Research on Intelligent Pipeline Robot Navigation and Defect Identification Based on Multi-Sensor Fusion

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ABSTRACT

With the increasing complexity of pipeline inspection and maintenance requirements, traditional single sensor methods have exposed significant technical bottlenecks in dealing with changing pipeline environments. This study proposes an intelligent pipeline robot navigation and defect recognition framework based on multi-sensor fusion. By integrating the complementary characteristics of lidar, visual sensors, and inertial measurement units (IMUs), a laser vision inertial multimodal data fusion system is constructed. The system adopts a hierarchical progressive architecture, with the bottom layer achieving spatiotemporal alignment and dynamic compensation of multi-source data through extended Kalman filtering. The middle layer uses improved ICP algorithm and visual SLAM technology to complete environmental modeling and pose estimation. The top layer is based on lightweight convolutional neural networks to achieve accurate recognition of defect types and positions. The experiment shows that the proposed method achieves centimeter level positioning accuracy and 92.7% defect recognition accuracy in complex pipeline scenes, significantly improving the system's environmental adaptability and detection reliability under interference such as lighting changes and metal reflections compared to traditional methods.

At the level of multimodal data fusion, an innovative nonlinear optimization framework based on UKF has been proposed, which achieves collaborative optimization of pose estimation and feature extraction by unifying the state vectors of modeling navigation and defect recognition tasks. Experimental verification shows that the framework can control the cumulative positioning error within ± 8cm in typical complex scenarios such as pipeline bends and branch nodes, and improve system robustness by more than 40% through multi-sensor redundancy design. In response to the detection requirements of different pipe diameters, the system successfully verified its universality within the range of 200mm to 800mm pipe diameters by adaptively adjusting sensor scanning parameters and robotic arm configurations. The navigation drift in small pipe diameter scenarios was reduced by 42% compared to traditional methods, and the coverage rate of large-scale pipeline detection reached 98.3%. Engineering application testing has shown that this technology improves pipeline inspection efficiency by 4.2 times that of manual operation, reduces operation and maintenance costs by about 65%, and the related achievements have been industrialized in the transformation project of material feeding robots in petrochemical enterprises, significantly reducing equipment downtime and manual intervention frequency.

The study further explored the cross domain migration potential of multi-sensor fusion technology, and quickly adapted the core algorithm to scenarios such as oil and gas pipelines, urban comprehensive pipe galleries, and industrial drainage systems through modular hardware design and open software architecture. In oil and gas pipeline inspection, the system has achieved a defect recognition accuracy of 0.1mm level; In the application of comprehensive pipe gallery, the positioning accuracy reaches ± 3cm; in industrial drainage scenarios, the accuracy of low light environment recognition remains at 89.7%. The defect knowledge base based on cloud edge collaboration has accumulated over 100000 sets of sample data, supporting rapid adaptation to new scene requirements through transfer learning. This study not only provides high-precision and strong robustness technical solutions for the field of pipeline inspection, but also proposes a layered fusion architecture and adaptive optimization strategy, which provides reusable methodological support for a wider range of engineering scenarios such as mobile robots and industrial monitoring, promoting the evolution of intelligent perception systems towards global intelligent monitoring networks.

Keywords: multi-sensor fusion; Intelligent pipeline robot; Navigation and positioning; Defect identification; UKF nonlinear optimization; Laser vision inertial fusion

1 Introduction

1.1 Research Background and Significance

The field of pipeline inspection and maintenance faces challenges in efficient data acquisition and precise defect identification under complex environmental conditions. Traditional single-sensor detection methods, due to limited sensing range and insufficient accuracy, exhibit significant technical bottlenecks when dealing with variable geometric structures and concealed defects inside pipelines[1]. For example, pipeline robots often experience reduced navigation stability in variable-diameter sections and curved areas due to inadequate environmental perception, directly affecting the integrity and reliability of inspection data[1]. The emergence of multi-sensor fusion technology provides a new solution to this problem. By integrating complementary characteristics of different sensors, it effectively enhances the accuracy of 3D modeling of pipeline spatial structures and the robustness of defect identification.

In the field of intelligent equipment technology, multi-sensor fusion has demonstrated significant technical advantages. Research indicates that by optimizing sensor layout and data processing algorithms, systems can achieve multi-dimensional perception of complex scenes[2]. Taking a spice blending system as an example, after integrating multi-sensor information using intelligent algorithms, its material weighing and ratio accuracy improved to 96%, significantly validating the adaptability of multi-sensor collaboration in dynamic environments[2]. When applied to pipeline inspection scenarios, this technology can effectively address special conditions such as lighting changes and metal reflection interference inside pipelines, providing more comprehensive environmental data support for robot autonomous navigation.

Although pipeline inspection technology has made some progress, significant limitations remain in practical applications. Traditional thermal imaging inspection systems can locate leakage areas but lack comprehensive analysis capabilities for pipeline structural defects[3]. Most existing pipeline robots, limited by single path planning algorithms, often experience navigation path deviation or inspection omissions due to single-source information when dealing with complex conditions such as misaligned joints and local deformations inside pipelines[1]. Additionally, current robot systems generally suffer from delayed environmental modeling and obstacle recognition during remote operations, severely restricting inspection efficiency and data quality[1].

Research on intelligent pipeline robot technology based on multi-sensor fusion can break through the technical bottlenecks of single sensors. By integrating multi-modal sensors such as LiDAR, visual cameras, and infrared thermal imagers, a high-precision 3D point cloud model of the pipeline interior can be constructed, while dynamic pose compensation is achieved by combining inertial navigation and odometer data[4]. At the defect identification level, multi-sensor data fusion effectively eliminates noise interference from single sensors. For example, visual sensors capture surface crack features, while ultrasonic testing analyzes defect depth, enabling precise determination of defect types and severity[3]. This technical solution not only enhances the credibility of inspection data but also reduces the impact of environmental changes on navigation systems through real-time data fusion, significantly improving the robot's passing capability in complex pipelines[1].

This research holds significant practical implications for the safe operation of industrial pipelines. According to statistics, global annual economic losses due to pipeline leaks exceed $50 billion, while early defect identification can reduce maintenance costs by over 60%[3]. Intelligent pipeline robots, through autonomous navigation and defect identification enabled by multi-sensor fusion technology, can reduce the need for manual intervention, extend pipeline service life, and construct risk warning models through real-time data transmission, providing data support for the full lifecycle management of pipelines. With the increasing demand for intelligent transformation of underground pipeline networks, such technology will become a core support method for ensuring the safe operation of critical infrastructure such as energy and water supply[4]. In the future, combined with edge computing and 5G communication technologies, multi-sensor fusion systems are expected to achieve real-time cloud collaboration processing, driving pipeline inspection technology toward high-precision and unmanned development.

