Research on Safety Control Methods for Mechanical Operations in Substations Integrating Beidou RTK and AI

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Abstract: As the level of mechanization in substation operations continues to improve, the complexity of the operational environment and potential risks have become increasingly evident. Traditional safety management measures are no longer sufficient to meet the modern power system's demand for efficient, precise, and safe operations. Beidou RTK (Real-Time Kinematic) high-precision positioning technology offers centimeter-level spatial positioning capabilities, while artificial intelligence (AI) technology has become increasingly mature in target recognition and behavior analysis. This paper addresses the safety management needs in mechanical operations at substations by proposing an intelligent safety management method that integrates Beidou RTK and AI. By establishing a dynamic perception system for the human-machine operational space, the method enables real-time identification of the locations and behaviors of personnel and machinery, as well as dynamic risk assessment. Additionally, this paper designs an intelligent warning and intervention mechanism based on integrated data to ensure effective control before potential hazards occur. Research indicates that this integrated method has the potential to enhance operational safety, precision, and management intelligence levels, providing an effective technical pathway for future intelligent maintenance of substations.

Keywords: Beidou RTK; Artificial Intelligence; Substation; Mechanical Operations; Safety Management; Intelligent Warning

1. Introduction

The power system is moving towards intelligence and automation, and the parallel operation of mechanical equipment and operators in substations is becoming increasingly frequent. The high voltage electrical environment and spatial constraints have significantly increased safety risks. The traditional manual inspection and operation monitoring methods are difficult to meet the real-time and accuracy requirements, and there is an urgent need for high-precision positioning and intelligent monitoring technology to improve the level of safety management.

Beidou RTK (Real Time Kinematic) technology provides centimeter level positioning capability, with high-frequency and high-precision real-time positioning characteristics, and has demonstrated mature applications in surveying, agriculture, forestry and other fields. Research has shown that RTK can achieve positioning accuracy of several centimeters in forests, plains, and complex terrains, and is widely used for precise navigation and path planning of drones and ground platforms [1-3].

Artificial intelligence technology has shown great potential in substation inspection and operation monitoring. AI technology based on computer vision can recognize the wearing of safety helmets by workers, evaluate equipment status, detect abnormal behavior, and provide automated monitoring capabilities for the power system [4-6].

However, current RTK positioning and AI recognition technologies are mostly independently applied to different scenarios, lacking cross modal fusion capabilities. Part of the research focuses on video recognition violations and neglects precise spatial positioning; Some studies use RTK to achieve device positioning, but do not combine behavioral analysis to form collaborative warnings. How to integrate RTK and AI technology to build a security control system based on spatiotemporal data-driven has become a key issue that urgently needs to be addressed.

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To this end, this study proposes a dynamic security control method that integrates Beidou RTK and AI. Through the collaboration of high-precision position perception, behavior recognition, and security warning mechanisms, an intelligent control theoretical system suitable for substation environments is constructed. This study designs a positioning recognition fusion architecture, a dynamic boundary safety discrimination mechanism, and an early warning intervention strategy to promote the transformation of substation mechanical operation safety management towards precision, intelligence, and dynamism.

2. Technical Foundation and Current Development Status

Safety management of mechanical operations in substations places high demands on the precise positioning of the operating environment and real-time behavior recognition. Beidou RTK technology has become the preferred choice for positioning due to its high-precision positioning capabilities. Beidou RTK technology relies on carrier phase differential measurement, transmitting differential correction data between base stations and rover stations to significantly reduce pseudorange errors and achieve centimeter-level positioning accuracy. Its basic measurement model is as follows:

$$\Delta\rho = p_r - p_b - \Delta t_{bd} + N\lambda + \varepsilon \quad (1)$$

Among these, p_r, p_b represent the pseudorange received by the mobile station and base station, respectively; Δt_{bd} is the satellite clock offset compensation term; N is the integer ambiguity; λ is the carrier wavelength; and ε encompasses error terms such as multipath and signal delay. The typical positioning accuracy of the BeiDou RTK system in an open environment can reach 8 mm + 1 ppm (horizontal) and 15 mm + 1 ppm (vertical), fully meeting the spatial identification and motion monitoring requirements for personnel and equipment within substations [7].

