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Internet of Things Multi-area Monitoring Application Research by Integrating Data Warning and Blind Area Data Processing

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In the context of the rapid development of Internet of Things technology, improving the efficiency and accuracy of multi-area monitoring systems has become an important issue. This study aims to address the shortcomings of traditional monitoring systems in blind spot data processing and reduce resource consumption. By constructing a model based on RFID and finite state machine, and integrating probabilistic methods, a comprehensive data warning and blind spot data processing multi-area monitoring model for the Internet of Things has been formed. The results showed that the labels were randomly distributed within a range of 0-20 meters and moved at a speed of 2 meters per second. Under the change in the proportion of the main monitoring area from 0 to 1, warning time windows of 3 seconds, 5 seconds, and 7 seconds were applied. The experimental results showed that when the main monitoring area was 0%, the data capture efficiency of the 7-second window was the highest. Within a 180 second monitoring cycle, the number of alarms exceeding 10 seconds in the inner blind spot was 12, and the number of alarms exceeding 10 seconds in the outer blind spot was 6. The total number of alarms reached 18. Among the 35 predicted alerts, the 7-second window had the lowest warning error rate. The results demonstrate the effectiveness of this method in reducing early warning error rates in multi region monitoring, and its performance is superior to traditional fixed time window settings. This study provides a new and efficient solution in the field of multi-area monitoring in the Internet of Things.

Povzetek: Študija obravnava izboljšanje delovanja večobmočnih nadzornih sistemov IoT z uporabo modela, ki združuje obdelavo podatkov slepih območij in opozarjanja.

1 Introduction

With the rapid development and widespread application of Internet of Things (IoT) technology, new challenges have been posed for effective monitoring in complex environments. Especially in the field of multi region monitoring, how to accurately and efficiently process a large amount of data has become a key issue. Currently, IoT monitoring systems are generally facing issues such as how to process and analyze blind spot data within the monitoring area, and how to reduce excessive consumption of system resources [1-3]. In the processing of blind spot data, traditional monitoring systems often suffer from issues such as inaccurate data recognition and delayed response time, which not only affects monitoring efficiency but also increases system operating costs. In addition, the imperfect data processing and warning mechanisms in multi region monitoring systems make it difficult to ensure the accuracy and real-time performance of monitoring results. Therefore, studying how to optimize IoT monitoring systems, especially in multi-area monitoring environments, has become an urgent task [4-6]. In response to these challenges, this study proposes a new multi-region monitoring model. Firstly, a basic model of Radio Frequency Identification (RFID) technology and Finite State Machine (FSM) is constructed. Then, in order to better process blind spot data and improve monitoring efficiency, probabilistic models were introduced to optimize and improve the RFID model. Through this method, the study successfully integrates data warning and blind spot data processing, forming a comprehensive multi-area monitoring model. The overall structure of the study includes four parts: The first part summarizes the relevant research achievements and shortcomings of RFID and the IoT at home and abroad. In the second part, the study first constructs a model based on RFID and FSM, and integrates probability methods to form a comprehensive data warning and blind spot data processing multi-area monitoring model for the IoT. The third part is to compare and analyze the proposed model through research experiments. The fourth part summarizes the experimental results, points out the shortcomings of the research, and proposes future research directions.

2 Related works

Wireless RFID technology, as a key component of the development of the IoT, has an increasingly wide range of applications, especially playing a crucial role in multi-area monitoring systems. RFID technology achieves automatic object recognition and data collection through wireless waves, providing efficient data collection and processing capabilities for the IoT [7]. The following introduces some related research by scientists and scholars. Zhu proposed the integration of wireless sensor networks and RFID technology to solve the problem of energy imbalance and design and improve the network structure. An RFID system was developed based on ZigBee, and hardware interfaces and communication protocols were studied. Data were collected through environmental collection terminals, and GPRS technology was combined to achieve data aggregation and transmission. The monitoring system was based on the B/S architecture and was experimentally validated to improve efficiency and accuracy [8]. Tran et al. proposed a battery free device for collecting and processing electrocardiogram signals, which was composed of passive hyper RFID tags and RF energy harvesters. The RF collector operated at 902-928 MHz, providing power to the system within a maximum of 2 meters. Algorithms were used to extract the r-peak of the electrocardiogram signal and it was stored in the tag ID. The reader collected r-peak data at a sampling rate of 100ms, and the system performance provided a new solution for healthcare applications [9]. Meng et al. proposed RFID and sensing technologies to improve the efficiency and convenience of data collection and integration in the industrial IoT. They introduced the basic knowledge of RFID, including RF energy collection and communication interfaces. The study showed an RFID based industrial monitoring and data integration system. The advantages of RFID in online sensing and expanding industrial IoT information links were elaborated, providing adaptability in industrial process control and integration [10]. Qian et al. proposed a new flexible RFID sensor label suitable for non-contact liquid analysis. The tag was powered and interrogated through the built-in high-frequency RFID module of the smartphone. By using a battery-free sensing and energy-saving hardware solution with high-frequency RFID on smartphones and near-field communication data transmission, measurements could be made without the need for additional software. The experimental results and quantitative analysis verified the effectiveness of this method [11].

Bouzaffour et al. proposed that RFID sensors were based on the coupling between the antenna of a dipole RFID tag and a layer of steel exposed to chloride in concrete. The intensity of the received signal measured by the reader indicated changes in the air from two sources, namely the moisture level of the concrete and the presence of a steel layer. By minimizing the impact of seawater on antenna performance, the presence of metal films with a thickness of several micrometers was detected [12]. Khadka et al. proposed detection and physical layer security regulations for printed sensor label systems in IoT applications. This printed chipless RFID sensor tag had the characteristics of complete printability, non line of sight reading, low cost, and environmental robustness, which helped accelerate the development of the intelligent world of the IoT. Experiments showed that the system effectively detected and recognized the unique physical properties of labels [13]. Tzitzis et al. proposed a method for three-dimensional positioning of ultra-high frequency RFID tags using mobile robots. This method was based on the extension of phase re-locking in three-dimensional space, collecting phase measurement data through at least two antennas to form a multi-antenna synthetic aperture. Confidence measures were introduced to identify and eliminate measurement data that may reduce estimation accuracy. The results indicated that the estimated time for each label was only 0.17 seconds on a regular laptop, with better accuracy and computational speed than existing technologies [14]. Chen et al. proposed a compact circularly polarized ultra-high frequency RFID tag antenna design based on complementary split ring resonators, manufactured using 3D printing technology. By measuring the reading range, the real and imaginary parts of the complex dielectric constant of the liquid were extracted from specific frequency points. The circular polarization of the antenna achieved a large reading range and miniaturization size. The results indicated that the complex relative permittivity of liquids with real parts ranging from 1 to 81 was extracted at a distance of 1.97 meters [15].