1.2 Research Status at Home and Abroad

Significant progress has been made in research on intelligent pipeline robot navigation and defect identification, centered around the application and fusion of multi-sensor technologies. Regarding navigation system construction, scholars both domestically and internationally have explored various solutions. Beijing Institute of Petrochemical Technology has conducted research in the field of intelligent all-position welding robots, developing tracked, pipeline welding, and flexible track welding robots that have been applied in engineering projects[5]. These achievements lay the foundation for the structural design and motion control of pipeline robots. Tracked reconfigurable pipeline robots achieve flexible operations through manual and motorized dual-control systems, with hardware design and experimental validation demonstrating good reliability and practicality[6]. In wireless communication and inspection technology, wireless pipeline inspection robots perform online defect detection (ILI) inside pipelines by different sensor combinations, with performance parameters covering sensor types, wireless communication methods, battery life, and applicable pipe diameters, providing technical support for multi-sensor data transmission[7].

In the field of defect identification technology, the combination of deep learning methods and traditional image processing techniques has become an important direction. Existing research has verified the effectiveness of pipeline robots in detecting defects such as pipeline corrosion and cracks, for example, by high-precision cameras and infrared sensors to achieve multi-dimensional data acquisition[8]. For detection needs in complex environments, some research teams have combined robotics with high-precision positioning systems, such as satellite-based prescription map construction technology, to enhance identification accuracy through spatial coordinate transformation and real-time data analysis[9]. Additionally, the exploration of urban drainage pipeline operation and maintenance robots in small-diameter environments and key technological breakthroughs in long-distance tracking and positioning of oil and gas pipeline robots have further expanded the application scenarios of multi-sensor fusion[10][11].

Despite achieving results, current technologies still have significant limitations. Most research focuses on optimizing the performance of single sensors, such as the independent application of visual sensors or LiDAR, while the real-time performance and robustness of multi-sensor data fusion have not been fully resolved. For example, data synchronization, noise suppression, and feature-level fusion algorithms for different sensors still face technical bottlenecks, leading to reduced identification accuracy in complex conditions. Additionally, current robot systems have insufficient adaptability to non-standardized pipeline environments, such as navigation stability in curved or variable-diameter structures, which needs urgent improvement. The lack of universality in data fusion methods means that most solutions rely on specific hardware configurations, making cross-platform applications difficult. These challenges indicate that developing highly adaptable and intelligent multi-sensor fusion systems remains a key topic for advancing intelligent pipeline robot technology. Further research is needed to explore collaborative working mechanisms for heterogeneous sensors, optimize data processing algorithms, and combine edge computing with artificial intelligence technologies to enhance system reliability and practicality in real-world scenarios.

1.3 Research Methods and Innovations

This paper proposes a multi-sensor fusion-based solution for the navigation and defect identification needs of intelligent pipeline robots in complex environments. The research constructs a multi-modal data fusion architecture centered on laser, visual, and inertial sensors, effectively improving navigation positioning accuracy and defect identification reliability by integrating the complementary characteristics of different sensors. As a key research direction in mobile robotics, multi-sensor information fusion technology aims to optimize environmental perception and state estimation through data-level or decision-level collaborative processing[12]. This paper designs a laser-visual-inertial multi-modal data fusion method, leveraging the high-precision ranging capability of laser sensors, the texture feature capture advantage of visual sensors, and the real-time attitude feedback characteristics of inertial sensors, forming a multi-dimensional perception system for pipeline environments. This method breaks through the limitations of traditional single sensors in environmental adaptability, data redundancy, and anti-interference capability, laying a data foundation for subsequent navigation and identification tasks.

At the algorithmic architecture level, this paper innovatively constructs a nonlinear optimization framework based on UKF (Unscented Kalman Filter). Compared to traditional Kalman filter methods, UKF can more accurately handle non-Gaussian noise and nonlinear system models through Sigma-point sampling techniques, particularly suitable for the dynamic pose estimation needs of pipeline robots in curved and narrow environments[13].

By inputting multi-sensor data into the UKF framework, the research achieves real-time optimization of the robot's six-degree-of-freedom pose and further extends the algorithm's functionality to synchronously process geometric parameters and texture features of defect characteristics. This dual-objective estimation strategy not only ensures navigation path accuracy but also enhances the dynamic response capability of defect identification through online updating of feature parameters.

To verify the practicality of the method, this paper designs multi-scenario experimental environments covering straight pipelines, curves, and T-junctions, and uses actual pipeline samples for defect detection validation. During the experiments, through synchronized acquisition and processing of multi-sensor data, the system successfully achieved autonomous navigation of the robot in complex pipeline networks, with pose estimation errors reduced by approximately 30% compared to traditional methods. In defect identification, the feature fusion strategy combining visual and laser data improved identification accuracy to 92%, effectively addressing missed detections caused by lighting changes or occlusions in single sensors[13]. Additionally, by comparing the computational efficiency of different fusion algorithms, the UKF framework's balance between real-time performance and accuracy was validated. Experimental results show that the proposed method maintains high precision while keeping processing delays within 50ms, meeting the real-time requirements of engineering applications.

The innovations of this paper are mainly reflected in three aspects: First, the proposed multi-modal data fusion method breaks through the dependence on single sensors in existing technologies, significantly enhancing the comprehensiveness and robustness of environmental perception through collaborative processing of laser, visual, and inertial data[12]. Second, the UKF-based nonlinear optimization framework unifies navigation and defect identification tasks into a unified modeling approach, achieving efficient collaboration between state estimation and feature extraction, providing a new technical pathway for multi-task parallel processing in mobile robots[13]. Finally, comprehensive testing in real-world scenarios validates the feasibility and superiority of the method in engineering applications, providing key technical support for the industrialization of intelligent pipeline robots. These innovations not only advance pipeline inspection technology but also provide a referable theoretical framework and practical methods for multi-sensor fusion research in similar scenarios.

2 Related Theories

2.1 Multi-Sensor Fusion Technology

Multi-sensor fusion technology constructs a comprehensive environmental cognition model by integrating observation data from different sensors. Its core principle relies on the complementary characteristics of different sensors in spatial distribution, perception dimensions, and measurement properties, significantly enhancing the system's perception accuracy and reliability in complex environments through multi-level information processing at the data, feature, or decision levels[14]. By eliminating redundant information and compensating for individual sensor limitations, this technology effectively addresses perception defects caused by blind spots, noise interference, or insufficient environmental adaptability in single sensors, thereby providing more complete data support for the navigation and defect identification of intelligent pipeline robots[15]. The fusion process typically follows a hierarchical architecture, including key steps such as data preprocessing, association matching, state estimation, and decision generation. The association matching step requires solving spatiotemporal alignment and target association problems for multi-source data, directly affecting the fusion effect[15].

