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Anomaly Detection in Ground Moving Target Trajectories via Chan-Taylor Collaborative Localization

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ABSTRACT

To address the limitations in positioning accuracy and environmental adaptability of vibration-aware target monitoring systems, an enhanced TDOA acoustic source localization method based on Chan-Taylor collaborative algorithm is proposed in this study. A two-phase collaborative localization model is constructed by integrating the high-precision characteristics of Chan's algorithm with the strong robustness of Taylor series expansion method. A virtual-real mapped simulation monitoring platform is established through digital twin technology, achieving dynamic interactive verification between physical and virtual spaces. Experimental results demonstrate that the improved algorithm attains 92.7% positioning accuracy in target trajectory reconstruction. Under virtual-real fusion testing conditions, the system achieves continuous target tracking within an 80-100 meter radius monitoring range in complex terrains.

KEYWORDS

Chan-Taylor; Ground Moving Target Trajectories; Virtual-real Mapped Simulation Monitoring Platform.

1. INTRODUCTION

As an advanced monitoring methodology, it is through vibration-sensing target monitoring technology that minute vibration signal variations are captured by precision-engineered sensors, enabling the efficient identification of potential intrusions or anomalous activities. In critical public security domains such as airports and government facilities, it is the real-time surveillance capability of this technology that is leveraged to detect unauthorized access, thereby being recognized as a critical enhancement to security response timeliness.It is the system's highly automated operational capacity that has completely eliminated dependence on manual intervention, resulting in labor costs being substantially reduced and security monitoring efficiency being significantly optimized[1]. Furthermore, it is the exceptional adaptability and stealthiness inherent to vibration-sensing technology that are highlighted. The system is designed to flexibly adapt to diverse environmental conditions—whether rugged terrain or extreme weather—with operational stability being consistently maintained. However, it has been identified through comprehensive analysis that current vibration-sensing monitoring systems are universally plagued by the following issues:

1. Insufficient Real-Time Capability

In conventional vibration-sensing monitoring systems, data is typically collected first and processed afterward[2,,3], resulting in a critical limitation: analysis is confined to historical data, leaving real-time situational awareness unachievable.

2. Limited Adaptability

These systems are generally trained and optimized for specific scenarios, where high accuracy is attained only within predefined conditions. When deployed in new environments, data must be re-collected and models re-trained, severely compromising their generalization capabilities.

3. Deficiencies in Intelligent Analysis

Most legacy systems are designed to perform isolated functions, such as target localization or classification, with comprehensive solutions integrating multiple tasks rarely being implemented. Moreover, decision-making processes still rely heavily on manual intervention, preventing full automation.

Constrained Data Sharing[4]

Despite leveraging multi-sensor inputs and large datasets, cross-sensor information exchange is inadequately facilitated, which is identified as a major bottleneck hindering algorithmic advancements.

To address the aforementioned challenges, a ground moving target trajectory anomaly monitoring method based on Chan-Taylor collaborative localization is proposed in this study, driven by an in-depth analysis of practical requirements. The key innovations of this methodology are outlined as follows:

1. Functional Integration and Intelligent Decision-Making

By unifying seismic wave first-arrival detection, target localization trajectory mapping, and classification capabilities, the system is engineered to autonomously conduct risk-level assessments and execute intelligent decisions. During emergencies, rapid event localization and categorization are achieved, enabling the provision of actionable response strategies to users.

2. Optimized User Experience

A streamlined human-machine interface is designed to simplify system operation and expedite information retrieval, thereby significantly enhancing user interaction efficiency.

In summary, our ground moving target trajectory anomaly monitoring system not only overcomes existing technological constraints but also delivers a smarter, more efficient surveillance solution, marking a transformative advancement in public security monitoring technologies.

2. ALGORITHM PRINCIPLES

2.1. TDOA Localization Algorithm

In the field of intelligent monitoring, it is of critical importance that the movement trajectories and categories of targets are accurately analyzed to identify potential security threats within specific areas. Passive positioning technology[5], regarded as an advanced monitoring method, achieves precise target localization through a series of sophisticated processes: signals emitted by the target are captured while being treated as transmission sources. This technology is endowed with numerous notable advantages, including superior concealment capability, obstacle-penetrating capacity, robust anti-interference performance, and low energy consumption, which have rendered it highly promising across diverse application scenarios.

