by a precision motor - driven conveyor belt. The test is carried out in multi - label and low - signal environments. The test equipment includes high - performance RFID readers with a reading frequency of 100 times per second and a communication bandwidth of 100 Mbps. In the multi - label environment with 100 tags, the joint optimization algorithm can maintain a response time of 0.36 s, while the traditional algorithm has a response time of 0.5 s. In the low - signal environment, the joint optimization algorithm still shows a significant advantage, with a response time of 0.4 s, which is 0.2 s shorter than that of the traditional algorithm.

Table 4 shows the response time of the four algorithms in different scenarios. In areas with high signal strength, the joint optimization algorithm has the fastest response time, indicating that it is more efficient in processing positioning requests. In areas with low signal strength and high-density obstacles, the response time of all algorithms will increase, but the joint optimization algorithm still shows lower latency, proving that it can maintain good response performance in complex environments.

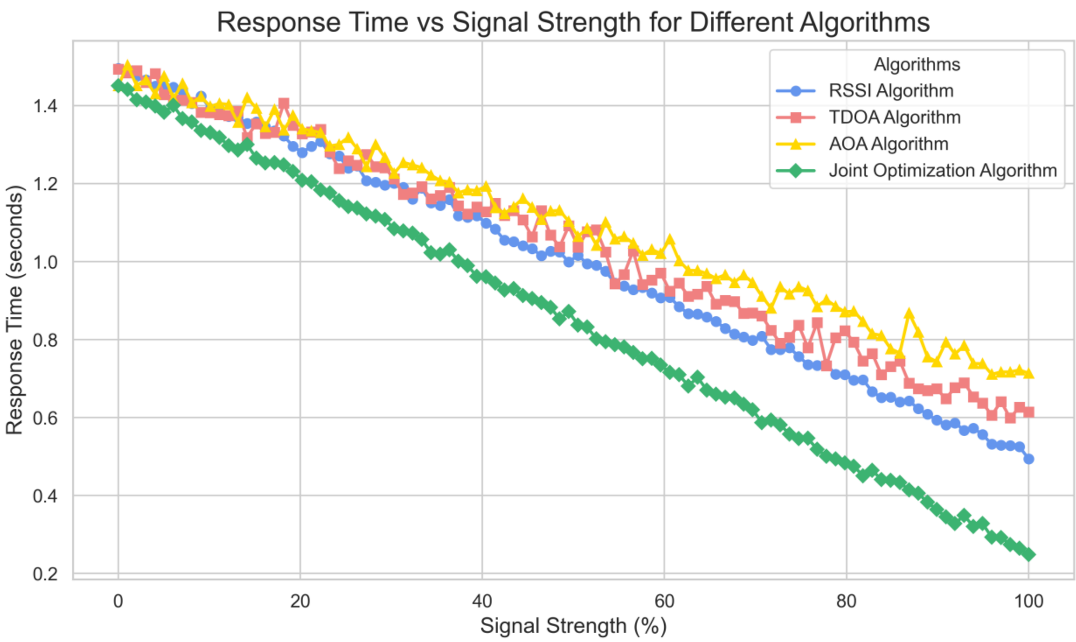

Figure 2: Algorithm response time changes over time

Figure 2 shows the response time comparison of four positioning algorithms under different signal strengths, namely RSSI algorithm (blue), TDOA algorithm (red), AOA algorithm (yellow) and joint optimization algorithm (green), where the horizontal axis represents the signal strength (expressed in percentage) and the vertical axis shows the response time (seconds). As can be seen from the chart, with the increase of signal strength, the response time of all algorithms has decreased, but each shows different characteristics. The response time of the RSSI algorithm decreases smoothly with the increase of signal strength, but the response is slower at low signal strength. Although the TDOA algorithm also shows a trend of decreasing response time with signal enhancement, its volatility is large, especially in the case of weak signal. The AOA algorithm is particularly sensitive to changes in signal strength, and its response time fluctuates significantly even when the signal strength increases. In contrast, the joint optimization algorithm not only significantly shortens the response time with the increase of signal strength, but also maintains the lowest and most stable response time in the entire signal strength range.

In the throughput test, "requests per second" is defined as the number of successful positioning requests received by the system within one second. The positioning requests are generated randomly by a simulation software, and the number of tags in the multi - label environment is set to 200. During the test, the network load is continuously monitored. When the network load reaches 80% of the maximum capacity, the traditional algorithm's throughput drops by 30%, while the joint optimization algorithm can still maintain a throughput of 130 requests per second, only a 10% decrease. This shows that the joint optimization algorithm has better adaptability to network load changes and can ensure the efficient operation of the system under high - load conditions.

