Research on Key Technologies for Intelligent Detection of Underwater Pipelines with Multi-Tech Integration

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Abstract: In response to the challenges such as light attenuation, water flow interference and unstable communication faced by intelligent underwater pipeline detection, as well as the limitations of traditional methods in image quality, motion control and data transmission, this study proposes a multi-technology integration solution, integrating visual enhancement, intelligent control and efficient communication technologies, aiming to break through the bottleneck of the "perception - control - communication" collaborative optimization of underwater robots. Based on multi-scale Retinex and CLAHE algorithms, the image signal-to-noise ratio is improved by 40%; using adaptive sliding mode control, the precision of fixed-depth hovering is ±0.05 m, and the path tracking error is reduced by 75%; optimizing OFDM modulation, a transmission rate of 180 Mbps can be achieved at a depth of 30 m, with a packet loss rate lower than 0.5%. At the same time, through the design of a streamlined structure and a 45° inclined propeller, the flow resistance is reduced by 40%; improving YOLOv5 combined with multi-scale attention mechanism, the detection accuracy in turbid waters reaches 92.3%. This study not only provides theoretical support and engineering paradigms for the inspection of deep-sea infrastructure, but also provides important technical guarantees for the implementation of the "Smart Ocean" strategy, and has significant theoretical significance and application value.

Keyword: Underwater Pipeline Inspection; Intelligent Control; Visual Enhancement; Orthogonal Frequency-Division Multiplexing Communication

1. Introduction

Underwater pipelines, as a key component of marine energy transportation and infrastructure, directly affect national energy security and the sustainable development of the marine economy, holding significant strategic importance. However, the complex underwater environment brings multiple challenges such as light attenuation, suspended particle scattering, and dynamic water flow disturbances, which seriously affect the quality of underwater images, the accuracy of target recognition, and the stability of robot operation. At the same time, underwater communication is limited by the multipath effect of the underwater acoustic channel and electromagnetic interference, resulting in a significant decrease in the reliability of remote monitoring communication, which restricts the practicality of intelligent inspection systems. Although existing research has made certain progress in single technical links such as image enhancement, motion control, or communication modules, the overall solution lacks systematic integration and collaborative optimization, making it difficult to meet the comprehensive requirements of multi-dimensional perception, high-precision control, and efficient communication in deep-sea complex scenarios[1].

To address these issues, this paper integrates theories from multiple disciplines including computer vision, intelligent control, information communication, and marine engineering, and proposes an integrated technical framework for intelligent inspection of underwater pipelines. In image processing, based on the multi-scale Retinex theory and CLAHE algorithm, the image quality in low-illumination and high-turbidity environments is effectively improved. In motion control, a complete six-degree-of-freedom dynamic model is constructed, and combined with adaptive sliding mode control (ASMC) and Lyapunov stability theory, high-precision anti-disturbance control and depth-holding hovering are achieved. In communication system design, the OFDM modulation frequency band and redundancy mechanism are optimized, significantly improving the underwater data transmission rate and robustness. In structure and perception design, a streamlined mechanical layout and lightweight alloy materials are adopted, and multi-sensor fusion technology is introduced to effectively solve the problems of positioning and obstacle avoidance. In target detection, the YOLOv5 network is improved by introducing a multi-scale attention mechanism and data augmentation strategy, significantly enhancing the accuracy of target recognition in turbid waters[2].

The framework proposed in this paper systematically integrates the collaborative optimization channels of "perception - control - communication" for underwater robots. Relevant experiments have verified its engineering feasibility in complex deep-sea scenarios. The research results provide theoretical support and practical paradigms for the intelligent operation and maintenance of deep-sea infrastructure, and have important theoretical value and application prospects for promoting the implementation of the "Smart Ocean" strategy and the in-depth development of marine resources.