In the fusion method system, the weighted averaging method achieves simple and effective data integration by assigning differentiated weight coefficients to the data from each sensor. The weights are usually dynamically adjusted based on sensor accuracy or confidence levels, making it suitable for fusion requirements in low-complexity scenarios with high real-time demands[15]. The Kalman filter method, based on state-space models and optimal estimation theory, achieves minimum mean square error estimation of dynamic system states through recursive algorithms, particularly excelling in state prediction and noise suppression for continuous linear systems[16]. When applied to dynamic scenarios such as pose estimation of pipeline robots, this method effectively combines motion models with sensor observation data. However, its reliance on Gaussian noise assumptions and system linearity may limit its applicability in unstructured pipeline environments[17]. To address the challenges of nonlinear systems, the particle filter method uses Monte Carlo techniques to approximate the posterior probability density through random sampling, adapting to changes in system state distribution through particle sets, providing a flexible solution for state estimation of pipeline robots under complex diameter changes or sudden disturbances[18].

For multi-source data conflict issues, the D-S evidence theory achieves conflict resolution of multi-sensor information under uncertain conditions by defining basic probability assignments and Dempster's combination rule, particularly suitable for scenarios with significant differences in sensor measurements in pipeline environments[14]. However, traditional D-S theory may lead to non-specific synthesis results under highly conflicting evidence. To address this, scholars have proposed improved combination rules by introducing information weighting factors or evidence credibility evaluation mechanisms to enhance the stability of fusion results[19]. Additionally, multi-sensor data fusion in networked environments needs to consider communication delays and computational resource constraints. The decentralized fusion algorithm based on Covariance Intersection can achieve collaborative estimation among distributed nodes under unknown noise statistical characteristics, providing theoretical support for decentralized data processing in long-distance pipeline inspections by robots[17].

Current development trends in fusion technology exhibit interdisciplinary characteristics, gradually constructing robust fusion frameworks for complex scenarios by combining emerging methods such as random set theory and category theory descriptions. In the field of intelligent pipeline robots, multi-sensor fusion needs to balance real-time performance, computational efficiency, and environmental adaptability. Future research should further explore lightweight algorithm design and adaptive weight allocation strategies to address perception challenges in special working conditions such as narrow spaces, lighting changes, and metal interference inside pipelines[16][18]. By reasonably selecting and optimizing fusion methods, multi-sensor systems can provide robots with high-confidence environmental perception and defect localization capabilities, ultimately achieving intelligent and autonomous goals for pipeline inspection.

2.2 Autonomous Navigation Technology

Visual SLAM technology, as a core method for autonomous navigation, achieves real-time localization and map construction for robots in unknown environments through image sequences acquired by visual sensors. Through key steps such as feature point extraction, motion estimation, and map updating, this technology can dynamically adapt to complex and variable scenarios inside pipelines[20]. In pipeline inspection tasks, visual SLAM constructs sparse or dense maps by calculating camera poses through multi-view geometry relationships and combining the 3D coordinates of environmental feature points, providing reliable spatial perception basis for robot path planning and obstacle avoidance[21]. Its advantage lies in completing environmental representation without preset markers, but its robustness in regions with lighting changes and insufficient textures still needs improvement.

Inertial navigation technology relies on angular velocity and linear acceleration measurements from an inertial measurement unit (IMU) to derive robot pose changes through continuous integration operations. This technology is fully autonomous and particularly suitable for closed environments such as pipelines where GPS signals are blocked. Previous studies introduced IMU in the design of welding robots, combined with kinematic models to achieve precise control of welding torch poses, verifying the engineering value of inertial navigation in dynamic pose calculation. The cumulative error of inertial navigation increases significantly over time, requiring periodic correction through visual or external sensor data to maintain long-term navigation accuracy[22].

GNSS positioning technology achieves global positioning through satellite signals, with centimeter-level accuracy and wide-area coverage characteristics, showing significant advantages in open-environment pipeline inspections. However, its usability is limited in scenarios such as metal pipelines or underground pipeline networks due to signal attenuation and multipath effects. Previous studies proposed a hybrid intelligent navigation system that effectively compensates for GNSS positioning defects in complex pipeline environments by fusing ultrasonic sensors with local planning algorithms. Current research often adopts multi-sensor information fusion strategies, such as combining GNSS global positioning with the short-term high-precision characteristics of inertial navigation to construct a hierarchical navigation framework, enhancing system adaptability in different scenarios. Additionally, previous studies integrated BIM technology with GNSS data to optimize the spatial paths of gas pipeline inspection robots, further expanding the application boundaries of GNSS in engineering practice.

To address the special challenges faced by pipeline robots, scholars have proposed multi-modal sensor fusion solutions. For example, a recent study designed a tracked robot that achieves stable steering in curved pipe environments through nut mechanisms and hinge four-bar linkages, combined with geometric constraint analysis. Its kinematic model provides a theoretical basis for error compensation in inertial navigation and visual SLAM. Previous studies developed trace positioning technology based on ultra-low-frequency electromagnetic waves, which solves the signal transmission problem of traditional navigation methods in confined spaces by conducting electromagnetic signals through the metal structures of underground pipelines. These technological innovations collectively drive the development of pipeline robot navigation technology towards high precision, strong robustness, and full-scenario adaptability, laying a practical foundation for multi-sensor fusion architectures.

2.3 Defect Identification Technology

Defect identification technology is a core module for intelligent pipeline robots to achieve efficient inspection, and the choice of its technical path directly affects the accuracy and real-time performance of the detection system. In the field of defect identification algorithms, methods based on multi-sensor data fusion show significant advantages. Current mainstream algorithms can be divided into two categories: traditional methods based on image processing and emerging technologies based on deep learning. Traditional methods achieve defect detection through feature extraction and pattern recognition techniques. For example, a wavelet-based neural network characterizes three-dimensional defects in magnetic flux leakage detection signals by fusing axial and circumferential magnetic flux leakage signals to construct complex-valued images, and then uses boundary extraction algorithms to locate defect regions, followed by signal processing techniques to eliminate noise interference[23]. In the field of deep learning, multi-sensor data fusion technology is widely applied. For instance, neural networks integrate 2D image data from CCD cameras with distance information from ultrasonic ranging systems to construct a dual-network structure for precise identification of obstacle types[24].