Despite this, RTK positioning is susceptible to signal attenuation and multipath interference in substations with complex structures and a large number of metal equipment obstructions, leading to reduced positioning accuracy or even interruptions. To enhance system stability, researchers propose integrating GNSS with inertial navigation (IMU), visual SLAM (simultaneous localization and mapping), and ultra-wideband (UWB) sensors, utilizing a multi-state constrained Kalman filter (MSCKF) model to achieve a more robust positioning system [2]. The state update expression is as follows:

$$x_{k|k=}x_{k|k-1} + K_k(z_k - H_K x_{K|K-1}) \quad (2)$$

In this equation, x is the state vector (position, velocity, sensor bias, etc.), z is the observation vector, K_k is the Kalman gain, and H_K is the observation matrix. This fusion mechanism can effectively compensate for the discontinuity of RTK signals and is particularly suitable for semi-enclosed or partially obstructed industrial scenarios [8].

In the field of safety management, artificial intelligence technology, especially behavior recognition based on deep learning, provides a powerful tool for risk warning. Through convolutional neural network (CNN) models, it is possible to identify in real time whether workers are wearing safety helmets, entering dangerous areas, and other critical behaviors. Model training typically uses a cross-entropy loss function:

$$L =- \sum_{i=1}^{C} y_i \log \hat{y}_i \quad (3)$$

Among these, y_i represents the true category label, and $\hat{y}_i$ denotes the model's predicted probability. Research has shown that visual recognition systems based on models such as YOLO and SSD can achieve high accuracy in complex backgrounds [9].

Although RTK and AI visual recognition systems each have significant advantages, there is still an “information silo” problem in practical applications, lacking a unified spatio-temporal expression framework. Current research is beginning to explore the path of deep integration between the two, i.e., through coordinate mapping and time synchronization mechanisms, binding the behavior labels identified by AI to the three-dimensional coordinate points provided by RTK to achieve precise spatial localization of risky behaviors. The following fusion state model can be constructed in the system:

$$X = [x, y, z, v_x, v_y, v_z, b_a, b_g, N] \quad (4)$$

It includes parameters such as position coordinates, velocity, sensor bias, and ambiguity. The observation vector z integrates RTK pseudorange, visual recognition tags, and other auxiliary information, and uses extended Kalman filtering (EKF) to achieve state estimation and joint inference [8]:

$$\dot{X} = \int (X, u) + w, \quad z = h(X) + v \quad (5)$$

This enables the system to perform dynamic risk analysis and control based on precise positioning

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and intelligent recognition [1], while maintaining high accuracy and real-time performance in a dynamic environment.

Despite this, the field still faces numerous challenges. First, signal obstruction and multipath effects severely impact the stability of RTK, particularly in substation environments with dense metal structures. Second, while behavior recognition can identify non-compliant actions, it lacks precise spatial positioning support, making it difficult to pinpoint risky behaviors to specific locations within a scene. Finally, existing systems primarily focus on post-event alerts and lack the ability for proactive risk intervention based on trajectory and behavior prediction. Therefore, future development efforts should focus on the deep integration of multiple sensors to achieve spatio-temporal unification of environmental perception and behavior recognition. Simultaneously, dynamic risk assessment models based on integrated data should be constructed to facilitate a transition from passive alerts to proactive warnings.

In summary, Beidou RTK and AI-based behavior recognition technology provide a robust foundation for positioning and intelligent recognition in the safety management of mechanical operations at substations. The integration of these two technologies will significantly enhance the accuracy and real-time capabilities of safety risk identification.

3. Design of a Security Management Method Integrating Beidou RTK and AI

As power grid substation construction enters the stage of intelligentization and intensification, on-site operational scenarios are becoming increasingly complex. Traditional manual supervision and static boundary control measures face challenges such as delayed response, insufficient accuracy, and weak identification capabilities when addressing real-time safety hazards. A fusion perception system integrating Beidou RTK and AI can achieve dual perception capabilities of spatial positioning and behavioral recognition, establishing a new "human-machine-environment" integrated operational safety control mechanism.