Mellit et al. designed a novel embedded PV system remote monitoring and fault diagnosis system, which employs an artificial neural network with an overlay of integrated learning algorithms. The results showed that the method could effectively realize the diagnosis and monitoring of PV arrays [16]. To ensure efficient data transmission and privacy protection in cloud-based public auditing of IoT data transmission, Gai et al. designed an identity-based privacy-preserving public auditing scheme, which achieved efficient data transmission in IOT and ensured the privacy of the data owner's identity [17]. IoT was well used in real-time monitoring and evaluating the operating conditions of complex mechanical systems. Zhao et al. developed a monitoring system for amusement rides based on devices with IoT technology and sensor networks. It aimed to provide timely warnings when monitoring signals auto-scaling. It integrated a the normal range or violate relevant standards [18]. In response to the growing demand for remote patient monitoring, Alasmary designed a scalable digital health framework by integrating health solutions with latency-aware edge computing auto-scaling. It integrated a scalable IoT-based architecture and an innovative microservice auto-scaling strategy in edge computing. Experimental results showed that the approach was highly accessible, cost-effective and responsive to patient needs [19].

The results of the related research work are summarized in Table 1. In summary, although many previous experts and scholars have conducted in-depth research on the application of RFID technology in the field of IoT monitoring and successfully applied it to multiple industries, there is still relatively little research on multi-area monitoring, especially blind spot data processing and early warning accuracy. There are still shortcomings in existing research in improving monitoring efficiency and reducing resource consumption, which are particularly evident in complex monitoring environments and often lack universality. To achieve reasonable and efficient improvement of multi region monitoring, this study has built a multi region monitoring model that combines RFID technology and FSM. This study has positive significance for improving the overall performance of the IoT multi-area monitoring system.

Table 1: Summary of related research work

Literature code	Method	Main contributions and advantages	Result
[7]	RFID	A review was conducted on RFID based wireless manufacturing systems	RFID plays a crucial role in multi area monitoring systems
[8]	Wireless sensor network, RFID, ZigBee	Solved the problem of energy imbalance injection into the network and increased the communication scale	The efficiency and accuracy of monitoring system software design have been improved
[9]	Battery free sensing and computing device composed of passive ultra-RFID tags and RF energy harvesters	The circuit has low power consumption, strong algorithm robustness, and short processing time	User applications can monitor heart rate variability
[10]	Ultra high frequency dual-mode RFID sensor solution	Efficiency and convenience improvement in data collection and integration	RFID has advantages in online sensing and expanding industrial IoT information links
[11]	New flexible RFID sensor tag	Using near-field communication data transmission method, measurement can be conveniently carried out on smartphone devices without the need to add software	This method is feasible
[12]	Concrete embedded sensor	Minimize the impact of seawater on antenna performance	The presence of metal thin films with a thickness of several micrometers can be detected.
[13]	Robust tag detection technology based on deep learning and RFID	Physical layer security	Unique physical properties that can detect and identify tags
[14]	Three-dimensional positioning of ultra-high frequency RFID tags	Better accuracy and computation time	Robots can create maps of unknown environments
[15]	Compact circularly polarized ultra-high frequency RFID tag antenna based on complementary split ring resonator	Implemented a larger reading range and miniaturization of antenna size	The complex relative permittivity of liquids with real parts between 1 and 81 can be extracted from a reader at a distance of 1.97 meters
[16]	Remote monitoring and fault diagnosis system for embedded photovoltaic system based on artificial neural network	Better monitoring and diagnostic performance	Can effectively diagnose and monitor photovoltaic arrays
[17]	Identity based privacy protection public audit scheme	Efficient data transmission and privacy protection	Efficient data transmission for IoT can be achieved while ensuring the identity privacy of data owners
[18]	IoT technology and sensor networks	Filling the gap in application technology	Timely warning can be given when the monitoring signal deviates from the normal range or violates relevant

[19]	Health solution and delay aware edge computing auto scaling integration	Strong accessibility, cost-effectiveness, and responsiveness	standards Real time IoT for remote patient monitoring

3 Multi-Area monitoring model for the iot integrating data warning and blind area data processing

The study first constructs RFID and FSM models, and based on this, proposes a multi region monitoring FSM model. Due to the challenges of blind spot data processing, probabilistic models are introduced and RFID models are improved. Finally, a multi-area monitoring model for the IoT is formed that combines data warning and blind spot data processing.

3.1 Construction of FSM model for multi-area monitoring of data processing based on wireless radio frequency identification

The IoT technology has greatly promoted mobile material tracking and intelligent data management through intelligent data collection and analysis. In this field, wireless RFID technology plays a crucial role, integrating microelectronics, computer systems, data storage, and wireless communication. The core components include readers, tags, and backend systems. Each label has a unique identifier, making it easy to attach to items for effective tracking and management. Its working principle is that the reader emits energy to the tag, while the tag returns data. When processing labels within a specific area, traditional models rely on a triplet structure, as shown in Equation (1).

$$< EPC, Position, Timestamp > \quad (1)$$

In Equation (1), ETC is the RFID code on a moving object, $Position$ is the location of the reader and is determined by its network and port address. $Timestamp$ represents the moment when the record label is read. When monitoring multiple regions, the data structure is extended to a composite model, as shown in Equation (2).

$$< Id, Area, Timestamp, Position > \quad (2)$$

In Equation (2), Id is the unique identifier of the moving object, $Area$ is to the monitoring area it is located in and is determined by the reader range. $Timestamp$ records the time when the object is detected, and $Position$ is determined by the global positioning system within the region to determine the possibility of connectivity between regions. This model extends the infrastructure of wireless RFID by adding multi region monitoring and constraint relationships between regions. By examining the positional relationships between objects in different regions, it is possible to determine whether they can be transferred to other regions. The proximity relationship between regions can be divided into adjacent and separated [20].