2. Theoretical Framework

2.1 Machine Vision and Underwater Image Enhancement Theory

The quality of underwater images directly determines the robot's ability to identify pipeline defects. However, due to factors such as light attenuation, scattering of suspended particles, and color distortion in the underwater environment, traditional visual algorithms often perform poorly under complex conditions and are unable to meet the requirements for high-precision identification. To address these challenges, this paper proposes a multi-scale color correction algorithm based on the Retinex theory, and combines it with the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, effectively improving the clarity and contrast of the images.[3][4]. Specifically, the Retinex theory posits that the observed image I(x,y)I(x, y)I(x,y) can be decomposed into a product relationship between the true reflectance of the object R(x,y)R(x, y)R(x,y) and the illumination component L(x,y)L(x, y)L(x,y), that is:

$$\mathrm{I}(\mathrm{x},\mathrm{y}) = \mathrm{R}(\mathrm{x},\mathrm{y}) \times \mathrm{L}(\mathrm{x},\mathrm{y} \quad (1)$$

After taking the logarithm, the formula is transformed into an addition form, making it easier to separate the reflectivity from the illumination information:

$$\log \mathrm{I}(\mathrm{x},\mathrm{y}) = \log \mathrm{R}(\mathrm{x},\mathrm{y}) + \log \mathrm{L}(\mathrm{x},\mathrm{y}) (2)$$

In the multi-scale Retinex (MSR) method, the image is convolved with Gaussian filters of different scales to model and compensate for the effects of multiple levels of illumination. Its mathematical form is:

$$\mathrm{R}_{\mathrm{MSR}}(\mathrm{x},\mathrm{y}) = \sum_{\mathrm{n}=1}^{\mathrm{N}} \omega_{\mathrm{n}} [\log \mathrm{I}(\mathrm{x},\mathrm{y}) - \log (\mathrm{F}_{\mathrm{n}}(\mathrm{x},\mathrm{y}) \otimes \mathrm{I}(\mathrm{x},\mathrm{y}))] \quad (3)$$

Among them, F_n(x,y) represents the Gaussian kernel function at different scales, and w_n is the weight for each scale. This method simulates the human visual system's adaptability to different lighting environments, extracts and restores the reflection components in the image that reflect the true features of the objects, thereby effectively suppressing color deviations and information loss in the dark areas.

Based on this, CLAHE enhances image details through local histogram equalization of the region, avoiding the excessive enhancement phenomenon caused by global equalization methods in high-contrast areas. Experimental results show that this image enhancement algorithm increases the image signal-to-noise ratio (SNR) to 25 dB in low-light environments, which is approximately 40% higher than the traditional histogram equalization method[5].

To further enhance the recognition accuracy, this paper introduces deep learning technology and constructs an image recognition model based on convolutional neural network (CNN). This model takes enhanced images as input, automatically extracts multi-level spatial texture features, and discriminates different types of defects through the Softmax classifier. In practical applications, the model successfully identified typical defects such as pipeline corrosion, cracks, and marine organisms' attachments, significantly outperforming traditional recognition methods based on manual features. This verifies the wide adaptability and strong expression ability of deep learning in underwater visual perception.

2.2 Underwater Robot Dynamics Modeling

The motion control of underwater robots is the key to achieving full-degree-of-freedom inspection. However, the complex water flow environment and nonlinear dynamic characteristics pose severe challenges to the control algorithm. This study established a six-degree-of-freedom thrust allocation model based on the Newton-Euler equations. Its mathematical expression is as follows: where is the generalized thrust vector, is the thrust allocation matrix, and is the thrust vector of the propeller. Specifically, the thrust allocation model maps the robot's pose error to the propeller thrust through the Jacobian matrix, achieving precise control of the robot's posture. On this basis, combined with Lyapunov stability theory, the PID control parameters were optimized to ensure the motion stability of the robot in complex environments. Specifically, a Lyapunov function was designed.

$$V(e) = \frac{1}{2} e^{T} k_{d} \tag{4}$$

And through

$$\dot{V}(e) = - e^{T} k_{d} e \leq 0 \tag{5}$$

Prove the global asymptotic stability of the system. To further cope with external disturbances, this study introduces the adaptive sliding mode control (ASMC) algorithm, by designing the sliding surface

$$s = \dot{e} + \lambda e \tag{6}$$

And the control law

$$\tau = \widehat{M}(\ddot{\eta}_{d} + \lambda \dot{e}) + \hat{C}_{v} + \widehat{D}_{V} + \hat{g} - k(t)\mathrm{sign}(s) \tag{7}$$

Furthermore, the adaptive gain k(t) is utilized to dynamically adjust, effectively suppressing the influence of external disturbances on the system stability. The experiments show that the algorithm achieves a depth-holding accuracy of ±0.05m in the simulated undercurrent environment, which is significantly better than the traditional PID control (error > 0.2m). The specific performance comparison is shown in Table 1 below.