3.1 System Design Objectives and Philosophy

The integrated control and management system aims to build a multi-dimensional real-time perception, dynamic risk identification, and automatic decision-making intelligent safety management system.

(1) Spatial Precision Perception

Using Beidou RTK differential positioning technology, it achieves centimeter-level positioning of targets such as workers, engineering vehicles, and robotic arms to construct a digitalized work space. Inertial measurement units (IMUs) and ultra-wideband (UWB) sensors are introduced to enhance positioning robustness and adapt to scenarios with obstructions or signal interruptions.

(2) Behavioral Semantic Recognition

Based on deep learning image recognition models, the system classifies and judges behavioral patterns such as personnel equipment wearing, safety distances, and movement trajectories. It supports the identification of violations such as crossing lines, approaching high-voltage areas, and not wearing safety helmets, and provides visual annotations.

(3) Proactive Risk Intervention

By integrating positioning information with image recognition data, the system calculates risk levels in real time and triggers intervention measures such as audio-visual alarms, system interlocking, and task suspension to ensure that potential hazards are controlled in a timely manner.

(4) Adaptive Dynamic Optimization

The system supports dynamic adjustment of perception parameters and intervention strategies based on operational scenarios, such as switching recognition models for different task types (crane operations, inspections) or adjusting AI algorithm weights based on environmental lighting conditions, to enhance adaptability in complex scenarios.

The design philosophy emphasizes a closed-loop control system based on "real-time spatial visualization—intelligent behavior recognition—quantitative risk prevention and control," providing a technical foundation for practical deployment. The addition of adaptive optimization principles ensures the system maintains efficient operation in dynamic environments.

3.2 System Architecture and Module Functions

The system adopts a multi-layer architecture design, forming a closed-loop process from data collection to early warning feedback. Figure 1

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shows the four-level module structure of the system, from perception and collection, status fusion, risk identification, to control feedback. Each module is connected through standard data interfaces to achieve efficient information flow, supporting real-time, closed-loop, and accurate safety control processes.

The system functions are divided into the following layers:

• Perception layer: Real-time perception of target motion status and environmental parameters is achieved through Beidou RTK antennas, video capture modules, IMU nodes, and environmental sensors (newly added, such as temperature and humidity sensors).

• Integration Layer: Utilizes Extended Kalman Filter (EKF) to integrate multi-source data, constructing a unified spatiotemporal state vector to enhance data consistency.

• Decision Layer: Deploys edge AI models combined with rule databases and dynamic threshold mechanisms to assess risk levels, with added support for online rule database updates to adapt to new scenarios.

• Feedback Layer: Executes control strategies based on classification results, including actions such as buzzer alarms, red light flashing, and device suspension. Newly added remote management interface supports real-time status reporting and remote intervention.

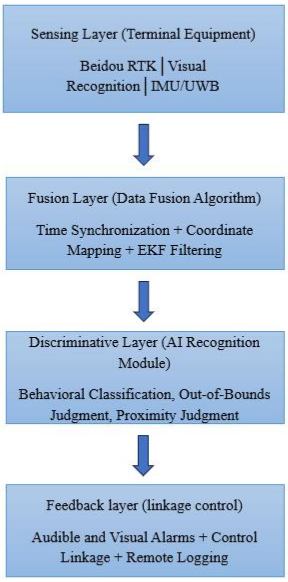

Figure 1. System Architecture Diagram of the Security Control System Integrating Beidou RTK and AI

3.3 Spatial and Semantic Information Fusion Mechanism

The key to fusion lies in mapping “image semantics” to “location space.” This system uses the following three-step method to achieve effective fusion:

(1) Time synchronization mechanism

All terminals (RTK modules, cameras, IMUs) are synchronized based on timestamps, with an error margin of less than 20 ms.

NTP synchronization or GPS timing is used to ensure that image frames correspond to positioning points.