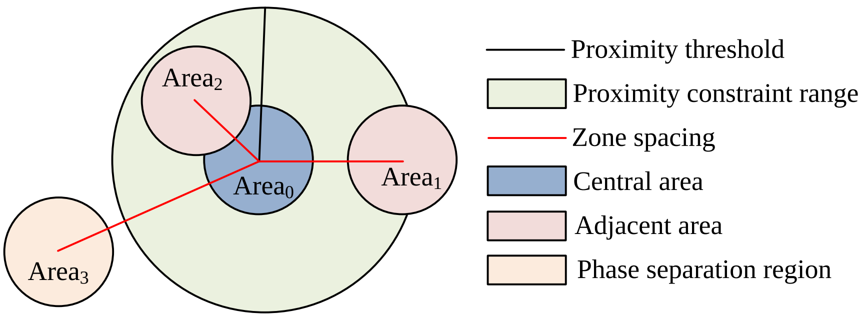


Figure 1: The definition of the area proximity diagram

Fig. 1 illustrates the definition of regional criticality: assess whether the monitoring area is connected, and then determine whether the area is connected or separated, which determines the migration of mobile entities. If the distance between the center of the region is below the threshold, it indicates connection. If it exceeds the threshold, it indicates separation. During monitoring, the area can be moved or static. Isolation of non critical relationship areas, entities leaving cannot enter other areas, and a brief departure is considered a violation. When there is a critical relationship, entities may migrate across regions, increasing migration time to reduce false positives. The study uses FSM to process data, track entities' perception, constraints, and pre state between regions, predict the current state, and ensure accurate monitoring. FSM includes states, transitions, events, and actions. For example, when an entity is detected in a region, its status is region monitoring. When leaving the area, the status changes to leaving the monitoring area, the event is signal loss. Moreover, the action is system status update, data transmission to the server, and judgment warning. A multi-area monitoring FSM model consisting of five elements is constructed, as shown in Equation (3).

$$M = (S, \Sigma, f, S_0, Z) \qquad (3)$$

In Equation (3), S represents a set of states that contain different states. Σ is an input set that collects basic information about the moving medium, such as number, area, proximity status, and previous sensing status. f is a state transition function that defines the response of a state to an input. S_0 is the initial state, indicating that the medium is not activated and has not been detected by the reader. Z is a failure state, which means that the medium cannot be detected again. As shown in Fig. 2, the process of state migration media from never activating to label invalidation is shown. After the label is activated, the medium enters the area for monitoring. Within a region, the time state continues. When the medium changes the region, the region state changes, and the time state also updates accordingly. Once the medium has vacated the area, and if it is not detected beyond the designated warning period, it will enter the warning state.

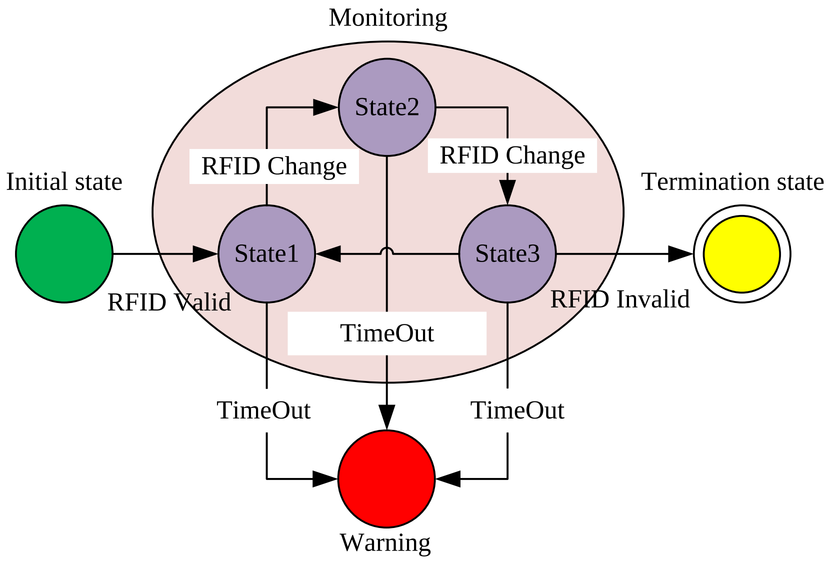


Figure 2: State transition process diagram

Fig. 3 shows the structure of the multi region monitoring FSM model. In each monitoring area, the system includes industrial computing equipment, wireless RFID tools, and display units. It is mainly used to collect and process information about moving objects. Firstly, preliminary cleaning and logical analysis of the data are carried out, and then these data are uploaded to the cloud platform to determine the final state of the moving object data while capturing key activity states. This final status information will be displayed on display devices and central monitoring stations in various regions. It is important to note that the initial inference of moving objects within the region is not their final state. The data of moving objects is first processed locally, and then uploaded to the server for further processing and synchronization to ensure the accuracy and integrity of the final data [21-22].

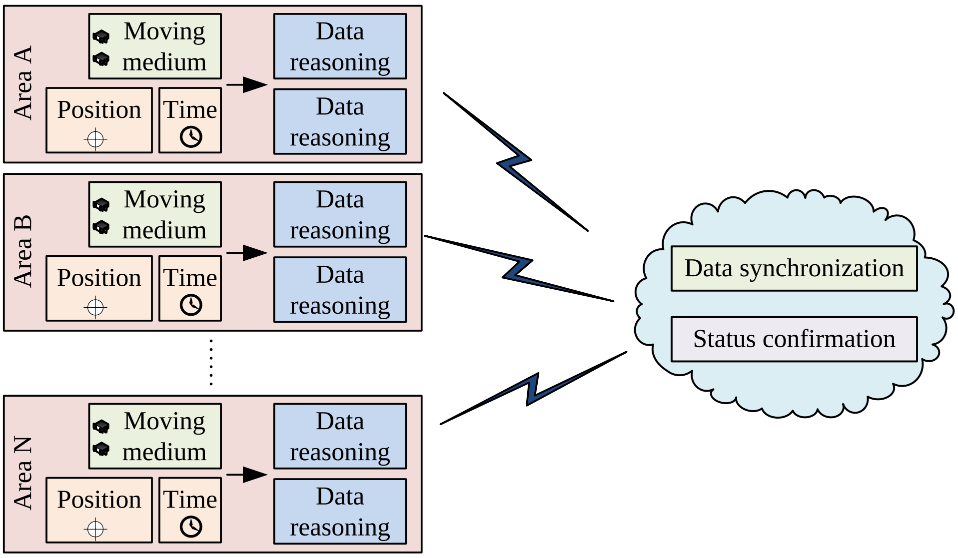


Figure 3: Monitor the FSM model in multiple regions

3.2 Construction of blind area data warning model based on RFID probability

Due to the need to clean the data captured by RFID technology before applying it to advanced systems to avoid increasing the complexity and resource consumption of backend system design, further research has proposed improving RFID. This includes handling missing or excessive data, using probability theory to design warning mechanisms to reduce false alarms, and finally developing multi-area monitoring FTM warning algorithms with processed data to accurately analyze the monitoring status of mobile media. Due to the complexity of the environment (e.g., obstacles, multipath effect, mutual interference between tags, etc.) and the fact that tags can momentarily move out of range of the reader, resulting in the problem of tag misreading or signal loss. To improve the reading efficiency and accuracy of the RFID system, the study uses the sliding window technique for smooth reading. The sliding window technique is a method of repeated reading and data processing of RFID tags in multiple consecutive reading cycles. It can capture tag information that is not read immediately due to transient occlusion or positional changes. The operation process is shown in Fig. 4.