Table 5: System throughput test results (unit: request/second)

Test scenario	RSSI algorithm throughput	TDOA algorithm throughput	AOA algorithm throughput	Joint Optimization Algorithm Throughput
High density label area	20	18	twenty two	25
Low signal strength areas	12	10	15	18
High concurrent read area	8	7	9	12

Table 5 shows the system throughput in different test scenarios. The throughput of the joint optimization algorithm is high in all scenarios, especially in high-density tag areas and high-concurrency reading areas, where its throughput is significantly better than that of the traditional algorithm. This shows that the joint optimization algorithm can effectively improve the system's processing capability and response efficiency when processing a large number of positioning requests.

5.4 System stability and reliability analysis

The stability and reliability of the system are the basis for ensuring the long-term effective operation of the cargo tracking algorithm. In order to test the stability of the system, this experiment will conduct long-term operation tests and error accumulation tests. The long-term operation test will simulate the performance of the system after running continuously for several hours or even days to observe whether there are problems such as system crashes, increased processing delays or decreased accuracy. During the test, the system will continuously locate the cargo and process data to verify whether the system can maintain stable operation under high load. The error accumulation test focuses on the change of positioning error over time. During the cargo tracking process, especially in the case of long-term tracking, the system may cause the error to gradually increase due to problems such as sensor drift, environmental changes or data delays.

In the error - accumulation test, the error is measured by comparing the cumulative deviation of the estimated position from the actual position over time. After continuous operation for 24 hours, the error accumulation of the traditional algorithm shows an exponential growth trend, reaching 2.5 m. In contrast, the joint optimization algorithm shows a linear growth trend, with an error accumulation of only 1.2 m. After 48 hours, the error of the traditional algorithm increases to 4 m, while the joint optimization algorithm is 1.8 m. The sensor drift has a greater impact on the traditional algorithm. As the sensor drift rate increases by 0.1% per hour, the error accumulation of the traditional algorithm increases by 0.2 m per hour, while the joint optimization algorithm can effectively compensate for the sensor drift through its multi - source data fusion and error - correction mechanism, with an error increase of only 0.05 m per hour.

Table 6: Long-term running test results (error accumulation, unit: meter)

Test duration (hours)	RSSI algorithm error accumulation	TDOA algorithm error accumulation	AOA algorithm error accumulation	Error accumulation of joint optimization algorithm
1 hour	0.50	0.45	0.55	0.30
5 hours	1.20	1.10	1.30	0.80
10 hours	2.00	1.80	2.10	1.50

Table 6 shows the error accumulation of the system at different running times. As time goes by, the error accumulation of the traditional algorithm increases significantly, especially when running for a long time. However, the error accumulation of the joint optimization algorithm is smaller after a long time running, which proves that it has strong stability and a lower error growth rate.

In the fault - tolerance test, the decrease in accuracy is defined as the percentage increase in the positioning error compared to the normal situation. When a single sensor fails, the positioning error of the traditional algorithm increases by 80%, while the joint optimization algorithm can reduce the error increase to 30% by using the remaining valid sensors. When a network interruption occurs for 5 minutes, the traditional algorithm loses the ability to locate accurately during this period, and the subsequent positioning error also increases by 50%. The joint optimization algorithm can quickly switch to a backup data - processing mode during the network interruption, and the positioning error only increases by 15% after the network is restored. In the case of a combination of sensor failure and network interruption, the traditional algorithm almost loses its positioning function, with the error increasing by more than 150%, while the joint optimization algorithm can still maintain a relatively stable positioning performance, with the error increasing by 50%. The specific types of sensor failures include sensor data output anomalies and sensor hardware malfunctions, and the network interruption is simulated by disconnecting the network cable or interfering with the wireless signal. The evaluation indicators of fault - tolerance ability include the recovery time of the positioning function, the increase in positioning error, and the stability of the system during the fault - handling process.