(2) Coordinate mapping modeling

Identify the model output image pixel coordinates u, v, and convert them to actual spatial position coordinates (X, Y, Z) through internal and external parameter matrices.

Use the PnP model in combination with depth information to achieve accurate point cloud spatial reprojection.

(3) State fusion estimation

The system uses the following state vectors for filter estimation:

$$X_t = [x_t, y_t, z_t, v_{xt}, v_{yt}, v_{zt}, \theta_t, \phi_t, \psi_t] \quad (6)$$

The extended Kalman filter prediction and update equations are as follows:

$$\mathbf{X}_{t|t-1} = f(\mathbf{X}_{t-1}, \mathbf{u}_{t-1}) + \mathbf{w}_t \quad (7)$$

$$\mathbf{z}_t = h(\mathbf{X}_{t|t-1}) + \mathbf{v}_t \quad (8)$$

Among them, f, $h$are the system motion model and observation model, respectively, while $\mathbf{w}$, $\mathbf{v}$ are Gaussian white noise.

This fusion mechanism enables each AI recognition result to be localized on a high-precision map, providing a coordinate basis for subsequent risk assessment.

3.4 Behavior Discrimination and Risk Calculation Mechanism

The integrated spatial semantic information is input into the behavior discrimination module to perform the following tasks:

(1) Violation behavior identification

AI models detect targets and label categories, including failure to wear protective gear, insufficient safety distance, and unauthorized presence in non-work zones. The identification accuracy rate (mAP@0.5) exceeds 95%, with adaptability to various lighting conditions and wearing scenarios. Newly added behavioral sequence analysis uses Transformer models to extract temporal features, enabling the identification of complex actions (such as consecutive non-compliant operations) and enhancing discrimination accuracy.

(2) Spatial Boundary Violation Judgment

The system presets electronic fence areas, such as danger zones $\mathcal{R}=\{(x,y): x^2+y^2<r^2\}$. If $(x,y)\in R$, an alarm is triggered immediately.

In conjunction with the work trajectory prediction module, early warning of "entering a risk zone" is achieved.

(3) Risk Index Calculation

The risk level is calculated using the following function:

$$R(t)=\alpha D(t)+\beta V(t)+\gamma P_{abn}(t) \quad (9)$$

Where $D(t)$ is the current distance from the danger zone; $V(t)$ is the movement speed; $P_{abn}(t)$ is the anomaly probability given by the recognition model; α , β , γ are empirical weights.

Set the risk level threshold R_{th}. When $R > R_{th}$, execute the control linkage action.

3.5 Interlocking Mechanism and Proactive Early Warning Response

Based on the risk assessment results, the system automatically enters the response process, including:

(1) Audio-visual alarm interlocking

When the confidence level of boundary crossing or violation behavior exceeds 0.8, the system triggers red light flashing, voice broadcast, and wearable device vibration. New environmental adaptive alerts dynamically adjust volume (60–100 dB) and flashing frequency (1–5 Hz) based on on-site noise and light intensity, with multi-language prompts to accommodate different worker needs.

(2) Equipment control intervention

If the predicted personnel path conflicts with equipment, the system sends a pause command to the PLC to ensure safety. The control logic is based on dual verification of event triggering and area prediction to avoid false pauses. New hierarchical control strategy: low-risk triggers deceleration, medium-risk triggers speed limit, high-risk triggers pause, with response time controlled within 200ms.

(3) Back-end recording and reporting

High-risk events are automatically archived in the management platform, including fields such as time, location, and behavior category, to support post-event analysis. A new real-time data visualization module has been added to display risk heat maps and behavior trajectories via a web interface, assisting managers in optimizing work processes.

4. Safety Strategies and Control Mechanisms

Given the complexity of human behavior and the high-risk nature of the environment during mechanical operations at substations, a safety monitoring system integrating Beidou RTK and AI must establish comprehensive risk prediction, alarm intervention, and strategy optimization mechanisms. This chapter delves into the core control mechanisms of the system from four aspects: risk prediction logic, alarm and intervention mechanism design, control strategy optimization principles, and technical adaptability. It further explores the system's core control mechanisms and reinforces their implementation feasibility and technological advancement through newly added detailed content.