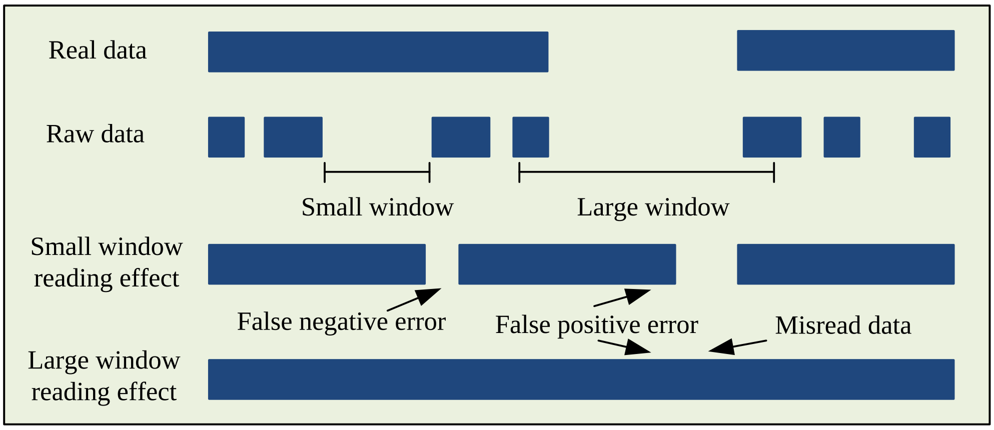


Figure 4: Comparison of misread data and missed read data for large and small windows

To solve the problem of RFID tag reading, this study uses probability techniques to adjust the reading window. The label reading in this window is considered as a random sample and dynamic window adjustment is implemented. The window period w_i of the label i is defined as a specific time period W_i. Based on the current time t, if w_i is a reading cycle, W_i is represented as $(t-w_i)$. S is the label data actually captured in the window i. Based on these parameters, the equation for the average probability p_i^{avg} of W_i inner labels i is shown in Equation (4).

$$p_i^{avg} = (\frac{1}{S_i}) \times \sum_{t \in S_i} p_i \tag{4}$$

If a moving medium is detected within a W_i time range in S_i, the label i follows a binomial distribution of $|S_i|$ times. This indicates that the behavior of the labels during the W_i period follows a binomial distribution $B(w_i, p_i^{avg})$, and the relevant equation of $|S_i|$ is shown in Equation (5).

$$\begin{cases} E[|S_i|] = w_i g p_i^{avg} \\ Var[|S_i|] = w_i g p_i^{avg} g (1 - p_i^{avg}) \end{cases} \tag{5}$$

In stable areas, expanding the window ensures capture, while shrinking the window improves capture accuracy when labels may leave. The goal is to fully read the label within a large time window, with a reading probability of each cycle set to p_i^{avg}. According to the set threshold, calculate the likelihood of successful tag reading within the time frame, as shown in Equation (6).

$$(1 - p_i^{avg}) \le \delta \tag{6}$$

Through the calculation of Equation (6), when the window w_i size reaches a specific condition, it can ensure that the label is successfully captured by the reader during this window period. The specific expression is shown in Equation (7).

$$w_i \ge \left\lceil \frac{\ln(1/\delta)}{p_i^{avg}} \right\rceil \tag{7}$$

In Equation (7), δ is a decimal number close to 0, which has little impact on the result and is usually set to be less than 0.1. The sliding average update and read frequency method is an effective approach for accurately capturing labels. By adjusting the window size, this method employs over-detection technology to circumvent label leakage issues that may arise due to a large window. When the probability of tag reading decreases, the window is narrowed to reduce false positives. This process is based on the binomial distribution, observing the deviation within the time window. If the label does not move significantly within the window, its expected value is determined by Equation (8).

$$\pm 2\sqrt{Var[|S_i|]} \tag{8}$$

When the changes detected by the reader meet specific conditions, it is determined that the label has undergone transition detection within the current time window. The specific conditions are shown in Equation (9).

$$||S_i| - w_i p_i^{avg}| > 2 \cdot \sqrt{w_i p_i^{avg} (1 - p_i^{avg})} \tag{9}$$

Label probability and window size adjustments are utilized to ensure that labels are accurately read within the region. When the label undergoes excessive transfer, the time window is narrowed for precise capture. Although this method reduces missed reads, it may lead to false positives when the moving medium is at the edge of the area or obstructed by obstacles. For multi-area mobile monitoring, this method needs to be more tolerant of blind spots in data processing and inference. As shown in Fig. 5, when mobile media detaches from monitoring within a single area, immediate warning is required, while in multi-area handover or internal blind spots, no warning can be given temporarily [23-24].

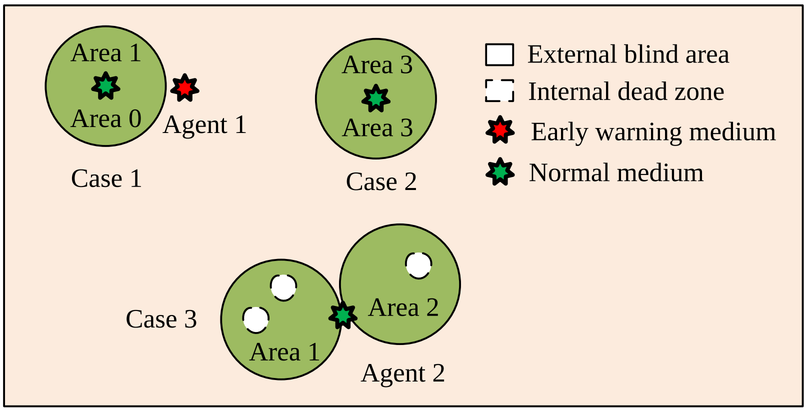


Figure 5: Multi-area monitoring and early warning scenario

In a multi-area early warning system, the adaptive window is adjusted according to a preset threshold to capture labels within the area. Uncaptured tags trigger an alert, limiting window size to prevent infinite growth. In single area monitoring, the departure of moving media reduces the read probability, while in multi-area monitoring, attention is paid to inter area movement. Mobile media that does not appear in other areas for a long time is considered as leaving. False alarms are reduced by setting a maximum threshold and maintain unique label states. The probability model for label recognition is shown in Fig. 6.