Among various passive positioning methods, the TDOA (Time Difference of Arrival) algorithm[6] has emerged as a mainstream technology in this field, attributed to its streamlined algorithmic design, high accuracy, and broad applicability. In this approach, the time differences of vibration signals arriving at seismometers are measured to calculate target distances and determine positions. This method, also referred to as hyperbolic positioning, has been extensively adopted not only in wireless communication localization but also in seismic source positioning. As illustrated in Figure 1, when four sensors are arranged in a specific array configuration, spatial intersection points formed by their detection radii are utilized to pinpoint target locations.

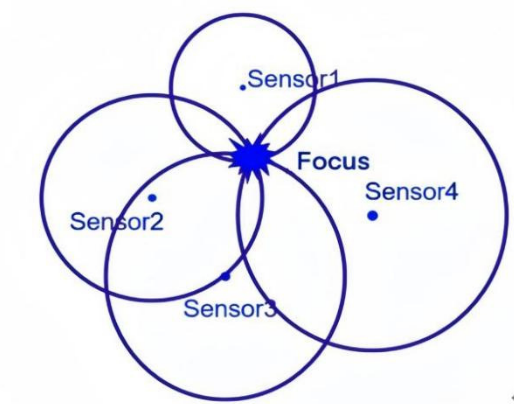

Fig 1. Schematic diagram of TDOA.

The unknown source coordinates are denoted as (x, y), and the sensor positions are set as (x_i, y_i), where $\mathrm{i} = 1,2,\cdots,\mathrm{n}$ and $\mathrm{n}$represent the number of sensors. The distance from each sensor to the target is defined as, from which n-1 equations can be obtained:

$$\begin{gathered} \sqrt{(x_2-x)^2+(y_2-y)^2}+\sqrt{(x_1-x)^2+(y_1-y)^2}=R_2-R_1 \\ \sqrt{(x_3-x)^2+(y_3-y)^2}+\sqrt{(x_1-x)^2+(y_1-y)^2}=R_3-R_1 \\ \cdots\cdots \\ \sqrt{(x_n-x)^2+(y_n-y)^2}+\sqrt{(x_1-x)^2+(y_1-y)^2}=R_n-R_1 \end{gathered} \tag{1}$$

$$R_{i1}{}^2+2R_{i1}R_1=x_i{}^2+y_i{}^2-2X_{i1}x-2Y_{i1}y-x_1{}^2-y_1{}^2 \tag{2}$$

By solving Equation (2), the target location (x, y) can be determined. The TDOA equations are primarily solved using two methods: the Chan algorithm and the Taylor algorithm.

2.2. Chan Algorithm

$$R_{i1}{}^2+2R_{i1}R_1=K_i\text{-}K_1-2X_{i1}x-2Y_{i1}y \tag{3}$$

The original nonlinear problem is ingeniously converted into a linear one by the Chan algorithm, significantly simplifying the computational process. Only two least-squares procedures are required to be executed by this algorithm to efficiently and accurately determine the source location. In two-dimensional space, at least three detection devices are necessitated for this method to ensure the feasibility of localization. As the number of detection devices increases, a greater amount of redundant information is acquired by the system, thereby enhancing the accuracy and reliability of the localization significantly. In other words, the improvement in localization precision is directly driven by an increase in the number of detection devices. As derived from Equation (2):

In formula $K_i = x_i{}^2 + y_i{}^2$, when the number of sensors is three, location (x, y) can be determined by formulas (4).

$$\begin{bmatrix} x \\ y \end{bmatrix} = -\begin{bmatrix} X_{2,1} & Y_{2,1} \\ X_{3,1} & Y_{3,1} \end{bmatrix}^{-1} \times \left\{ \begin{bmatrix} R_{2,1} \\ R_{3,1} \end{bmatrix} R_1 + \frac{1}{2} \begin{bmatrix} R_{2,1}{}^2 - K_2 + K_1 \\ R_{3,1}{}^2 - K_3 + K_1 \end{bmatrix} \right\} \tag{4}$$

The superiority of Chan's algorithm is demonstrated through its higher computational efficiency, enabling data to be processed and results generated rapidly. However, deviations in final positioning outcomes may be induced when initial estimations lack sufficient accuracy.