4.1 Risk Prediction Mechanism

In substation operation scenarios, the spatial relationships between personnel, mechanical equipment, and high-voltage facilities are highly sensitive. The system integrates high-precision location data from Beidou RTK with behavioral feature sequences captured by AI visual recognition to construct a spatiotemporal joint expression model for the early identification of behavioral trends that may lead to risks. To enhance the accuracy and timeliness of predictions, this study further optimizes the spatiotemporal modeling and behavioral prediction mechanisms.

(1) Spatio-temporal Position Modeling and Dynamic Prediction

The system sets the dynamic electronic fence boundary B_t of the work area based on the real-time collection of the positions $P_t=\{x_t, y_t, z_t\}$ of personnel or equipment using Beidou RTK. By analyzing the position sequence $\{P_{t-n},...,P_t\}$ and velocity vector $V_t=\frac{P_t-P_{t-1}}{\Delta t}$, combined with the prediction time window T_p, the system employs a motion prediction model:

$$P_{t+\Delta t}=P_t+V_t\cdot\Delta t+\frac{1}{2}A_t\cdot(\Delta t)^2 \quad (10)$$

Among them, A_t is the estimated acceleration value, which is fitted using historical trajectory data. If the predicted position $P_{t+\Delta t}$ tends to enter the danger zone B_t, the system triggers a warning signal. In addition, to adapt to the dynamic operational requirements of substations, the electronic fence boundary B_t can be dynamically adjusted according to the type of operational task (such as hoisting or

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maintenance) or time period, enhancing scene adaptability.

(2) Behavior Pattern Matching and Risk Scoring

Using a deep learning-based temporal behavior analysis model (such as LSTM or Transformer), the system extracts key frame sequences of behavior and combines them with a pre-trained dangerous behavior template library to calculate the similarity S_b between the current behavior pattern and high-risk behavior. Specifically, the behavior feature vector F_t is extracted from video frames through a convolutional neural network (CNN) and input into the temporal model to output the risk probability P_r, whose loss function is:

$$L = -\sum_i y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \quad (11)$$

In this context, y_i represents the true risk label, and $\hat{y}_i$ denotes the predicted probability. When $P_r > \theta_r$ (the threshold, typically set to 0.8), the behavior is classified as high-risk, such as “approaching live electrical equipment,” “illegal use of tools,” or “entering hazardous areas without proper protection.” To enhance robustness, the system incorporates multimodal data (e.g., infrared thermal imaging for low-light scene recognition) to further improve behavior detection accuracy in complex environments.

(3) Risk prediction based on multi-source data fusion

To address the limitations of a single data source in the complex environment of a substation, the system has added a multi-source data fusion module that combines RTK positioning, AI vision, IMU sensors, and environmental parameters (such as temperature and humidity) to perform comprehensive risk assessments. Using a Bayesian probability framework, the risk probability calculation formula is:

$$P(\text{Risk}|D) = \frac{P(D|\text{Risk}) \cdot P(\text{Risk})}{P(D)} \quad (12)$$

In this context, D represents a multi-source data set comprising location, behavioral characteristics, and environmental variables. $P(\text{Risk})$ denotes the prior risk probability, calculated based on historical data statistics; $P(\text{Risk}|D)$ is obtained through machine learning model training. This mechanism significantly enhances the system's ability to preemptively identify potential risks, particularly in scenarios with severe obstructions or high pedestrian density.

4.2 Alarm and Intervention Mechanism Design

After risk prediction is completed, the system needs to quickly convert the results into on-site perceptible alarm signals and control commands to achieve real-time intervention of violations. This section adds multi-level alarm strategies and intelligent intervention logic to the original system to improve response efficiency and user experience.