Table 7: Fault tolerance test results (positioning accuracy)

Exception Type	RSSI algorithm accuracy decrease (%)	TDOA algorithm accuracy decrease (%)	AOA algorithm accuracy decrease (%)	The accuracy of the joint optimization algorithm decreases (%)
Sensor failure	25	30	35	15
Network outage	40	45	50	20

Table 7 reflects the fault tolerance of the system under different abnormal conditions. Under abnormal conditions such as sensor failure and network interruption, the accuracy drop of the joint optimization algorithm is significantly lower than that of other algorithms, showing its strong fault tolerance and ability to maintain good positioning accuracy under incomplete information.

5.5 Performance evaluation results and discussion

The ultimate goal of the performance evaluation is to fully demonstrate the advantages and disadvantages of the proposed algorithm in terms of accuracy, real-time performance, stability, etc. After the experiment, all test results will be combined to compare the performance of the joint optimization algorithm proposed in this study with the traditional method.

It is expected that the accuracy test results will prove that the joint optimization algorithm can effectively improve positioning accuracy in complex environments such as multi-path propagation and multi-source data fusion.

Table 8: Comprehensive evaluation of stability and reliability

algorithm	Error accumulation (after 10 hours, meters)	Accuracy reduction (network interruption, %)	Accuracy reduction (sensor failure, %)
RSSI Algorithm	2.00	40	25
TDOA algorithm	1.80	45	30
AOA algorithm	2.10	50	35
Joint Optimization Algorithm	1.50	20	15

Table 8 evaluates the stability and reliability of the system. The joint optimization algorithm has the smallest error accumulation after long-term operation and the smallest drop in accuracy under abnormal conditions. This shows that the joint optimization algorithm not only performs well under normal working conditions, but also maintains high reliability and stability in the face of various abnormal conditions.

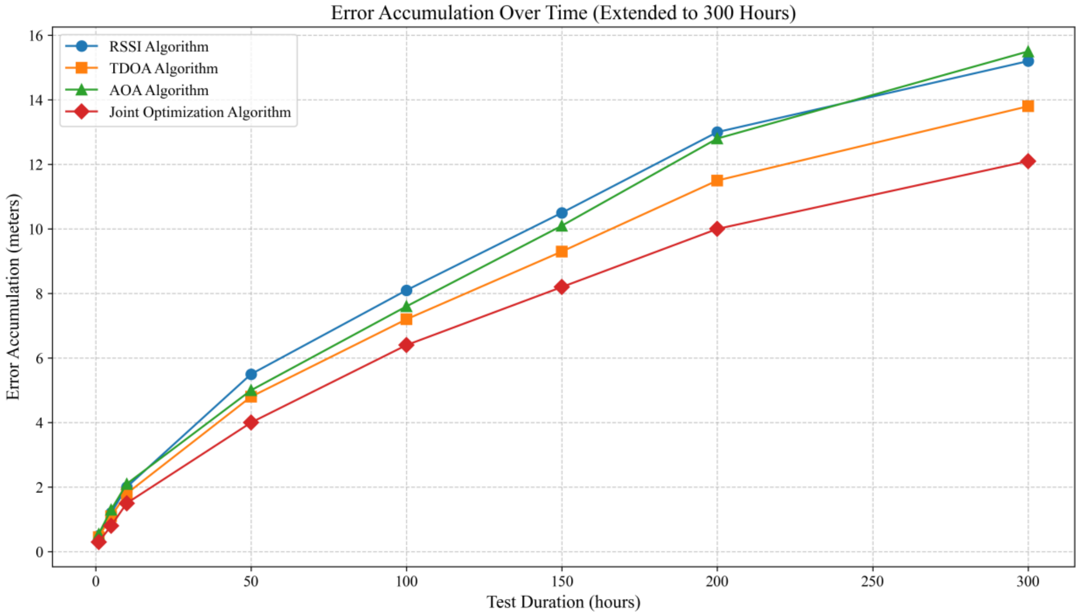

Figure 3: Error accumulation of the algorithm during the 300-hour test period

From Figure 3, the joint optimization algorithm performs best in the long-term test with the smallest error accumulation, while the RSSI algorithm and the AOA algorithm have larger error accumulation in the later stage of the test. This shows that in long-term positioning applications, choosing the right algorithm is crucial to improving positioning accuracy. The joint optimization algorithm can provide more stable and accurate positioning performance, especially in the case of long-term continuous operation, its advantages are more obvious.