2.3. Taylor Algorithm

The Taylor algorithm employs a recursive approach for computation, initially requiring the establishment of an initial estimate for the source location. Subsequently, this estimate is continuously optimized through an iterative process within the Taylor algorithm. In the Taylor algorithm, first, an initial estimate value for the signal source position is selected; then, at the initial estimate (x_0, y_0), the system of equations (1) is expanded using a Taylor series, typically retaining only the first-order terms, resulting in a linear system of equations:

$$\mathrm{h} = \mathrm{G}\Delta + \varepsilon \tag{5}$$

$$\Delta = \begin{bmatrix} \Delta \mathrm{x} \\ \Delta \mathrm{y} \end{bmatrix}, \mathrm{h} = \begin{bmatrix} R_{2,1} - (R_2 - R_1) \\ R_{3,1} - (R_3 - R_1) \\ \cdots\cdots \\ R_{n,1} - (R_n - R_1) \end{bmatrix} \tag{6}$$

$$\mathrm{G} = \begin{bmatrix} (\mathrm{x}_1 - \mathrm{x})/R_1 - (\mathrm{x}_2 - \mathrm{x})/R_2 & (\mathrm{y}_1 - \mathrm{y})/R_1 - (\mathrm{y}_2 - \mathrm{y})/R_2 \\ (\mathrm{x}_1 - \mathrm{x})/R_1 - (\mathrm{x}_3 - \mathrm{x})/R_3 & (\mathrm{y}_1 - \mathrm{y})/R_1 - (\mathrm{y}_3 - \mathrm{y})/R_3 \\ \cdots\cdots & \\ (\mathrm{x}_1 - \mathrm{x})/R_1 - (\mathrm{x}_\mathrm{n} - \mathrm{x})/R_n & (\mathrm{y}_1 - \mathrm{y})/R_1 - (\mathrm{y}_\mathrm{n} - \mathrm{y})/R_n \end{bmatrix} \tag{7}$$

He estimation of Δ can be achieved through the application of the weighted least squares (WLS) method to Equation (5)

$$\Delta = (\mathrm{G}^\mathrm{T}\mathrm{Q}^{-1}\mathrm{G})^{-1}\mathrm{G}^\mathrm{T}\mathrm{Q}^{-1}\mathrm{h} \tag{8}$$

WhereQrepresents the covariance matrix of TDOA measurements. Following the acquisition of the initial value, parameter $\mathrm{x} = \mathrm{x}_0, \mathrm{y} = \mathrm{y}_0$ is initialized for the first iteration process, yielding intermediate result $\Delta\mathrm{x}, \Delta\mathrm{y}$to refine the outcomes. The iteration termination criterion is triggered when the measurement error reaches a sufficiently small magnitude, specifically when the condition specified in Equation (8) is satisfied, thereby obtaining the final estimated value (x^M, y^M).

$$|\Delta x| + |\Delta y| < \varepsilon \tag{9}$$

High-precision location results can be provided by the Taylor algorithm during the solving process. The performance of the algorithm is heavily dependent on the selection of initial values. A suitable initial estimate must be selected to ensure the convergence of the algorithm and the accuracy of the location.

2.4. Chan-Taylor Collaborative Localization

In the Taylor algorithm, the selection of initial values has a crucial impact on the positioning results. If the initial values are chosen improperly, the algorithm may fail to converge, thereby affecting the accuracy and reliability of the positioning[7]. Therefore, an effective strategy is to first use other algorithms for preliminary positioning to obtain relatively accurate initial estimates, which can then be used as the starting point for iterative computations in the Taylor algorithm. To reduce the overall complexity of the algorithm and further improve efficiency, the algorithm used to determine the initial values should be characterized by rapid execution and relatively high accuracy. The Chan algorithm meets these requirements and can provide an ideal initial estimate for the Taylor algorithm. As shown in Figure 2, the collaborative positioning process between the Chan algorithm and the Taylor algorithm is as follows: First, the Chan algorithm is used to perform positioning calculations based on TDOA measurements, yielding preliminary positioning results; subsequently, these results are taken as the initial values for the Taylor algorithm, which iterates until condition $|\Delta x| + |\Delta y| < \varepsilon$ is met, resulting in (x^M, y^M).