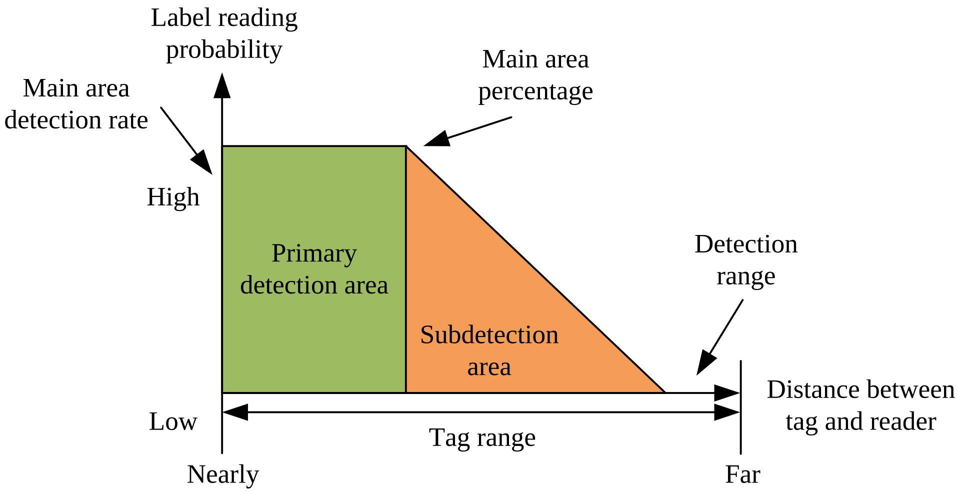


Figure 6: Label recognition probability model

According to Fig. 6, the calculation method for the recognition rate of labels can refer to Equation (10).

$$P(D)=\begin{cases}1-\dfrac{1-p_h}{r_2}\times D, D\in(0,r_1)\\ \dfrac{p_1}{r_1-r_2}\times D-\dfrac{p_1\times p_2}{r_1-r_2}, D\in(r_1-r_2)\end{cases} \quad (10)$$

In Equation (10), D represents the distance between the reader and the moving medium, p_h and p_i represent the reading probability of the primary and secondary detection areas, and r represents the radius of the monitoring area. The data processing indicators include raw data, namely directly captured labeled data, and effective data, namely mobile media data with unchanged regions and states. The data compression efficiency is shown in Equation (11).

$$\begin{aligned}&CompressionRation=\\&EffectiveData/RawData\end{aligned} \quad (11)$$

The calculation of average error rate, false positive error, and false negative error is shown in Equation (12).

$$\begin{cases}AvgErrors=\\ \sum_{j}^{WT}(FalsePositives_j+FalseNegatives_j)/Totalcount\\ AvgPositives=\\ \sum_{j}^{WT}(FalsePositives_j)/Totalcount\\ AvgNegatives=\\ \sum_{j}^{WT}(FalseNegaatives_j/Totalcount)\end{cases} \quad (12)$$

Effective warning data is obtained through warning technology and is consistent with the actual warning situation. The calculation formula is shown in Equation (13).

$$WD=\sum_{i=0}^{tc}wcount_i, i\in N \quad (13)$$

In Equation (13), tc represents the total number of tags and $wcount$ represents the number of alerts triggered by a specific mobile medium. The warning error rate reflects the proportion of difference between the expected alarm and the actual alarm that should be issued. The calculation of this error rate is shown in Equation (14).

$$ER=\frac{|WD_{predict}-WD_{dected}|}{WD_{predict}}\times 100\% \quad (14)$$

In Equation (14), $WD_{predict}$ and WD_{dected} represent the actual number of correct warnings and the total number of warnings generated after data processing and multi region warning strategies, respectively.

4 Integration of data warning and blind spot data processing for multi-area monitoring results and analysis of the iot

This research experiment first focused on the processing and analysis of redundant and missed data. Next, an experimental scenario for multi-area monitoring of the IoT was set up, and the warning data generated under different warning thresholds and their error rates were analyzed. Finally, a comprehensive analysis of adaptive windows and data warning was conducted.

4.1 Results and analysis of redundant data processing and missing data processing

In this research experiment, the labels were randomly and uniformly distributed within a range of 0-20 meters around the reader. The tag moved at a random speed and switched from motion to static every 100 reading cycles at a speed of 2 meters per second. The proportion of the main detection area was simultaneously adjusted from 0 to 1. Omission and redundant data processing techniques were applied, the reading cycle parameter in the window was gradually increased, and the label cleaning efficiency of 3-second, 5-second, and 7-second windows was compared, which were S-3, S-5, and S7, respectively. As shown in Fig. 7, the results of redundant data processing revealed a slight increase in data compression rate but overall stability as the time window expanded. The number of time windows had a smaller impact on compression rate, and the larger the window size, the more significant the data compression effect.

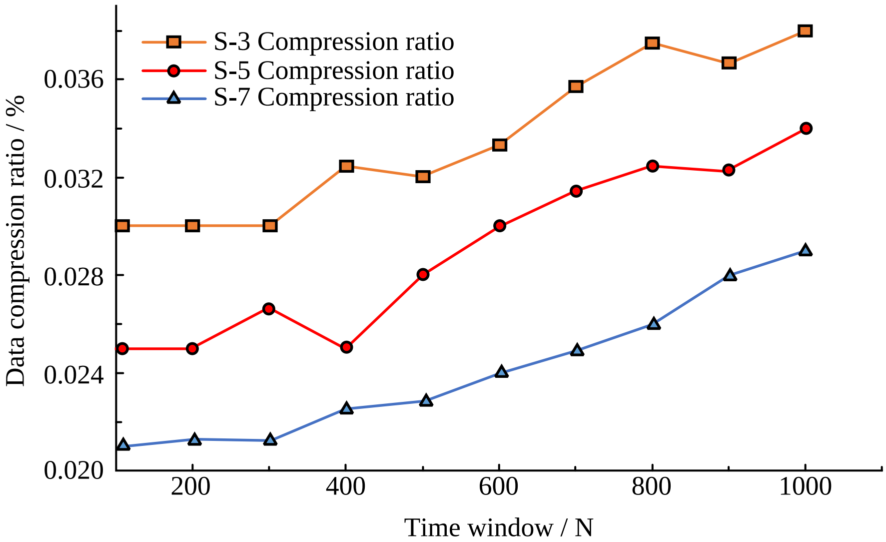


Figure 7: Redundancy data cleaning compression rate

Next, an experimental analysis of the average error rate of missed data processing and cleaning was conducted, as shown in Fig. 8. This indicated that when the main monitoring area was 0%, the large window setting captured data more effectively. As the credibility of the main monitoring area increased, the accuracy of the algorithm was improved, thereby reducing misidentification of labels. However, increasing the window size led to an increase in false positive errors. In monitoring areas, especially in single area monitoring, mobile media effectively triggered alerts. But at the junction of adjacent areas, smaller window settings may lead to more false positives. In addition, the obstruction of moving objects within the area may also lead to the occurrence of false alarms. In addition, the study divided the experimental dataset into test set and training set for robustness comparison analysis. It was found that the accuracy of the algorithm was closer to the results obtained on different datasets, the data variation was small, and the robustness of the algorithm was verified.