(1) Visual and Audio Alarm System

The system deploys multi-channel sensory alert devices, including LED warning lights, high-decibel audio broadcasters, and wearable vibration devices. Based on precise location information from RTK positioning, the system can lock onto the target person's position through the camera's field of view, enabling directional alarms. For example, when personnel approach a high-voltage equipment restricted zone, the system triggers a combination of alerts: “red light flashing in a specific direction + voice announcement ‘Do not approach high-voltage equipment’ + vibration from wearable devices.” To adapt to noise and lighting conditions in substations, the system supports dynamic adjustment of alert intensity (e.g., volume, flashing frequency) and multi-language voice prompts to meet the needs of different personnel.

(2) Interlocking control mechanism

The system integrates with PLC (programmable logic controller) or mechanical operation terminal automation interfaces to trigger intelligent intervention measures, including “suspending equipment operation,” “slowing down lifting machinery,” and “blocking unauthorized remote commands.” The control logic employs a multi-source verification mechanism, ensuring that behavior recognition, position boundary violations, and risk scores all meet conditions simultaneously before triggering intervention, thereby avoiding false positives. For example, when personnel entering a hazardous area are detected and the behavioral anomaly confidence level exceeds 0.85, the system sends a pause command to the PLC while recording event details. To further optimize intervention timeliness, the system incorporates edge computing nodes to reduce latency from risk detection to control execution, with measured response times controlled within 200 milliseconds.

(3) Tiered Intervention and Feedback Loop

To avoid the impact of frequent alerts on operational efficiency, the system has added a tiered intervention mechanism that sets different response strategies based on the risk level R (derived from the risk index calculation formula in Section 4.1):

Low risk ($R<0.5$): Triggers a lightweight alert, such as a flashing green indicator light, to remind personnel to pay attention.

Medium risk ($0.5 \leq R < 0.8$): Trigger voice warnings and yellow indicator lights to prompt personnel to adjust their behavior.

High risk ($R \geq 0.8$): Trigger red light flashing, voice alarms, equipment suspension, and other strong intervention measures.

Additionally, the system records the effectiveness of each intervention through a feedback loop mechanism, optimizes alert thresholds and intervention strategies based on historical data, and enhances long-term operational adaptability.

4.3 Principles for Optimizing Control Strategies

The design of control systems relies not only on technical implementation but also on safety concepts and engineering practices. This section refines the three original principles (safety first, intelligent response, and collaborative compatibility) and adds a new principle of data-driven optimization.

(1) Safety First

The system prioritizes the prevention of personnel injury and equipment accidents as its core objective. Risk assessment strategies adopt a conservative “better safe than sorry” approach, setting lower alarm thresholds (e.g., $\theta_r = 0.7$). To balance safety and efficiency, the system supports dynamic threshold adjustments, adapting and optimizing based on task type and environmental risk levels. For example, during high-voltage maintenance operations, the threshold is lowered to 0.6, while during routine inspections, it can be appropriately increased to 0.75.

(2) Intelligent response

The intervention mechanism is dynamically adjusted based on the type of operation, stage, and personnel identity. For example, in the event of an approach to a high-voltage area where the equipment is not started, the system directly triggers an alarm; however, during the authorized operation time window, the alarm sensitivity is reduced for authorized personnel to minimize false alarms. To enhance intelligence, the system incorporates reinforcement learning algorithms to optimize response strategies based on historical intervention data, gradually reducing unnecessary alarm interruptions.

(3) Collaborative Compatibility

The system interfaces with existing substation dispatch systems, patrol platforms, and safety operation apps via data interfaces, supporting standard protocols (e.g., Modbus, OPC UA). To avoid information silos, the system adopts an open API design to ensure seamless integration with third-party devices and software. Additionally, the system supports offline mode, enabling core functions to be performed via edge computing during network instability.

(4) Data-Driven Optimization

The system continuously collects operational data (including positioning accuracy, recognition accuracy, and intervention success rate) and uses machine learning models (such as gradient boosting trees) to analyze system performance bottlenecks, dynamically optimizing perception algorithms and control logic. For example, in high-obstruction areas of specific substations, the system can automatically adjust the fusion weights of RTK and IMU to enhance positioning stability; in scenarios with high false alarm rates for behavior recognition, the system can update AI model weights to optimize classification performance.