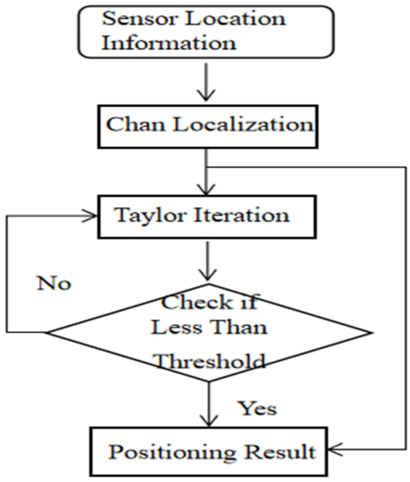

Fig 2. Chan-Taylor Collaborative Localization flowchart.

3. SOFTWARE DESIGN

3.1. Monitoring System Construction

Based on the need for wisdom monitoring platforms to meet core demands such as remote monitoring, scalability, and flexible interaction capabilities, a WebGL-based B/S architecture technology solution was ultimately selected. This technology supports the import of models in industrial standard formats such as obj and glTF [8,9]. By leveraging the collaborative mechanism between JavaScript and OpenGL ES2.0, developers can directly construct interactive three-dimensional visualization scenarios within an HTML environment.

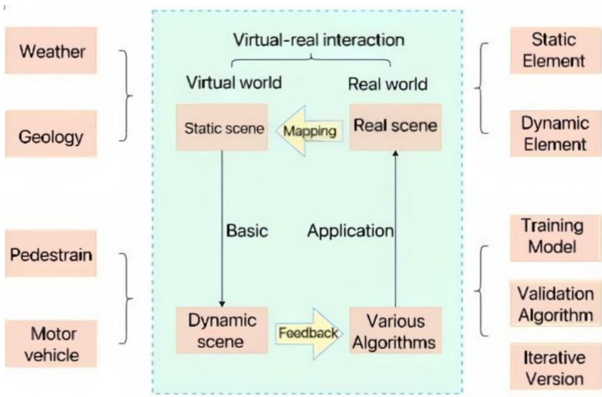

Fig 3. Architecture Diagram of Digital Twin Simulation System.

In digital twin technology, fidelity is considered a core metric for assessing the similarity between a digital twin and its physical counterpart. A digital twin must not only exhibit a high level of consistency with the physical entity in terms of geometric structure but also achieve tight coupling in state, phase, and time to ensure precise mapping and dynamic response to the physical world. As shown in Figure 3, virtual-real interaction between the physical and virtual worlds is an indispensable component of the digital twin system architecture. However, current research has primarily focused on geometrical modeling and data-driven approaches to achieve the fusion of digital twins with the physical world, while in-depth exploration and application of physical knowledge in the real world have been relatively lacking. To address this situation, NVIDIA's PhysX[10] engine has been introduced in this study. By presetting the physical properties of different targets, seismic wave propagation characteristics, interactions between models, and the physical states of models after contact with terrain, a digital twin with high fidelity to physical world characteristics has been constructed. This method not only significantly improves the generalization capability of target classification algorithms but also enhances the robustness of early warning algorithms, enabling precise predictions of potential future conditions in the monitored area and providing strong support for decision-making.

3.2. Hardware Design

The data acquisition equipment was employed with distributed wireless seismic instruments, which were self-developed by the School of Instrumentation and Electricity, Jilin University. The working nodes were equipped with Raspberry Pi 4B. As illustrated in Figure 4.

Fig 4. Hardware diagram.

The deployment of the seismometers was carried out using a grid-like array, as shown in Figure 5. This layout allows for comprehensive coverage of the monitoring area and effectively eliminates localization blind spots. Additionally, when differences exist between the data processing results collected by different nodes, the accuracy of the positioning results can be significantly improved through mutual verification with data from other nodes.

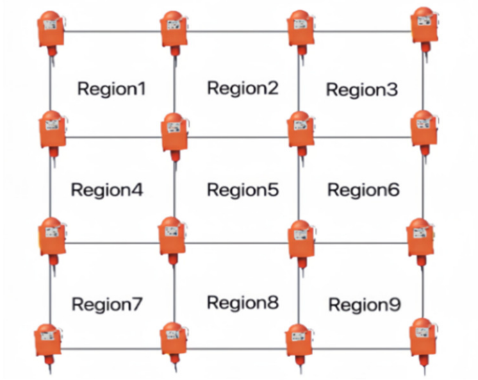

Fig 5. Seismometer deployment diagram.