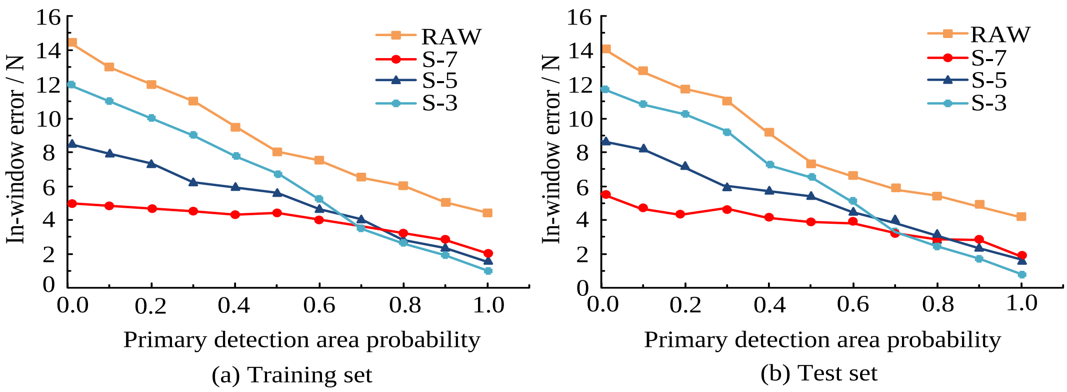


Figure 8: Average error rate for cleaning missed read data processing

4.2 Experimental results and analysis of a data warning model for multi-area monitoring in the IoT

This research experiment used a comprehensive active RFID technology reader and active RFID electronic tags to collect data on mobile media. The signal gain of the RFID technology reader was set to 10dB, the monitoring radius was set to 5 meters, the reading frequency was set to once every 0.5 seconds, the proximity judgment threshold was set to 5 meters, and the maximum warning time was limited to 10 seconds. The experimental layout is shown in Fig. 9, where region 0 was separated from regions 1 and 2, while regions 1 and 2 were connected. Under this setting, the experiment specified the repeated path pattern for moving objects. The trajectory of an object from region 0, passing through 1 to 2, and then returning to 0 was considered a repeated path. During this process, the object's dwell time inside and outside each region gradually increased from 2 seconds to 10 seconds, each time increasing by 2 seconds. In each repeated path, the mode transitions from zone monitoring to zone alarm, and each repeated path generated 6 key data.

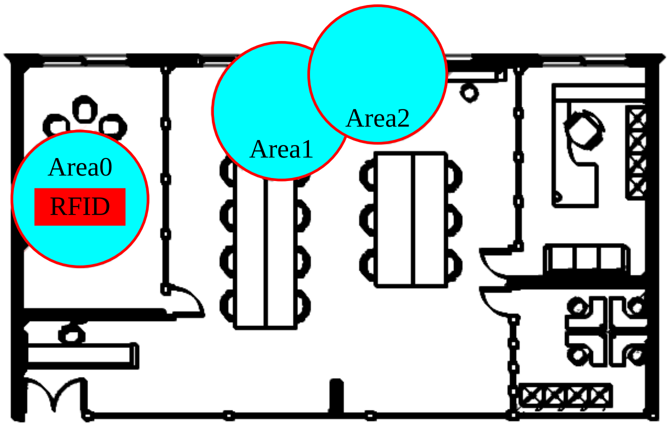


Figure 9: Multi-zone monitoring FTM model experiment

The next research experiment analyzed the generation and error rate of warning data under different warning thresholds, as shown in Fig. 10. Five moving objects were subjected to repeated activities at different warning thresholds 1, 3, 5, 7, 9, and 11, corresponding to different window sizes S-3, S-5, S-7, S-9, and S-11. Within a 180 second time frame, the total number of predicted alerts was 35. Moving objects could effectively monitor activities within a region, but lower warning thresholds could lead to multiple false alarms during region switching. Although a larger window reduced the number of alerts, it might lead to missed alerts. Therefore, under the size window setting, the error rate was relatively high. Taking a value of 7, which was S-7, achieved a lower warning error rate.

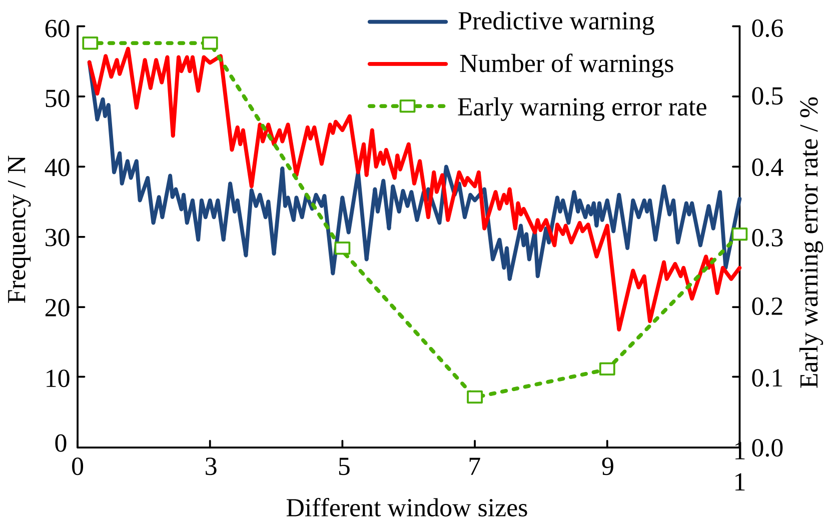
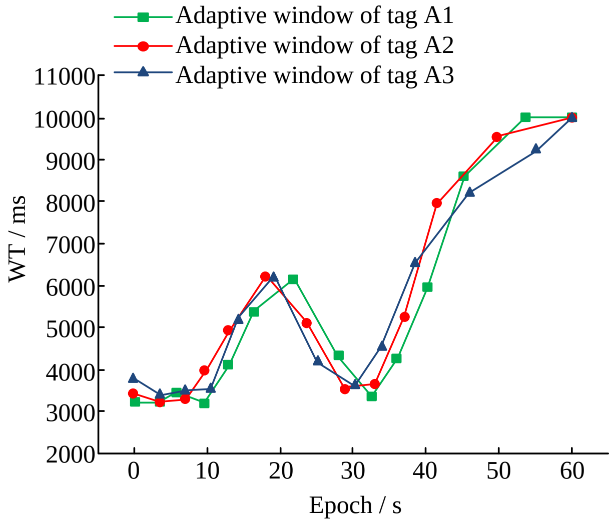