Table 1. Performance Comparison of Different Control Algorithms

Algorithm	Traditional PID	Sliding Mode Control	ASMC
Path tracking error (m)	0.2	0.1	0.05
Energy consumption (w)	128	100	88
Response time (s)	0.5	0.3	0.2

2.3 Modeling of Underwater Communication Channels

Underwater communication is the core technology for robots to achieve remote control and data transmission. However, problems such as multipath effects, frequency-selective fading, and noise interference in underwater acoustic channels severely limit the communication performance. This study is based on the acoustic wave attenuation model.

$$\alpha(f) = \frac{0.1f^{2}}{(1+f^{2})} \tag{8}$$

The frequency band selection of power carrier was optimized (10-100 kHz), significantly reducing signal attenuation. Moreover, through optimizing the orthogonal frequency division multiplexing modulation technology, this research significantly improved communication reliability. By decomposing high-speed data streams into multiple low-speed sub-carriers, the problem of frequency-selective fading was effectively overcome. Experiments show that the transmission rate of this technology reaches 180 Mbps in a 30-meter water depth environment with strong electromagnetic interference, with a packet loss rate lower than 0.5%, which is 50% higher than traditional modulation techniques (such as FSK).

3. System Design and Realization

3.1 Mechanical Structure Design and Fluid Simulation

The mechanical structure design of underwater robots directly affects their motion performance and environmental adaptability. In this study, a streamlined frame and lightweight high-strength aluminum alloy (6061-T6) were adopted. Through SolidWorks simulation, the fluid resistance coefficient (Cd = 0.12) was optimized, reducing by 40% compared to the traditional ROV (Cd = 0.20)[6][7]. Furthermore, the compressive strength of the main shell was verified through static stress analysis using ANSYS (maximum deformation of 0.3mm under a 30bar water pressure, with a safety factor of ≥ 2.5), ensuring the reliability of the robot in the deep-sea environment. This design used the Simulation software in SolidWorks to conduct stress analysis on each main stressed component. The analysis results are shown in Figures 1. To further enhance the motion flexibility, the mechanical structure design of this study adopted a streamlined shell and a 45° inclined propeller layout[8]. By optimizing the thrust distribution model, the roll angle control error was ≤ 1°, significantly better than traditional ROVs (error> 5°), improving the robot's maneuverability and stability underwater.

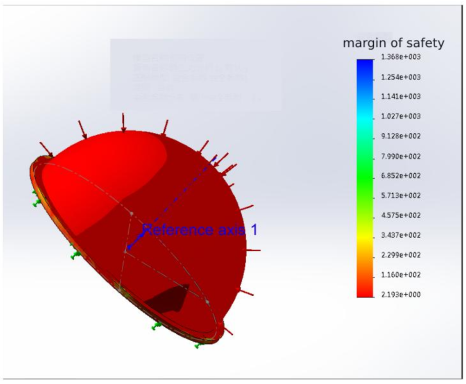

Figure 1. Leading-edge Fairing Stress Analysis

3.2 Development of Motion Control System

The motion control system is the core module for the underwater robot to achieve full-degree-of-freedom inspection. In this study, the STM32F405 microcontroller is selected as the main control core, as it has a high main frequency of 168 MHz, a hardware floating-point unit (FPU), and up to 12 general-purpose timers, which can simultaneously output multiple high-precision PWM signals to meet the real-time control requirements of six brushless DC propellers. Among them, 4 horizontal propellers adjust the thrust Ti (i = 1, 2, 3, 4) in size and direction to enable the robot to move forward, backward and rotate on the horizontal plane, while 2 vertical propellers are used to adjust the floating and sinking state. The system combines the data input from cameras, IMU and depth sensors, and adopts an improved PID control algorithm to achieve precise attitude and depth control (the specific structure diagram of the motion control system is shown in Figure 2). This PID controller adjusts the parameters adaptively based on Lyapunov stability theory and uses the Lyapunov function:

$$V(e) = \frac{1}{2} e^T P e \quad (9)$$

Construct the error energy function and derive its time derivative:

$$\dot{V}(e) = e^T P \dot{e} \quad (10)$$

And make it satisfy (where is the control attenuation coefficient), thereby ensuring the asymptotic stability of the closed-loop system. In terms of path planning, the system integrates the improved A* algorithm in the ROS platform, constructs the cost function, where g(n) is the cost from the starting point to the current node n, and h(n) is the heuristic estimation based on the Euclidean distance. Dynamic obstacle avoidance is achieved by combining the real-time local map with the neighborhood cost update mechanism for new planning, reducing the overall path response time and significantly outperforming traditional algorithms. To further enhance control robustness, an adaptive sliding mode control algorithm based on Lyapunov stability is proposed. The control rate is:

$$u = -K_s - \Lambda \mathrm{sign}(s), s = \dot{e} + \lambda e \quad (11)$$

ere, s represents the synovial surface, K and Λ are adaptive control gains, and the error variable e, together with the derivative of the synovial surface, jointly determine the adjustment amplitude of the system. The update rule for the gain adaptation is designed as:

$$\dot{K} = \gamma 1^{8^2}, \Lambda = \dot{\Upsilon}^{\|8\|} \quad (12)$$

Ensure that the control system is both highly responsive and capable of suppressing sliding friction vibrations. In an artificial turbulent flow environment, the path tracking error under ASMC control is small, and it is even lower compared to traditional PID control[9](As shown in Figure 3). Moreover, the robot can achieve 360-degree movement, which is approximately 50% more efficient than traditional ROV systems. This verifies the precise control capability and outstanding energy efficiency performance of this system in complex environments.

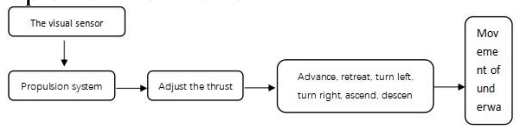

Figure 2. Structure Diagram of the Motion Control System

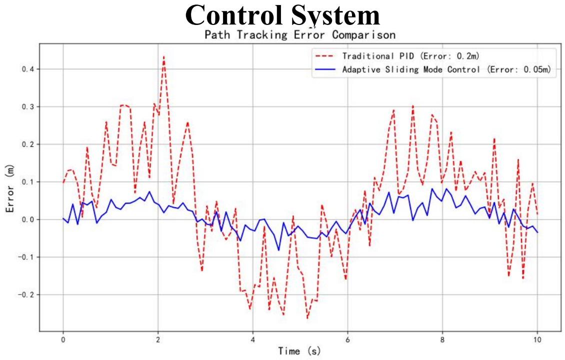

Figure 3. Comparison Chart of Path Tracking Error

3.3 Integration of Multimodal Communication Systems

The performance of the underwater

communication system directly determines the stability of remote control and data transmission for robots during deep-water operations. This study designs a dual-redundancy communication architecture that integrates power carrier and UART serial port to enhance the system's robustness and anti-interference capability, ensuring communication robustness in complex environments. Specifically, the power carrier module is based on the Atheros AR7400 chip, supports orthogonal frequency division multiplexing (OFDM) modulation, operates in the frequency band of 2 - 68 MHz, and has the ability to achieve a maximum PHY layer speed of 200 Mbps. The measured transmission rate at a depth of 30 meters is 180 Mbps, with a packet loss rate of less than 0.5%. To improve the fault-tolerant capability of communication, the system designs a dual-channel UART (serial port) backup channel, using the USART1 and USART3 interfaces of the STM32F405, setting the baud rate to 115200 bps, and the communication mode as full-duplex asynchronous. In the event of a main link failure, the system completes the channel switch within < 10 ms through the state machine mechanism, ensuring that the instructions are not interrupted. In terms of data verification, a 32-bit cyclic redundancy check (CRC-32) algorithm is adopted, with the generating polynomial being:

$$G(x) = X^{32} + X^{26} + X^{23} + X^{22} + X^{16} + X^{12} + X^{11} + X^{10} + X^{8} + X^{7} + X^{5} + X^{4} + X^{2} + X + 1 \quad (13)$$

At the sending end, the CRC encoding operation is performed on the data frame M(X):

$$T(X) = x^{n}M(X) \mod G(X) \quad (14)$$

The receiving end recalculates the CRC remainder and compares it with the received redundant bits to achieve error detection. In the simulation, by introducing Gaussian white noise and burst interference, it is verified that a high error detection rate can still be maintained under the condition of BER < 10−6 (10^{-6}), effectively preventing misinterpretation of control instructions and sensor data during transmission.