In this paper, all components are containerized and deployed based on K3s, an edge-native orchestration engine. Kubernetes clusters can be deployed with one click on both ARM and X86 architecture servers through K3s, which has been lightweight-optimized specifically for edge computing scenarios[11]. Compared with other edge orchestration tools, superior advantages in resource occupancy, deployment efficiency, and usability are demonstrated by K3s, making it particularly suitable for deploying the ground moving target trajectory anomaly monitoring system for public safety events described in this study. Real-time data transmission between the seismometers and worker nodes is achieved by configuring the sensors of the seismometers as Kafka producers and setting the worker nodes as Kafka consumers to subscribe to corresponding Kafka topics. This deployment approach is designed not only to efficiently cache message data across different topics but also to ensure seamless collaboration between the two Kafka clusters, leveraging their respective advantages[12].

To monitor the system's operational status in real time, Grafana is utilized for visualizing critical metrics such as processor usage, memory consumption, disk activity, and network performance, as illustrated in Figure 6.

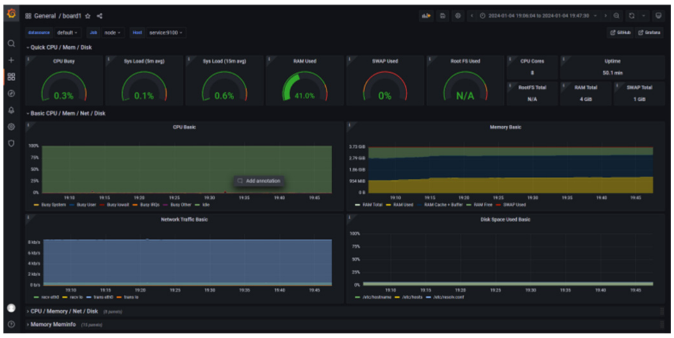

Fig 6. Cluster monitoring visual interface.

4. ACHIEVEMENT REALIZATION

4.1. Algorithm Simulation

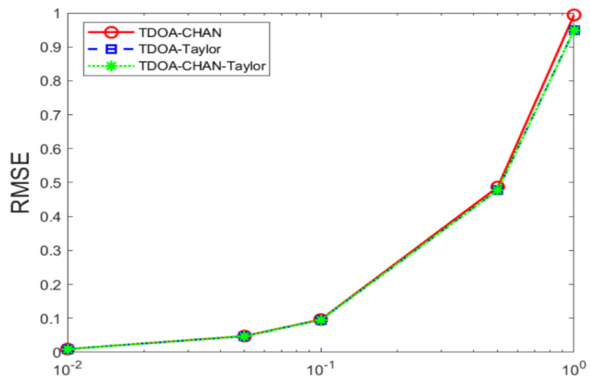

Fig 7. Comparison of positioning accuracy with different SNR.

First, the coordinates of the sensor array, the seismic source coordinates, and the site wave velocity were explicitly defined. In this experiment, the stratum model adopted was an isotropic homogeneous medium, which ensured that the wave velocity remained constant during seismic wave propagation. Based on this model, the wave velocity was set to 200 m/s. Subsequently, a set of simulated seismic data was generated using MATLAB software, into which Gaussian noise was intentionally incorporated to better approximate real-world scenarios and mimic potential random interference in practical environments. Following this, the generated data were processed using pre-programmed algorithm scripts. Through the TDOA algorithm, the seismic source location was inversely calculated, and the computed results were compared with the preset source coordinates to evaluate simulation effectiveness. Specifically, the Root Mean Square Error[13] (RMSE) was employed as an evaluation metric to quantify the positioning accuracy of different algorithms. To determine the final positioning algorithm for the system, three distinct positioning algorithms were compared.

As shown in the positioning accuracy comparison results in Figure 7, the three methods demonstrated comparable accuracy under low noise levels. However, as noise intensity increased, the positioning accuracy based on the Chan algorithm gradually lagged behind the other two methods. Meanwhile, while the Taylor algorithm and the Chan-Taylor collaborative algorithm exhibited similar positioning accuracy, the latter demonstrated superior computational efficiency. After comprehensive consideration of both positioning accuracy and computational efficiency, the Chan-Taylor collaborative algorithm was ultimately selected for system implementation.