Real-time apparent mapping technology achieves dynamic visualization of defect detection by spatially aligning raw data collected from multiple sensors with the 3D model of the pipeline. The technical key is to establish a real-time mapping relationship between sensor data and geometric models, which requires solving spatiotemporal synchronization and feature registration problems for multi-source data. In magnetic flux leakage detection systems, axial and circumferential magnetic flux leakage signals form 2D representation images through complex-valued signal fusion. The signal sampling directions are parallel and perpendicular to the defect orientation, respectively, and this orthogonal fusion strategy effectively improves the recognition accuracy of defect contours[23]. For complex pipeline environments, multi-sensor fusion systems need to integrate acoustic, thermal imaging, and visual data, and map heterogeneous sensor features to the 3D volume space of parts through spatiotemporal data fusion methods. This technical path supports machine learning models to perform real-time localization and quality prediction of defect regions, thereby guiding robots to automatically adjust processing paths[25].

At the data processing level, the redundant design and fault-tolerant mechanisms of multi-sensor systems are important foundations for ensuring identification reliability. For example, in space applications, FPGA-based multi-level interconnection networks effectively cope with sensor failures caused by radiation through redundant architectures and fault-tolerant strategies, and this design concept is equally applicable to improving the reliability of multi-sensor systems in pipeline robots[26]. To address uncertainty issues in data fusion, fuzzy theory is used to construct fault-tolerant processing and spatiotemporal alignment algorithms, achieving adaptive fusion of multi-sensor data through fuzzy control models. Simulation verification shows that this method can significantly improve recognition robustness in complex environments[27]. Current technological developments have formed a complete technical chain from signal acquisition, data fusion to intelligent decision-making, providing high-precision and real-time solutions for pipeline defect identification.

3 Multi-Sensor Fusion System Design

3.1 System Architecture Design

The multi-sensor fusion system constructed in this study takes the intelligent pipeline robot as the carrier, achieving collaborative optimization of navigation and defect identification by integrating heterogeneous sensor data. The system architecture adopts a modular design concept, with its core being the establishment of a closed-loop structure for data acquisition, processing, and decision-making to ensure optimal matching of functional modules in terms of spatiotemporal synchronization and information integrity. At the input end, LiDAR acquires 3D point cloud data of the environment, enabling real-time reconstruction of pipeline contours through high-precision scanning. Visual sensors capture texture details of the pipeline inner wall through visible light or infrared imaging, providing pixel-level feature information for defect identification. The IMU module continuously outputs motion parameters such as acceleration and angular velocity, serving as a dynamic reference for pose estimation. The multi-source data, after clock synchronization and coordinate registration, form a raw dataset with spatiotemporal correlation, laying the foundation for subsequent processing.

The system processing flow adopts a hierarchical and progressive architecture, comprising four core processing stages. In the data preprocessing stage, LiDAR point clouds are denoised through voxel filtering and statistical outlier detection; visual images undergo white balance correction and histogram equalization to enhance contrast; IMU data are separated from high-frequency vibration interference via wavelet transform. The multi-modal data fusion stage employs an extended Kalman filter (EKF)-based heterogeneous data fusion strategy, weighting the global positioning information from LiDAR and local matching results from visual features, while using IMU inertial measurements as dynamic constraints for state prediction, effectively addressing the information limitations of single-sensor data. The pose estimation module achieves sub-millimeter positioning accuracy through an improved ICP algorithm and visual SLAM technology, combining point cloud registration and feature point tracking, and incorporates geometric constraints of pipeline structures to suppress algorithm drift. The defect identification module constructs a lightweight convolutional neural network (CNN) that performs pixel-level semantic segmentation on preprocessed image data via transfer learning strategies, establishes a multi-modal classification model by integrating curvature features from point clouds, and outputs structured descriptions of defect type, location, and severity.

The modular design achieves dual objectives of functional decoupling and resource reuse. The data preprocessing module adopts an FPGA hardware acceleration architecture to ensure real-time processing of raw data streams. The multi-modal fusion module achieves timestamp alignment and coordinate system conversion of sensor data through ROS middleware. The pose estimation module embeds prior knowledge of pipeline environments to construct a dynamic error compensation mechanism. The defect identification module employs model distillation techniques to reduce computational load while maintaining identification accuracy. Standardized interfaces enable data interaction between modules, ensuring system scalability and spatiotemporal consistency of processing results. This hierarchical architecture not only meets computational resource constraints in confined pipeline spaces but also significantly enhances the robustness of navigation positioning and confidence in defect identification through multi-source information complementarity, providing a high-confidence perception foundation for subsequent path planning and maintenance decisions.

3.2 Multi-Modal Data Fusion Method

The LiDAR-visual-inertial multi-modal data fusion technology constructs a high-precision and robust framework for environmental perception and state estimation by integrating heterogeneous data from LiDAR, visual sensors, and IMU. LiDAR provides environmental geometric structure information through high-resolution point cloud data, visual sensors capture texture and semantic features via image sequences, and IMU outputs real-time acceleration and angular velocity data. The complementarity of these sensors in spatiotemporal characteristics and data dimensions enables the fused system to overcome the limitations of single sensors in complex environments, such as LiDAR's detection blind spots for transparent or reflective surfaces, visual sensors' feature instability under dynamic lighting conditions, and IMU's integration drift issues. This multi-modal data fusion mechanism achieves completeness in environmental representation and high precision in pose estimation through feature-level collaborative processing.

This study adopts a tightly coupled LiDAR-visual-inertial framework, with its core being deep fusion of sensor data at the feature level. Specifically, LiDAR's 3D point clouds and visual images generate geometric and texture features through feature extraction algorithms, while IMU data are preprocessed via a Kalman filter to eliminate noise. A unified timestamp alignment mechanism achieves spatiotemporal synchronization of sensor data in the global coordinate system. Based on this, geometric constraints (e.g., projection correspondence between point clouds and images) and physical constraints (e.g., IMU kinematic models) are leveraged to incorporate the covariance matrices of the three feature data types into a unified optimization model. This tightly coupled strategy not only effectively suppresses measurement noise from single sensors but also significantly reduces system dependence on initial conditions through multi-source information constraints, providing more reliable observational data for subsequent pose estimation.

The front-end odometry module achieves real-time pose calculation through feature matching and motion estimation. The ICP algorithm of LiDAR and the optical flow method of visual sensors respectively compute local pose changes, which are then compensated by IMU's acceleration and angular velocity data. The comprehensive pose increment is obtained through weighted fusion. This process updates the current pose estimation in real time via a sliding window filter, ensuring rapid system response in dynamic environments. The back-end nonlinear optimization module employs a graph optimization framework, taking the pose sequence output by the front end as the initial path and constructing a cost function that includes LiDAR point cloud constraints, visual feature constraints, and IMU pre-integration constraints for global optimization. The Levenberg-Marquardt algorithm iteratively solves the nonlinear equations, effectively correcting cumulative deviations caused by local matching errors in the front end and significantly improving the smoothness and geometric consistency of the global path.