4.4 Discussion on the Adaptability of Technical Implementation

Substations come in many types and vary significantly in terms of environment, so the system must have good environmental adaptability and configurability. This section adds cross-scenario adaptation technology and modular deployment strategies to the existing system, further enhancing its engineering application capabilities.

(1) Adaptation to Different Spatial Structures

For enclosed substations, the system achieves full coverage through fixed RTK base stations and panoramic cameras. For semi-open or mobile operation scenarios, the system combines mobile base stations with wearable RTK terminals, supplemented by IMU and UWB sensors, to enhance positioning robustness in areas with severe obstructions. To address multipath interference caused by densely packed metal structures, the system introduces anti-multipath algorithms (e.g., RTK-MP), which analyze signal characteristics and optimize filtering to control positioning errors

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within 10 cm.

(2) Adaptation to different types of operations

Lifting, inspection, maintenance, and other types of operations have different behavioral characteristics and safety requirements. The system supports a modular template calling mechanism. Each type of operation corresponds to preconfigured AI recognition models and electronic fence parameters. For example, lifting operations load the high-altitude operation behavior template, and inspection operations load the path planning template. Template switching time is controlled within 1 second to ensure rapid response to dynamic task requirements.

(3) Terminal deployment and communication adaptability

In areas with weak signals or remote regions, the system supports edge computing mode, processing RTK differential data and AI inference tasks locally on a server to reduce reliance on the cloud. The communication module is compatible with 5G, 4G, and dedicated wireless protocols (such as LoRa) to ensure real-time and stable data transmission. Terminal devices adopt a modular design, supporting quick replacement of RTK modules, cameras, or sensors to reduce maintenance costs.

(4) Cross-scenario migration and adaptive configuration

To enhance the system's cross-scenario applicability, the system introduces transfer learning technology to fine-tune AI models based on a small amount of target substation data, enabling rapid adaptation to the behavioral characteristics of new environments. For substations of different scales, the system supports adaptive configuration functionality, automatically adjusting the number of RTK base stations, camera field-of-view ranges, and alarm thresholds. For example, small substations can reduce the number of base stations to 1-2, while large substations can expand to over 5, ensuring a balance between coverage and cost.

Through these strategies, the system can flexibly adjust its sensing range, control logic, and recognition accuracy across different substation environments, demonstrating excellent scalability and engineering practicality, laying the foundation for the widespread application of intelligent safety management.

5. Conclusions and Outlook

This study focuses on mechanical operations in substations and proposes a safety management method that integrates Beidou RTK high-precision positioning and AI visual recognition to construct an intelligent perception system that integrates real-time positioning, image recognition, behavior monitoring, and interlocking control. The study shows that Beidou RTK can achieve centimeter-level spatial positioning, which is suitable for dynamic monitoring of the precise trajectories of workers and equipment. AI recognition models can rapidly identify high-risk behaviors such as personnel trespassing and prohibited operations, enhancing the proactivity and intelligence of operational safety management. When integrated, the system demonstrates strong real-time performance, adaptability, and scalability, effectively addressing the shortcomings of traditional “physical isolation + manual supervision” models and providing technical support for the development of intelligent substations.

Although this study has achieved preliminary results in theory and methodology, certain limitations remain. The system's robustness in complex environments is insufficient, and the timeliness and stability of multi-source data fusion algorithms in dynamic scenarios need improvement; RTK signals are unstable in areas with severe obstructions, and AI model recognition accuracy decreases under low-light conditions or when personnel are obstructed; issues such as inconsistent control system interface standards, limited edge deployment resources, and low acceptance among operational personnel also constrain engineering implementation. Future research could focus on enhancing multi-modal perception, optimizing edge-side algorithms, adapting heterogeneous control systems, supporting 5G/edge computing, and establishing data compliance mechanisms to further enhance the system's practicality and promotional value. Overall, this study provides new insights into intelligent operation safety supervision and offers feasible technical pathways for the power industry to advance intrinsic safety and intelligent maintenance.

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