Figure 8 illustrates the cumulative distribution of errors in four-node localization using the Chan-Taylor collaborative algorithm, from which it can be observed that most positioning errors are concentrated within the range of 0-1.5 meters.

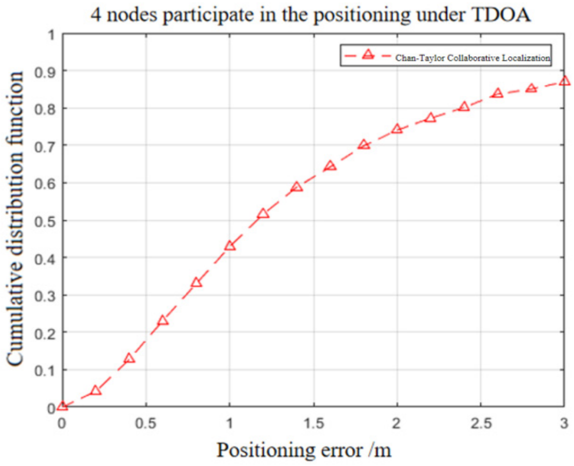

Fig 8. Chan-Taylor Collaborative Localization error cumulative distribution function.

The specific results of TDOA simulation positioning were presented in Figure 9, and the positioning performance of the algorithm was intuitively demonstrated. It can be seen from the figure that an accuracy rate of over 90% for recognizing moving targets was achieved by this algorithm, which demonstrates that high accuracy and reliability in target recognition are possessed by the algorithm.

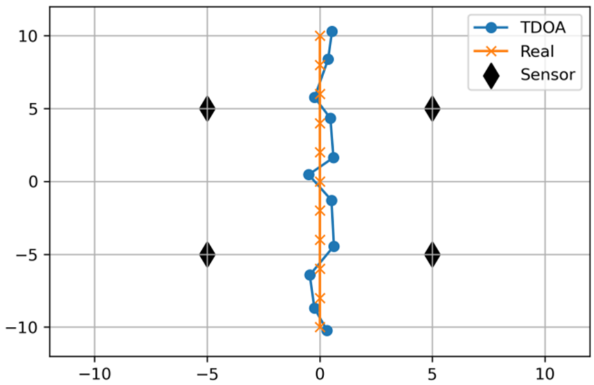

Fig 9. TDOA simulation diagram.

4.2. Software Display

The login function is recognized as a critical component of software security, with usernames and passwords assigned by administrators. As illustrated in Figure 10, users are required to enter the administrator-provided credentials upon launching the software to proceed with subsequent operations. Different levels of access permissions are granted based on user types, ensuring the rationality and security of functional access.

Additionally, unauthorized access attempts are prevented through an automatic account-lock mechanism triggered by multiple incorrect password entries, thereby further strengthening the software's security.

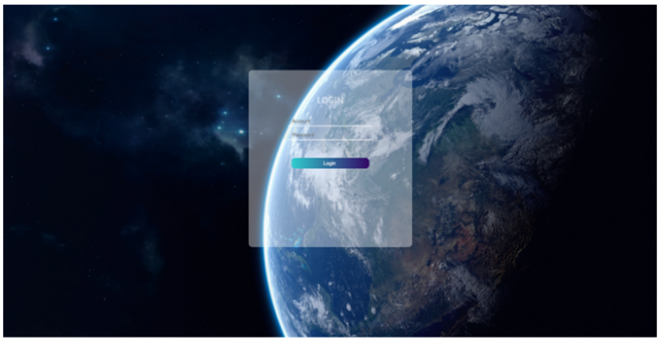

Fig 10. Login interface.

To achieve real-time visual monitoring of the surveillance area status, a three-dimensional visualization function was developed based on the model construction process described previously. As shown in Figure 11, the three-dimensional visualization interface of the surveillance area is first presented to users upon login. This interface is designed to dynamically display real-time status updates of the monitored area, with precise visualization of detected target locations and category information.