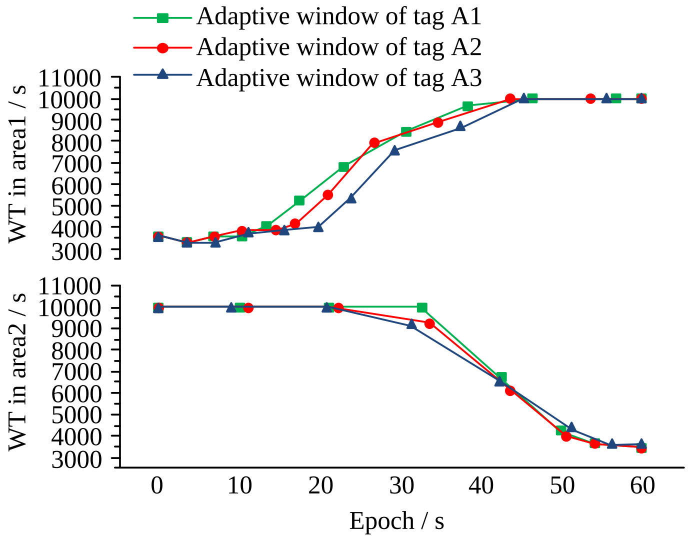
Figure 10: The warning data changes when the area moves

4.3 Adaptive window and data early warning results and analysis of iot multi-area monitoring

This research experiment tested the adaptive window adjustment technique using label groups A1, A2, and A3, as shown in Fig. 11. The equipment used in the experiment had a success rate of at least 80% in tag detection, and the adaptive parameter was set to 0.05 to optimize the experimental results. In region 0, these labels move within a 60 second time frame, and the change in their warning threshold is shown in Fig. 11 (a). When the tag entered the blind zone or exits zone 0, the threshold increased due to a decrease in detection rate. Moreover, when it re-entered the monitoring zone, the threshold stabilized. In the experiment of neighboring regions, the transition of carrying labels from region 1 to region 2 was studied, and Fig. 11 (b) shows the changes in the warning threshold during this process.



(a) The alarm threshold of area movement changed



(b) The alarm threshold of area migration changed. Procedure

Figure 11: The alarm threshold of area movement and transfer changes

During the first 30 seconds, the label leaving its area gradually increased the warning threshold for that area. When the tag entered the external blind spot, the reader cannot detect the signal, causing the warning threshold to reach its maximum. If the tag did not enter a new area within the following 30 to 60 seconds, the alert threshold for that area remained at its highest. It could be observed that the warning threshold increased when the label entered the blind spot, and decreased when it returned to the monitoring area, thereby optimizing the accuracy of the warning. Next, the study determined the alarm error, as shown in Fig. 12. The study used A1, A2, and A3 tags and conducted 10 rounds of simulation activities in the area, with the tag's dwell time in each blind spot increasing from

2 seconds to 10 seconds. For most of the time in the inner blind spot, the tag did not trigger an alarm and only triggered at the longest dwell time, a total of 6 times. However, once the tag leaved the area, it triggered an alarm every time, a total of 30 times, and the overall number of alarms was 36. Fig. 12 (a) shows the number and error rate of alerts triggered by data processing and early warning technologies in both internal and external blind spots. Due to the short time limit, S-3 had a high error rate in the inner blind area, while S-7 had a higher error rate in the outer area. S-5 was located between the two, with a high error rate in both regions. When there were adjacent regions, as shown in Fig. 12 (b), including multiple transitions between regions, the residence time of the label in the blind spot changed. After staying in the blind spot for more than 10 seconds, an alarm was triggered, with 12 internal alarms and 6 external alarms. The total number of alarms was 18.

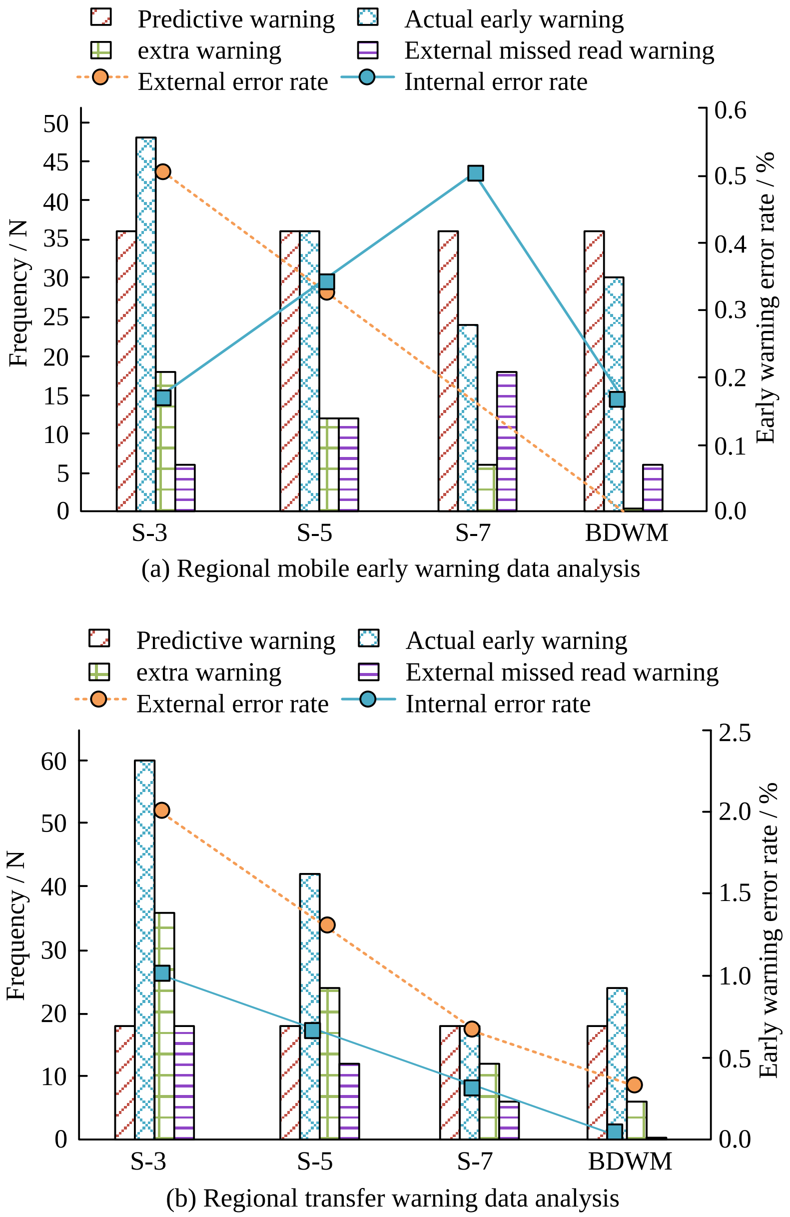


Figure 12: Internal and external generated warning data and error rates

The results showed that data processing and early warning technology effectively reduced the warning error rate by adjusting the alarm threshold, and was suitable for multi-area monitoring, with better performance than traditional fixed time window settings.