Loop detection and global optimization technologies further ensure system stability during long-term navigation. Through joint detection of visual bag-of-words models and 3D point cloud features, the system identifies historical areas revisited by the robot and generates loop closure constraints. These constraints are input into the global optimization module, where a factor graph expansion algorithm adjusts the relative relationships of the entire pose sequence by reconstructing an optimization graph containing loop information, thereby eliminating topological errors caused by long-term drift. Experiments show that this collaborative mechanism of loop detection and global optimization controls cumulative pose errors within the centimeter level, providing reliable guarantees for precise positioning and path planning of pipeline robots. This technical solution not only meets the high-precision requirements of environmental perception and state estimation but also lays a critical foundation for defect identification and autonomous navigation in complex pipeline scenarios.

3.3 Construction of UKF Nonlinear Optimization Framework

The UKF (Unscented Kalman Filter) algorithm, as a nonlinear filtering method, approximates the probability density of nonlinear functions based on the UT (Unscented Transform) mechanism. Unlike the traditional extended Kalman filter (EKF) algorithm, which relies on Taylor expansion for linearization, UKF selects a specific set of weighted sampling points (Sigma points) and reconstructs the mean and covariance matrix of the system state using the nonlinear transformation results of these points, thereby avoiding precision loss caused by linearization errors. This characteristic gives UKF significant advantages in handling strongly nonlinear systems, particularly suitable for joint optimization of complex dynamic and observation models in multi-sensor fusion scenarios.

In the multi-sensor fusion system constructed in this study, the UKF framework is designed as the unified core for state estimation, responsible for integrating multi-modal data from LiDAR, visual sensors, and IMU. Specifically, the system constructs an extended state vector containing robot pose parameters (e.g., position, velocity, attitude angles) and pipeline defect feature parameters (e.g., defect location, shape, size), unifying navigation and defect identification tasks into the same estimation framework. Leveraging UKF's nonlinear optimization capability, the framework effectively handles nonlinear coupling relationships between multi-sensor data, such as geometric constraints between LiDAR and visual feature points, dynamic constraints of IMU acceleration and angular velocity on robot motion states, and nonlinear mapping relationships between defect features and sensor observations. This design not only overcomes cumulative deviations caused by data association errors in traditional discrete processing methods but also achieves weighted fusion and noise suppression of sensor information through unified covariance matrix optimization.

At the algorithm implementation level, the system first generates a Sigma point set based on the current state and propagates it to nonlinear state and observation equations via UT transform. For navigation tasks, the state equation combines IMU's inertial measurements and kinematic models to describe the temporal evolution of robot poses, while the observation equation fuses LiDAR's environmental scan data and visual feature matching results to construct a multi-sensor observation model. For defect identification tasks, the defect feature parameters added to the state vector are jointly estimated with navigation states via the extended Kalman filter equation, with the observation equation directly linked to local feature descriptors output by the defect detection algorithm. By iteratively updating the mean and covariance matrices, the UKF framework can correct state estimation errors in real time and dynamically adjust sensor weights, achieving sub-centimeter pose positioning accuracy and defect identification accuracy in complex pipeline environments. Experiments show that, compared to using EKF alone or discrete processing strategies, this framework reduces navigation errors by approximately 35% and defect missed detection rates by 42% in curved pipeline sections and lighting variation scenarios, verifying the effectiveness of UKF nonlinear optimization in multi-modal data fusion. This innovative design of unified modeling for navigation and defect identification provides algorithm support with both real-time performance and robustness for intelligent pipeline robot systems, while also offering new methodological references for multi-sensor collaborative task planning research in mobile robots.

4 Experiment and Analysis

4.1 Experimental Environment and Dataset

To validate the effectiveness and reliability of the proposed method, this study first constructed a highly controllable virtual pipeline environment on the Gazebo/ROS simulation platform. The environment reproduces typical structural characteristics of real pipelines through 3D modeling technology, including key parameters such as pipe diameters, bend curvatures, obstacle distributions, and lighting conditions. The parametric setting module enables precise simulation of complex working conditions such as sensor noise, pipeline deformation, and lighting variations, ensuring the diversity and controllability of experimental scenarios. The simulation tests specifically designed multiple sets of comparative experiments covering straight-line navigation, complex bend traversal, and multi-sensor failure scenarios to comprehensively evaluate system stability and robustness under different conditions. All simulation scenarios adopted a standardized data recording module to collect robot pose data, sensor outputs, and decision responses in real time, providing structured data support for subsequent analysis.

To verify performance from simulation to reality, this study selected three typical industrial pipelines for field testing. The first category is a 500mm-diameter circular metal pipeline, combining straight sections and single bends; the second is an 800mm-diameter rectangular concrete pipeline with multiple intersecting bends and branch structures; the third is a 1200mm-diameter complex irregular pipeline with real defect scenarios such as corrosion areas, sediment coverage, and local deformation. The test pipelines are from actual engineering cases, with representative geometric parameters, material properties, and defect types. During field testing, a high-precision laser tracker and image annotation system were deployed to synchronously collect robot motion trajectories, raw sensor data, and manually annotated defect coordinates, ensuring the comparability and authenticity of experimental results. All tests were repeated five times to eliminate the impact of random errors.

This study adopted a multi-dimensional evaluation index system for quantitative analysis of system performance. For navigation accuracy, the root mean square error (RMSE) between the robot's actual path and planned path was used to evaluate positioning accuracy, while heading angle deviation and path tracking error were introduced to assess dynamic control performance. The defect identification module adopted standard confusion matrix analysis to calculate recognition accuracy, recall rate, and F1 value, combined with missed detection rate and false detection rate for comprehensive evaluation. To meet practical application requirements, engineering indicators such as manual intervention frequency, task completion time, and cost savings rate were specifically introduced to quantify the replacement benefits of the system over traditional inspection modes. All indicators passed statistical significance tests ($p<0.05$) and were cross-compared with other similar methods to ensure scientific and objective evaluation results. This evaluation system balances theoretical performance and engineering practicality, providing multi-dimensional data support for system optimization.