In this experiment, four seismometers were deployed across the Chaoyang Campus of Jilin University as the designated surveillance zone. Through these devices, the platform has successfully demonstrated its capability to detect target positions and classifications. Comprehensive monitoring data are systematically organized and presented through various statistical tables, which effectively display both node status and historical records. This implementation ultimately provides users with an integrated and intuitive monitoring solution.

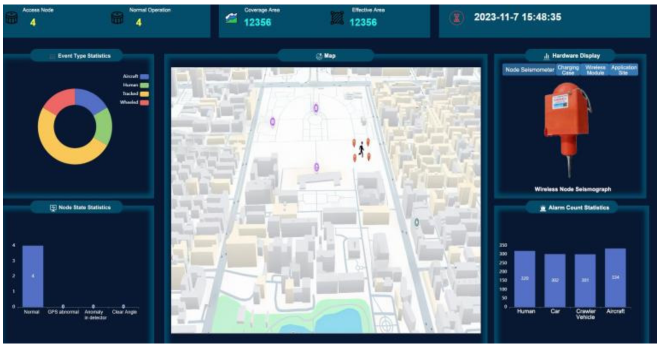

Fig 11. Main monitoring interface.

The management of seismometer nodes is facilitated to enable real-time monitoring of operational status across various zones. As depicted in Figure 12, which illustrates a segment of the backend management interface, the control platform is demonstrated to encompass functionalities including system initialization, power parameter configuration for seismic nodes, and real-time visualization of nodal geolocation, battery status, and storage capacity.

Fig 12. Background management interface.

The hazard warning module, recognized as the core functionality of the monitoring system, is designed to provide scientific, rational, and effective decision-making support for operators when addressing uncertainties, risks, and complexities. Given that this experiment was conducted in a school environment, the knowledge graph construction was primarily focused on urban application scenarios. As shown in Figure 4.4, the platform's automatic warning interface is implemented without requiring user-initiated queries. The vibration-sensing target monitoring technology adopted in this experiment is equipped with a detection radius of 80 to 100 meters, a critical parameter ensuring both extensive coverage and precise target detection capabilities. Operational principles are structured as follows: Threat levels are determined based on a comprehensive analysis of target categories and motion trajectories, with risk assessments conducted to evaluate potential public safety hazards. Upon anomaly detection, relevant information—including abnormal signals and target movement trends—is promptly delivered to monitoring personnel to strengthen decision-making support. Furthermore, in unmanned scenarios, the system autonomously evaluates the hazard index. When this value exceeds predefined thresholds, an automatic warning mechanism is activated to ensure monitoring zone security.

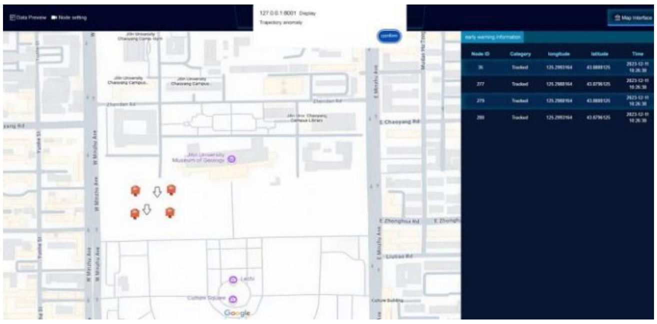

Fig 13. Trajectory abnormality detection function.

5. CONCLUSION

A novel methodology for abnormal trajectory monitoring of ground moving targets is proposed in this study, addressing technical bottlenecks in positioning accuracy and environmental adaptability of vibration-aware monitoring systems. By integrating the Chan-Taylor collaborative localization algorithm and digital twin technology, a virtual-physical mapping simulation monitoring platform is constructed. A multi-algorithm comparative experimental framework is established, through which the performance characteristics of different localization models are systematically evaluated. Experimental results demonstrate that the Chan-Taylor algorithm significantly outperforms conventional solutions in key metrics such as mean square error and signal-to-noise ratio, achieving a target trajectory reconstruction accuracy of 92.7%. The system is validated in a virtual-physical fusion test environment, exhibiting robust environmental adaptability and enabling continuous vibration target tracking within an 80–100 meter monitoring radius under complex terrain conditions, with the false alarm rate maintained below 5%. This research provides a new technical pathway for intelligent monitoring applications, while its digital twin-driven system architecture offers valuable insights for the intelligent upgrading of IoT-enabled sensing devices.

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