The results of the parameter sensitivity analysis of the model are shown in Table 2. There are significant differences in the sensitivity of different factors to the clustering performance of the model. Moreover, the sensitivity of the reading window size and the warning threshold is as high as 76.16% and 79.16%. The sensitivity of the dwell time is the lowest, which is only 16.71%.

Comprehensively analyzed, the adaptive window has a greater impact on the warning effect, and the sensitivity values all reach more than 70%. It could be concluded that the improvement strategy proposed by the study can improve the warning effect to a certain extent.

Table 2: Sensitivity analysis of ACO-DTW-DGI clustering model

Dimension	Influence factor	Absolute sensitivity valu
Parameter	Read window	76.16%
	Warning threshold	79.16%
	Adaptive parameters	51.58%
	Residence time	16.71%

5 Discussion

With the rapid development and wide application of IoT technology, how to accurately and efficiently process a large amount of blind area data has become an urgent problem in the field of multi-area surveillance. Currently, there are still many difficulties in the processing of blind area data. On the one hand, blind area data is often difficult to be accurately recognized by traditional surveillance systems due to signal blockage, equipment failure, or environmental factors, resulting in errors in the surveillance results, which affects the accuracy and reliability of surveillance. On the other hand, traditional surveillance models require longer time to analyze and identify blind area data, increasing the response time delay. Furthermore, the substantial quantity of unstructured data intensifies the computational burden on the system, potentially resulting in an over-consumption of system resources and a detrimental impact on the system's overall performance and operational costs. However, summarizing the existing research results related to RFID and IoT, it is found that the research on multi-area monitoring, especially blind area data processing and warning accuracy, is still relatively small. Most of the researches are mostly focused on improving the communication scale, increasing the algorithm robustness, and improving the efficiency of data collection and integration, e.g., Literature [8], Literature [9], Literature [10]. Otherwise, the studies address the aspects of IoT data transmission security, user privacy, etc., e.g., Literature [13], Literature [17]. However, the problem of blind area data processing and early warning mechanism improvement in multi-area surveillance environments still faces many challenges. There are more technical gaps in research and application.

In this regard, the study proposes a novel multi-area surveillance model. The study encompasses the construction of the fundamental model of RFID technology and FSM, as well as the introduction of a probabilistic model, optimization, and improvement of the RFID model. The results showed that the tags were randomly distributed in the range of 0 to 20 meters and move at a speed of 2 meters/second. Warning time windows of 3, 5 and 7 seconds were applied under the variation of the ratio 0 to 1 in the main monitoring zone. The experimental results showed that the 7-second window demonstrated the highest data capture efficiency when the primary monitoring zone was 0%. Out of 35 predicted alerts, the 7-second window showed the lowest error rate. The number of alerts exceeding 10 seconds in the inner blind zone was 12 and the number of alerts exceeding 10 seconds in the outer blind zone was 6 for a total of 18 alerts during the 180-second monitoring cycle. This was due to the adaptive window blind area data alerting method constructed based on a probabilistic model. The method employed a probabilistic model to automatically adjust the warning threshold in response to changes in the monitoring environment. This enabled more accurate determination of the state of the moving medium and reduced false alarms caused by fixed thresholds that are not optimally calibrated. Meanwhile, the method was able to effectively process the blind area data through the probabilistic model. By adjusting the warning strategy and parameters, it reduced the impact of blind zones on the warning results, thus reducing the occurrence of false warnings.

The design of the study achieves enhanced performance in real-time data processing and feedback, optimized resource allocation, and augmented system intelligence. However, the research-designed IoT multi-area monitoring system still faces challenges in scalability, cost, and integration with existing systems when deployed in actual IoT environments. First, the amount of data that the system needs to process will increase dramatically with the increase in the number of monitoring areas and the number of monitoring devices. It is essential that the system exhibits robust scalability, enabling the dynamic expansion of data processing and storage resources to accommodate the increasing demands of data processing. Second, IoT devices usually communicate with the data center through wireless networks, so the expansion of network bandwidth is also an important challenge. Third, IoT multi-area monitoring systems require a large number of monitoring devices and sensors, and the procurement and deployment costs of the devices are high. Fourth, the IoT multi-area monitoring system needs to be integrated with existing business systems and databases in order to realize data sharing and exchange. However, there may be differences in data formats and protocols between different systems, leading to difficulties in the integration task. Future research endeavors may address these challenges by incorporating intelligent algorithms, optimizing network configuration, adopting multi-source data fusion, and enhancing data compression and transmission optimization to enhance the precision and efficiency of IoT surveillance systems.

6 Conclusion

The main challenge faced by this study is the shortcomings of traditional IoT monitoring systems in processing blind spot data, such as the significant consumption of system resources and the inability to effectively identify data within the blind spot. To address these issues, this study constructed a model based on wireless RFID technology and FSM, and proposed a multi-area monitoring FSM model on this basis. By introducing probabilistic models, the RFID model has been improved, forming a comprehensive IoT multi-area monitoring model that combines data warning and blind spot data processing. The results showed that the tags were randomly distributed within a range of 0-20 meters around the reader, moving at a speed of 2 meters per second. The warning threshold settings for different time windows of 3 seconds, 5 seconds, and 7 seconds were applied to test the efficiency of label cleaning under the variation of the main detection area ratio from 0 to 1. Under the condition that the main monitoring area was 0, a 7-second window displayed the highest data capture efficiency. As the credibility of the monitoring area improved, the accuracy of the algorithm increased and false positive errors decreased. Out of 35 predicted alarms, the 7-second window displayed the lowest error rate. During the 180 second activity period, the number of alarms for internal blind spots exceeding 10 seconds was 12, and the number of alarms for external blind spots exceeding 10 seconds was 6. The total number of alarms was 18. The total number of alarms under the size window setting reached 36. In summary, the method used in this study significantly reduced the warning error rate in multi-area monitoring, which was superior to the fixed time window setting. Nevertheless, there is still room for improvement in the accuracy and real-time performance of label reading in complex environments using this method. Future research will focus on developing more efficient data processing technologies and algorithms to further improve the performance and reliability of IoT monitoring systems.

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