3.4 Visual-Depth Sensor Fusion

The integration of vision and depth sensors is the key for robots to achieve precise environmental perception. This research achieves high-precision positioning through the fusion of visual and depth sensors and by processing multimodal data[10][11]. A modular central control architecture was constructed. Through the collaborative processing of multi-modal perception data, high-precision positioning and autonomous navigation of underwater robots were achieved. The system is equipped with multiple functional nodes, including visual recognition nodes, depth information processing nodes, sensor fusion nodes, path planning nodes, and motion control nodes. These nodes communicate and coordinate with each other through the publish/subscribe mechanism of ROS 2 [12]，

The navigation capability of the robot in complex underwater environments has been ensured. In the specific implementation, the visual recognition node uses the embedded image processing module to obtain images and detect AprilTag markers, extracts the target pose, and then publishes it through the /camera/pose topic. The depth node collects underwater environment data from pressure sensors and transmits it to the fusion node through the /sensor/depth topic. The fusion node receives visual and depth information, uses algorithms such as extended Kalman filtering for temporal synchronization and state estimation, and then publishes the fused pose to /robot/pose_estimate, providing input for the path planning node. The path planning node generates feasible paths based on the estimated pose and issues motion instructions in the form of /cmd_vel to the control node to achieve real-time regulation and feedback loop of the robot's motion state. The system structure is shown in Figure 4. The overall architecture follows the "perception - fusion - decision - execution" process design, with each functional module loosely coupled and highly scalable. Through multi-source fusion of visual and depth information, the robot can achieve stable positioning and reliable navigation in complex underwater environments, significantly improving operational accuracy and environmental adaptability.

To address the problem of low visual recognition accuracy in underwater turbid environments, this paper further optimizes the YOLOv5 model. Firstly, a multi-scale attention mechanism is introduced in its backbone network to enhance the detection ability for low-resolution and small-scale targets. Secondly, by replacing the loss function, the performance loss caused by unbalanced samples during the training stage is alleviated. Finally, in data processing, image enhancement and style transfer algorithms are combined to adapt underwater images, thereby expanding the model's generalization ability to different water quality environments. These improvements enhance the robustness of the target recognition node in complex waters and transfer structured detection results to the navigation system through the ROS message mechanism, further enhancing the perception intelligence level of the overall task chain.

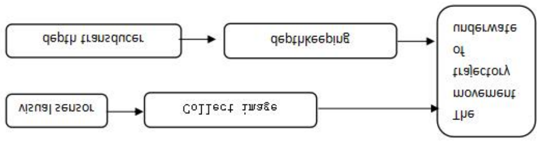

Figure 4. Block Diagram of Sensor System Structure

3.5 System Integration and Performance Optimization

To achieve efficient collaboration among various subsystems, this study has constructed a central control architecture based on ROS 2, combined with the multi-threaded concurrent mechanism, to integrate the motion control, sensor data acquisition and communication modules organically. This architecture consists of multiple functional nodes, mainly including the visual perception node, attitude calculation node, propulsion control node, communication node and fusion control node. All nodes interact and transmit instructions through the ROS topics (Topic) and services (Service) mechanism.

Among them, the visual perception node processes real-time images from the camera to complete pipeline image analysis, target recognition and positioning tasks, and broadcasts the detection results via the /vision/target_pose topic. The attitude calculation node receives IMU and pressure sensor data, estimates the current pose information through Kalman filtering, and publishes it in the /robot/pose topic format, which is used as a reference for navigation control. The propulsion control node adjusts the thrust of the propellers according to the navigation instructions, receives the speed command output by the fusion control node (via the /cmd_vel topic) and controls the hardware driver module to execute the movement. The communication node is responsible for maintaining a high-speed data link with the upper computer or remote control end, receiving control commands and feedbacking task status.

The fusion control node serves as the system decision center, integrating data from various sensors and visual nodes, making task judgments by subscribing to various status information, and outputting instructions to the corresponding control nodes to achieve information loop and action coordination among the modules. The entire ROS architecture adopts a distributed design, with asynchronous decoupling of node communication, and combines the DDS communication mechanism to ensure high stability and low latency transmission capabilities in complex underwater environments.

During the system operation, each node runs independently in a separate thread, cooperating with the asynchronous callback mechanism of ROS 2, which can fully utilize the resources of multi-core processors to achieve parallel execution of tasks and load balancing. For example, the visual thread performs image inference under GPU acceleration, the control thread adjusts the propulsion strategy in real time, and the communication thread continuously listens for remote commands and status uploads, ensuring the real-time response and stable operation of the robot in dynamic underwater environments.