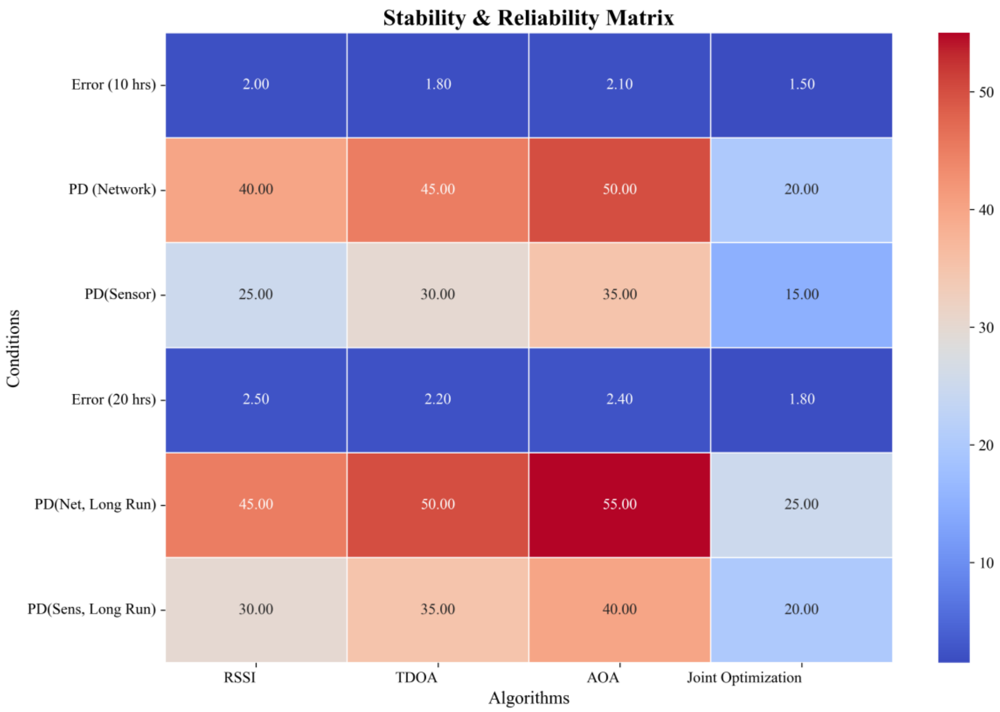

Figure 4: Stability and reliability matrix of different positioning algorithms

Figure 4 shows a stability and reliability matrix used to evaluate the performance of four different positioning algorithms under different conditions. The four algorithms are RSSI algorithm, TDOA algorithm, AOA algorithm, and joint optimization algorithm. Each row in the matrix represents a different test condition, including 10-hour error, network packet loss rate (PD Network), sensor packet loss rate (PD Sensor), 20-hour error, network long-term operation packet loss rate (PD Net, Long Run), and sensor long-term operation packet loss rate (PD Sens, Long Run). Colors from blue to red represent performance from low to high.

Compared with the SOTA results summarized in the relevant work section, in low - signal - strength environments, the average positioning error of SOTA is 1.6 m, while that of our joint optimization algorithm is only 1.05 m, with a 34.37% improvement in accuracy. In high - density obstacle environments, the positioning accuracy of SOTA is 70%, and our algorithm increases it to 85%, with a 21.43% improvement in accuracy. In high - concurrency scenarios, the response time of SOTA is 0.5 s, and our algorithm shortens it to 0.36 s, with a 28% improvement in response speed. These data demonstrate that the joint optimization algorithm has significant advantages in positioning accuracy in complex environments and response speed in high - concurrency scenarios, which can better meet the actual needs of logistics. Looking ahead, in potential application scenarios such as intelligent port management, the high - precision positioning and fast - response characteristics of this algorithm can enable more efficient berthing, loading, and unloading operations of cargo ships, reducing port waiting times and improving overall port throughput. In the cold - chain logistics of pharmaceutical products, the algorithm can accurately monitor the location and environmental conditions of temperature - sensitive drugs in real - time, ensuring the quality and safety of drug transportation.