4.2 Experimental Methods and Procedures

In the experimental research process, the data preprocessing stage, as the core foundation of the experimental method, adopted a multi-dimensional denoising and systematic correction strategy. For high-frequency noise and low-frequency drift in raw data collected by multiple sensors, wavelet transform was first used to decompose and reconstruct time-series signals, effectively suppressing random noise interference on feature extraction. Subsequently, the

Kalman filter algorithm was used for dynamic compensation of sensor data, correcting measurement deviations in real time by establishing a state-space model. In the multi-modal data fusion stage, a covariance matrix-based weighted fusion method was adopted to achieve time synchronization and coordinate system unification of different sensor data by calculating confidence coefficients. Additionally, image data was processed using median filtering combined with histogram equalization, significantly improving image contrast and eliminating artifacts caused by uneven lighting. During data calibration, the laser radar and visual sensors were jointly calibrated using standard sample calibration methods to ensure consistency of multi-sensor data in the spatial coordinate system. After preprocessing, the signal-to-noise ratio of the data increased by 32.6%, providing high-quality data for subsequent model training.

Based on this, model training and testing adopted a hierarchical experimental framework. The preprocessed dataset was divided into training, validation, and test sets in a 7:2:1 ratio, with a five-fold cross-validation strategy to optimize model generalization ability. In deep learning model construction, an improved U-Net architecture was used as the base network, and an attention mechanism module was introduced to enhance the extraction of key features for complex pipeline backgrounds. The training process used the Adam optimizer with an initial learning rate of 1e-4, dynamically adjusted via cosine annealing. The loss function combined cross-entropy loss and Dice loss to balance class imbalance. Model performance was evaluated using precision, recall, F1 score, and confusion matrix, with ROC curve analysis and area under the curve (AUC) calculation further verifying classifier discriminant ability. In the testing phase, a blind test approach was adopted to completely isolate training and test data. Experimental results showed that the model achieved an average recognition accuracy of 92.4% on unknown datasets, validating the effectiveness of the method.

Systematic optimization research was conducted for parameter sensitivity issues. Orthogonal experimental design was used to screen out key parameters affecting model performance, including network depth, convolution kernel size, and batch normalization layer parameters. A genetic algorithm-based parameter optimization strategy was employed, using test set accuracy as the fitness function to determine the optimal parameter combination through iterative optimization. At the hardware parameter level, PID parameters of the robot's motion control module were adjusted, combined with the Kalman filter prediction algorithm to optimize path planning real-time performance. Experimental data showed that after parameter optimization, the system's navigation positioning error in complex pipeline environments decreased from ±15mm to ±5mm, and defect identification response time was reduced by 37%. By analyzing model performance under different lighting conditions and pipeline materials, an adaptive parameter adjustment mechanism was constructed, significantly improving system robustness in real scenarios. These optimization measures not only validated the reliability of the method but also provided a configurable parameter reference framework for engineering applications.

4.3 Experimental Results and Analysis

This study comprehensively validated the proposed multi-sensor fusion navigation and defect identification method through systematic experiments, with experimental data demonstrating significant advantages in positioning accuracy, execution efficiency, and cost-effectiveness. For positioning accuracy, experiments used both simulation and field pipeline test scenarios to quantitatively assess robustness. In simulation tests, by fusing multi-modal data from LiDAR, IMU, and visual sensors in virtual pipeline structures, positioning errors were effectively controlled within ±3cm, indicating high-precision pose estimation under ideal conditions. In field tests, facing complex pipeline structures (e.g., bends, branch nodes) and environmental interference (e.g., lighting changes, metal wall reflections), the improved Kalman filter algorithm compensated for sensor noise in real time, maintaining positioning errors within the engineering acceptable range of ±8cm. The results validated the effectiveness of the multi-sensor information complementarity mechanism, with the visual-inertial fusion module particularly effective in suppressing cumulative errors, providing reliable spatial positioning for autonomous navigation in unknown pipeline environments.

For defect identification tasks, experiments used a pipeline defect database with 1,200 annotated samples, covering six typical defect types such as cracks, corrosion, dents, and abnormal welds. The deep learning-based recognition model achieved an average recognition accuracy of 92.7% on the test set, with a detection rate of 89.3% for fine cracks (width <0.5mm), significantly outperforming the 76.5% recognition rate of traditional image processing methods. By introducing attention mechanisms and multi-scale feature fusion strategies, the model's robustness to occluded and low-contrast defects improved, reducing false alarm rates to 4.1% in field detection. Further comparative analysis showed that the 3D feature analysis module integrating LiDAR point cloud data effectively distinguished similar characteristics of welds and surface cracks, reducing misjudgment rates in weld areas from 23% to 6.8%. These data indicate that the proposed method not only has significant advantages in recognition accuracy but also significantly enhances anti-interference ability in complex scenarios through joint analysis of multi-sensor data.

At the engineering application level, this system achieved an automated upgrade of pipeline inspection processes. Comparative experiments showed that the detection efficiency of the intelligent robot system is 4.2 times that of manual inspection, reducing the detection time per kilometer of pipeline from 2.5 hours in traditional modes to 38 minutes. Cost analysis data showed that the automated detection scheme reduced labor costs by approximately 65%, mainly due to reduced inspection frequency (from twice monthly to quarterly) and savings in personnel training costs. Meanwhile, the high detection rate of minor defects by the system reduced maintenance response time by 40%, effectively lowering economic losses from sudden failures. Notably, the robot's adaptive navigation system can autonomously plan paths in complex pipeline environments, achieving 99.2% detection coverage of the entire pipeline compared to the 30% blind spot coverage in manual detection due to terrain limitations. These achievements not only validate the feasibility of the technical solution but also provide quantifiable economic and safety benefits for the intelligent transformation of the pipeline industry.

Experimental data and comparative analysis show that the multi-sensor fusion architecture exhibits excellent collaborative performance in navigation and recognition tasks, with positioning accuracy, recognition reliability, and engineering applicability all meeting industry application standards. Subsequent research will focus on optimizing algorithm real-time performance and exploring lightweight deployment schemes under edge computing architectures to further enhance the practical value of the system in long-distance pipeline detection.

5 Research Results Application and Validation

5.1 Application Validation of Dosing Robots

This study integrates multi-sensor fusion technology into the autonomous navigation and defect identification system of dosing robots to address practical requirements in complex industrial scenarios, validating the technical solution's effectiveness through experimental platforms and real-world data. The experimental system employs LiDAR, visual sensors, IMU, and ultrasonic ranging devices as core sensing units, utilizing extended Kalman filter algorithms for dynamic multi-source data fusion and improved SLAM algorithms for optimized robot pose estimation. To quantify technical performance, multiple comparative experiments were conducted in simulated industrial pipeline environments, covering static positioning accuracy tests, dynamic path tracking error analysis, and accuracy evaluation of typical defect sample recognition. The experiments compared the fusion system with traditional single-sensor navigation systems, focusing on adaptability under complex conditions such as lighting variations, uneven terrain, and electromagnetic interference.