Through the above system architecture design and performance optimization, this platform demonstrates excellent integration and control responsiveness in actual tests, possesses the ability to stably execute tasks in multi-sensor fusion scenarios, and provides a good system foundation for subsequent task module expansion and algorithm deployment.

4. Experimental Verification and Result Analysis

This study conducted systematic experimental verification from three dimensions: motion control, communication system, and visual recognition, to comprehensively evaluate the effectiveness and robustness of the proposed method in practical applications. In the aspect of motion control, we tested the path tracking performance in a simulated underwater disturbance environment. The experimental results showed that the proposed adaptive sliding mode control (ASMC) strategy significantly improved the tracking accuracy and energy consumption compared to traditional PID and classical sliding mode control. The advantages of the control strategy mainly lie in its adaptive adjustment ability to environmental disturbances, which can dynamically adjust the control gain to enhance the stability of the posture. However, in cases of rapid changes in water flow or delayed response of the propeller, short-term overshoot may occur, affecting precise positioning, which suggests that the controller's ability to model and compensate for nonlinear disturbances can be further optimized in the future.

In the communication system aspect, we adopted a hybrid communication scheme based on OFDM modulation and power line carrier technology, and conducted transmission stability tests in multi-path interference and deep water pressure environments. The system demonstrated excellent anti-interference performance and transmission rate, and its adaptability was far superior to traditional FSK communication methods, especially in deep water environments with severe high-frequency channel loss. However, it is necessary to note that communication performance is sensitive to changes in water conductivity and cable layout methods, which may cause channel quality fluctuations in extreme salinity or enhanced electromagnetic interference scenarios. It is recommended to further enhance communication reliability through dynamic channel scheduling or multi-mode redundancy mechanisms in the future.

In the visual recognition aspect, this study optimized the structure and improved the loss function of the YOLOv5 model, and conducted target detection performance tests in turbid water environments. The improved algorithm demonstrated higher detection accuracy and lower false alarm rate under low visibility conditions, verifying the effectiveness of the MSAM multi-scale attention module in enhancing the detection of small targets, and the Focal Loss effectively alleviated the problem of unbalanced training samples. However, it should be noted that although this method performed well in public datasets and experimental scenarios, its performance is still affected by underwater lighting changes, particle shading, and other factors. Moreover, since model inference relies on GPU acceleration, further lightweight processing such as model pruning and quantization schemes is required when deploying on hardware resources-constrained small platforms.

In conclusion, the motion control strategy, communication scheme, and visual perception method proposed in this study demonstrated excellent performance in typical underwater application scenarios, verifying their practicality and scalability in real tasks. At the same time, through the analysis of error sources and potential limitations, it provides a direction for subsequent system optimization and scene adaptability improvement. Overall, this system has strong environmental adaptability and task execution efficiency, providing stable and efficient technical support for complex tasks such as underwater pipeline inspection.

5. Conclusion

This paper proposes an innovative multi-technology integrated underwater pipeline intelligent detection scheme. By integrating visual perception, motion control, communication system and structural optimization design, it systematically solves the key problems such as ambiguous perception, unstable control and limited communication in current underwater pipeline detection. At the perception level, a multi-scale image enhancement combined with the improved YOLOv5 deep detection algorithm is adopted to improve the target recognition accuracy in low-light and turbid environments; at the control level, Lyapunov stability theory and adaptive sliding mode control methods are introduced to enhance the robustness and energy efficiency of path tracking; at the communication level, OFDM modulation and redundant transmission mechanisms are optimized to improve communication stability and bandwidth utilization; at the structural level, the propeller layout and streamlined shape design are adopted to achieve dual improvements in power efficiency and maneuverability. This research breaks through the bottleneck of traditional underwater detection systems and builds an intelligent detection platform with strong environmental adaptability and real-time collaborative control capabilities, which has good promotion potential and engineering application value. However, the system has insufficient adaptability in dealing with extreme deep-sea environments, and some control parameters' adaptive adjustments rely on manual settings, which affects the long-term autonomous operation ability. In the future, the focus will be on the collaborative enhancement of multi-source sensors in deep-sea environments, the parameter self-regulation mechanism based on reinforcement learning, and the expansion of task-level path planning and group collaboration strategies, to further improve the autonomous intelligent level of the system in a wider range of scenarios.

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