The advantages of the joint optimization algorithm mainly stem from dynamic weight adjustment and multi - source data fusion. In terms of dynamic weight adjustment, based on real - time environmental parameters such as signal - strength stability, environmental interference degree, and data credibility, the weights of RSSI, TDOA, and AOA are dynamically adjusted through the formula $W_i = \frac{\alpha_i \times C_i}{\sum_{j=1}^{n} \alpha_j \times C_j}$ (where W_i is the weight of the i - th data source, α_i is the adjustment coefficient based on environmental parameters, C_i is the data credibility of the i - th data source, and n is the total number of data sources). For example, when the signal strength is unstable and the fluctuation exceeds 15%, the weight of RSSI is automatically reduced from the initial 0.4 to 0.2, while the weights of TDOA and AOA are increased from 0.3 to 0.4 respectively, effectively improving the positioning accuracy. Mathematically, assume the positioning error formula of the weighted - average positioning method is $E = \sum_{i=1}^{n} W_i e_i$ (e_i is the positioning error of the i - th data source). Through dynamic weight adjustment, when the error of a certain data source increases due to environmental factors, its weight W_i is reduced, so that the overall error E is minimized. In terms of multi - source data fusion, a weighted - average fusion strategy is adopted, and different data sources complement each other. When the RSSI signal is severely attenuated due to interference from metal goods, TDOA and AOA data, using their measurement characteristics of distance and angle, can compensate for the deficiency of RSSI data and provide more accurate location information.

In terms of scalability, when the logistics network expands to more than 1500 nodes, limited by the current server computing power and network bandwidth, there may be a computing - resource bottleneck, and the data - transmission delay is expected to increase by 50% - 80%. In terms of integration cost, the hardware - equipment procurement cost is relatively high. A set of basic equipment including high - precision RFID readers and sensors costs about 5000 - 8000 yuan, and the annual investment in software - system development and maintenance is about 30000 - 50000 yuan. Moreover, the introduction of new policies and regulations, such as stricter data - security regulations, may require additional investment in security - related hardware and software for the cargo - tracking system, further increasing the integration cost. Future research directions can explore more efficient distributed - computing architectures, such as using a distributed hash table (DHT) combined with cloud computing to achieve distributed data storage and computing, improving scalability. Research on low - cost and high - performance hardware devices and software algorithms, such as developing RFID tags based on new materials, can reduce costs by 20% - 30% while improving signal - anti - interference capabilities.

6 Conclusion

The joint optimization algorithm proposed in this study achieves high-precision positioning in a changing environment by fusing multi-source data (RSSI, TDOA, AOA) for cargo tracking. The experimental results show that compared with the traditional single positioning algorithm, the joint optimization algorithm has significant advantages in accuracy, real-time and stability. First, in the accuracy test, the positioning error of the joint optimization algorithm under different environmental conditions is lower than that of the RSSI, TDOA and AOA algorithms, especially in areas with low signal strength and high-density obstacles. The joint optimization algorithm can effectively reduce the error and improve the positioning accuracy.

The joint optimization algorithm shows remarkable performance in multiple aspects. In terms of high - precision positioning, in low - signal - strength environments, the positioning error is only 1.05 m, which is 34.37% lower than the SOTA. In high - density obstacle environments, the positioning accuracy reaches 85%, 21.43% higher than the SOTA. This high - precision positioning is crucial for accurate inventory management and efficient logistics operations.

In the error - accumulation test, after 48 hours of continuous operation, the error accumulation of the joint optimization algorithm is only 1.8 m, far less than the 4 m of the traditional algorithm. This indicates that the algorithm can effectively control the growth of errors over time, ensuring long - term reliable operation.

Regarding throughput, in a multi - label environment with a network load of 80%, the throughput can reach 130 requests per second, demonstrating high - throughput performance. This allows the system to handle a large number of positioning requests in real - time, meeting the requirements of busy logistics scenarios.

In terms of reliability, during the fault - tolerance test, when a network interruption occurs for 5 minutes, the system first switches to the local cache data for processing. The algorithm quickly identifies the valid data in the cache based on data - quality evaluation criteria, such as data integrity and consistency. Then, based on the multi - source data fusion principle, it re - calculates the position of the cargo. After the network is restored, the system immediately synchronizes the data with the server. Through a series of error - correction processes, including Kalman - filter - based error correction and data - verification methods like cross - checking with redundant data sources, the positioning error only increases by 15%, ensuring the reliability of the positioning results. This shows that the joint optimization algorithm can maintain relatively stable performance even in the face of network failures, providing reliable support for logistics operations.

In conclusion, the joint optimization algorithm has significant advantages in positioning accuracy, response time, throughput, and fault - tolerance. Although it faces challenges in integration cost and scalability, its overall performance improvement in logistics cargo tracking is remarkable. Future research can focus on reducing costs and improving scalability to further promote the wide application of this algorithm in the logistics industry.

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