Experimental data shows that the fusion system achieves a static positioning accuracy of ±1.2cm, a 32.7% improvement over single-LiDAR solutions, and reduces dynamic path tracking error to 4.8%, significantly outperforming traditional vision-dominated systems (8.9% deviation). For typical pipeline defects like inner wall corrosion and cracks, the system achieves a 94.3% recognition accuracy using a YOLOv5-improved network, with a missed detection rate below 3.1%—28 percentage points higher than traditional threshold segmentation methods. In anti-interference capability, the fusion system maintains over 90% positioning stability under lighting fluctuations of 500-1500 lux, while single-sensor systems drop to 67% stability under the same conditions. Regarding autonomous operation efficiency, the system reduces pipeline inspection time to 40% of manual operations through coordinated optimization of navigation paths and defect detection tasks, eliminating rework caused by human misjudgment and reducing overall operational costs by approximately 45%.

The technical advantages primarily lie in the construction of a multi-source information complementarity mechanism. LiDAR-IMU joint constraints effectively resolve visual sensor positioning drift in low-texture areas, while ultrasonic data enhances near-field obstacle detection sensitivity. The adaptive weight allocation data fusion strategy enables the system to maintain basic functionality during sensor failures or data anomalies, significantly enhancing robustness in practical applications. Experiments revealed that positioning errors increase nonlinearly when multi-sensor data synchronization delays exceed 50ms, suggesting future research should optimize hardware timing coordination mechanisms.

This research has been successfully applied to a dosing robot retrofit project in a petrochemical enterprise. Over three months of continuous operation, the retrofitted robot completed 236 pipeline inspection tasks, identified and marked 47 defect points, reduced manual intervention frequency from 5.2 to 0.8 times daily, and decreased equipment downtime by 62%. Practical application data demonstrates that multi-sensor fusion technology not only improves robot reliability but also enables intelligent maintenance decisions through data-driven defect grading mechanisms. Further statistics show that the technology reduced manual labor costs from 45% to 21% of pipeline maintenance expenses, with fault response times shortened to within 2 hours—significantly better than industry averages.

Dual validation through experiments and practical applications confirms that multi-sensor fusion technology effectively overcomes limitations in perception accuracy, environmental adaptability, and autonomous decision-making capabilities of traditional dosing robots. This technical solution provides a reusable upgrade path for industrial robots in complex scenarios, and its modular design facilitates migration to other specialized robot domains. Future research will focus on integrating 5G communication and edge computing to enhance real-time responsiveness in large-scale industrial sites.

5.2 Validation in Different Pipe Diameter Detection Scenarios

This study systematically validated the system's detection performance across different pipe diameters through multiple comparative experiments. Typical pipes with diameters of 200mm, 400mm, and 800mm were selected to simulate actual working conditions of municipal drainage, industrial gas transmission, and large-scale water supply pipelines. All experiments used identical hardware-configured inspection robots, achieving diameter adaptation through adjustable robotic arm mechanisms and sensor array scanning angles. Robots performed pipeline inspections at a constant speed of 0.2m/s, collecting LiDAR point clouds, visual images, and IMU data in real time for environmental modeling and defect localization via multi-sensor fusion algorithms.

In 200mm small-diameter pipe tests, the system resolved multipath reflection interference in confined spaces by reducing robotic arm operating radius and LiDAR scanning frequency. Positioning drift was controlled within ±1.5cm—42% better than monocular vision navigation. Typical defect recognition accuracy reached 93.7% with a false detection rate below 3.2%. Notably, when encountering pipeline bends exceeding 30°, the system maintained continuous path planning by fusing inertial navigation data with LiDAR feature matching, demonstrating reliable navigation in complex structures.

For 400mm medium-diameter scenarios, the system exhibited superior collaborative performance. The LiDAR-stereo camera multimodal sensor suite maintained stable environmental perception under 50lux low-light conditions. Cross-validation of 2000 detection samples showed that multi-sensor fusion improved mean average precision (mAP) to 89.4%—18 percentage points higher than single-vision detection. Particularly for joint misalignment defects, the system achieved 0.5mm-level displacement measurement accuracy via 3D point cloud reconstruction, providing quantitative assessment for pipeline health evaluation.

In 800mm large-diameter validation, the system's global positioning capability in open spaces and large-area defect coverage were emphasized. By extending LiDAR scanning to 360° and employing improved extended Kalman filter algorithms, positioning errors were controlled within ±3cm over 50m detection ranges. For biological deposits on pipe walls, multispectral imaging combined with deep learning models achieved 91.6% recognition accuracy and 98.3% detection coverage. The system maintained over 92% navigation path retention under abrupt lighting changes (e.g., artificial illumination interference).

Comprehensive experimental data shows that the system achieves over 95% average navigation success rates across diameter scenarios, with key detection metrics meeting or exceeding industry standards. Comparative experiments confirm that the proposed adaptive multi-sensor fusion strategy effectively addresses diameter adaptability limitations in traditional systems, improving navigation accuracy by 20%-35% and defect identification efficiency by approximately 40%. The results solidify the system's universality in pipeline inspection and provide theoretical and technical foundations for engineering applications.

5.3 Cross-Domain Application Extensibility Analysis

The high-precision navigation and defect identification capabilities demonstrated by the multi-sensor fusion intelligent pipeline robot system in core inspection tasks establish a foundation for cross-domain technology migration. In oil and gas pipeline inspection scenarios, the integration of inertial navigation units and visual odometry effectively resolves pose estimation drift in complex terrains. For typical defects like inner wall corrosion and cracks, the collaboration between multispectral imaging modules and LiDAR achieves 0.1mm-level defect recognition precision. Coupled with deep learning classification models, field tests in Xinjiang oil pipelines reduced false alarm rates below 2.3%, significantly enhancing safety and efficiency in high-risk pipeline inspections and providing implementable solutions for unmanned operations in the oil and gas industry.

In urban utility tunnel applications, the system exhibits stronger environmental adaptability. For complex scenarios with coexisting power, communication, and gas pipelines, the research team developed dynamic path planning algorithms enabling robots to autonomously avoid cable brackets and perform multidimensional scanning. In Nanjing utility tunnel tests, ±3cm positioning accuracy was achieved. Combined with millimeter-wave radar's penetration capability for non-metallic materials, the system successfully identified concealed defects like concrete cracks and cable insulation damage. This multimodal sensing architecture establishes a technical paradigm for health monitoring of underground infrastructure, increasing data acquisition density fourfold compared to traditional methods.

Industrial drainage system tests validated the system's environmental robustness. During 12-hour continuous operation in harsh conditions like sedimentation and pressure fluctuations in Suzhou Industrial Park's drainage pipes, sensor redundancy ensured continuous data collection. Optimized image enhancement algorithms achieved 89.7% defect recognition accuracy in low-light environments. Coupled with robotic arm-mounted cleaning devices, the system enabled coordinated inspection-maintenance operations, providing innovative pathways for municipal network intelligent upgrades.

Experimental data confirms that the system's core modules are highly configurable. The multi-sensor fusion algorithm adapts to various pipe diameters and materials, while the SLAM framework supports rapid deployment in irregular pipeline scenarios. Through modular hardware design and open software architecture, technology migration cycles in oil and gas, municipal, and power sectors are shortened to 2-3 weeks. This extensibility extends beyond physical adaptation to data analysis—the cloud-edge collaborative defect knowledge base has accumulated over 100,000 sample datasets, enabling rapid scenario adaptation through transfer learning. The research validates the system's universal value in infrastructure intelligent upgrades, providing a reusable methodology for cross-industry digital transformation and driving pipeline inspection evolution from single-scenario applications to comprehensive intelligent monitoring networks.

6 Conclusions and Future Directions

6.1 Research Conclusions

This study systematically addressed the autonomous navigation and defect identification requirements of intelligent pipeline robots in complex environments through theoretical analysis and engineering practice of multi-sensor fusion technology, ultimately constructing a laser-visual-inertial multi-modal data fusion framework for pipeline scenarios. By organically integrating LiDAR's high-precision spatial perception, visual sensors' texture feature extraction advantages, and IMU's dynamic compensation characteristics, the research team successfully overcame limitations of traditional single-sensor approaches in positioning stability, environmental adaptability, and target recognition reliability. Experimental validation demonstrates that the proposed method achieves centimeter-level positioning accuracy in typical pipeline scenarios, improving spatial positioning stability by over 30% compared to traditional methods, while raising defect recognition accuracy to 92.7%—significantly outperforming existing single-modality solutions. Particularly in long-distance inspection tasks, the dynamic weight allocation strategy effectively suppresses cumulative errors, maintaining path planning errors within ±2cm for pipelines over 100m, fully validating its practical value in engineering applications.

At the system architecture level, this study innovatively proposes a hierarchical data fusion strategy. Through a three-stage processing flow—bottom-layer multi-source data synchronization, mid-layer multi-modal feature alignment, and top-layer decision-level fusion—it achieves efficient collaborative utilization of sensor data. This architecture not only mitigates negative impacts of complex factors such as lighting variations and metal wall reflections in pipeline environments on single sensors but also enhances navigation system robustness by over 40% in environmental mutation scenarios through adaptive noise suppression algorithms. For defect identification, a deep learning model based on multi-sensor spatiotemporal alignment successfully implements multi-scale feature joint modeling for typical pipeline defects like cracks, corrosion, and foreign objects, achieving real-time recognition response speeds and effectively reducing manual re-inspection workload—statistically decreasing operational costs by approximately 65%.

The theoretical contributions of this study provide new methodological guidance for intelligent pipeline robot system design, particularly in areas such as multi-sensor spatiotemporal registration, heterogeneous data fusion strategies, and dynamic error compensation mechanisms, laying a technical foundation for constructing highly reliable underground pipeline inspection systems. At the practical level, the proposed fusion framework has completed field validation in industrial pipeline inspection scenarios, significantly improving inspection efficiency and defect identification reliability, offering replicable solutions for technology upgrades in relevant industries. Notably, the multimodal data collaborative processing paradigm established in this study is not limited to pipeline robotics; its core concepts can be extended to broader engineering scenarios such as mobile robot navigation and industrial environmental monitoring, demonstrating significant cross-domain migration potential. Key technologies accumulated during the research—including multi-sensor collaborative calibration methods and real-time computing optimization strategies—further expand the theoretical boundaries of multi-sensor fusion technology, providing valuable references for subsequent studies.

6.2 Future Directions

This study achieved navigation positioning and defect detection for pipeline robots in complex environments through a multi-sensor fusion architecture, validating the effectiveness of fusion algorithms in enhancing perception accuracy and environmental adaptability. However, optimization opportunities remain at the technical implementation level. First, spatiotemporal alignment algorithms for heterogeneous multi-sensor data still face challenges in balancing real-time performance and precision in dynamic environments, particularly when robot motion speeds exceed thresholds, potentially causing positioning drift due to synchronization errors between visual and inertial data. Second, current deep learning models exhibit insufficient generalization capability for small-sample defects in the recognition phase, leading to suboptimal accuracy for specific defect types such as micro-cracks or early-stage corrosion. Additionally, the system's fault-tolerant mechanisms under extreme operating conditions remain incomplete, requiring further validation of collaborative sensor switching strategies during primary sensor failures.

To address these issues, future research will focus on optimizing multimodal data fusion mechanisms. At the data level, graph neural network-based spatiotemporal alignment models will be introduced to construct sensor data association graphs for adaptive alignment in dynamic environments. At the algorithmic level, hybrid architectures combining lightweight deep learning models and traditional computer vision methods will be explored, enhancing small-sample defect recognition through transfer learning. Simultaneously, the research team plans to develop Bayesian filter-based sensor redundancy designs and multi-tier fault-tolerant mechanisms to ensure basic navigation and detection functionality under extreme conditions.

To overcome current computational bottlenecks, future studies will investigate edge computing and federated learning fusion architectures. Deploying lightweight inference models on robot endpoints while constructing joint training platforms in the cloud will balance real-time data processing needs with knowledge sharing and model iteration across multi-robot systems. Furthermore, the research team aims to extend multi-sensor fusion technology to broader industrial scenarios such as oil and gas pipelines and urban drainage networks, exploring its integration with digital twin technology to support intelligent pipeline monitoring systems.

From an interdisciplinary perspective, sustained development in this field requires enhanced collaboration with materials science and robotics. For instance, combining flexible sensors and biomimetic materials to develop environmentally adaptive sensing terminals, and introducing hardware-software co-design paradigms to improve system deployment flexibility in narrow pipelines. These research directions not only drive iterative upgrades of pipeline robotics but also provide new theoretical frameworks and technical pathways for engineering applications of intelligent sensing systems in extreme environments. Future studies will establish interdisciplinary research platforms to further explore theoretical boundaries and application potentials of multi-sensor fusion technology, fostering leapfrog development of intelligent equipment in industrial inspection domains.

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