DOI: 10.23977/acss.2026.100205
ISSN 2371-8838 Vol. 10 Num. 2

Design and Research of Autonomous Cruise Fish Disease Identification System Based on UAV Platform

Bing Chen[1, a], Ronghui Lin[1, b, #], Shimao Dong[1, c], Lihua Zeng[2, 3, d], Siyue Feng[1, e], Siruo Liu[1, f], Zichun Dai [1, 3, g,*]

[1]*College of Urban Transportation and Logistics, Shenzhen Technology University, Shenzhen, Guangdong Province, China*
[2]*College of Health Science and Environment Engineering, Shenzhen Technology University, Shenzhen, Guangdong Province, China*
[3]*School of Pharmaceutical Sciences, Shenzhen University, Shenzhen, Guangdong Province, China*
[a]*1783403261@qq.com*, [b]*2751185078@qq.com*, [c]*2654447562@qq.com*, [d]*1306318686@qq.com*, [e]*1933496623@qq.com*, [f]*ppeijdjndkdkd@qq.com*, [g]*757249200@qq.com*
[#]*Co-first author*
[*]*Corresponding author*

Keywords: Autonomous cruise; Fish disease identification; Unmanned aerial vehicle; Low-altitude economy; Path planning; Embedded deployment; Aquaculture

Abstract: To address the problems of low efficiency, delayed monitoring and limited coverage of manual fish disease inspection in traditional aquaculture, and adapt to the industrial application trend of low-altitude economy in agricultural fields, this paper designs an autonomous cruise fish disease identification system based on unmanned aerial vehicle (UAV) platform. Taking the PIX quadrotor UAV as the flight carrier and Raspberry Pi 5 as the core hardware, the system integrates autonomous cruise path planning technology and deep learning fish disease recognition algorithm, and constructs a three-layer technical framework consisting of management subsystem, cruise subsystem and identification subsystem. It realizes autonomous fixed-point cruise, real-time image acquisition, intelligent disease identification and comprehensive data management in aquaculture areas. This paper comparatively analyzes the adaptability of various path planning algorithms under complex water environments in fishery, completes software and hardware collaborative integration of algorithms, flight controller and Raspberry Pi. Combined with the fish disease identification model, real-time display and data export of recognition results are realized on the visual front-end interface. Experimental results show that the autonomous cruise positioning error of the system is ≤0.5 m, and the fish disease recognition accuracy reaches 92.3%. It can effectively replace manual daily maintenance and monitoring of fishery farms, and greatly improve the efficiency of fish disease prevention and control. The system provides a feasible technical scheme for the application of low-altitude economy in intelligent aquaculture, promotes the in-depth integration of aquaculture industry and low-altitude economy, and possesses favorable practical application value and industrial promotion prospect.

1. Introduction

Aquaculture is an important part of China's agricultural economy. Large-scale and intensive breeding modes improve production efficiency, but also increase the outbreak risk of bacterial, fungal and viral fish diseases. Early accurate identification and timely prevention of diseases are critical to reducing economic losses in breeding. At present, fish disease monitoring in domestic fishery farms still relies mainly on manual inspection. Restricted by water area range, light conditions and personal experience, manual monitoring has obvious drawbacks including large monitoring blind areas, delayed disease detection and strong subjectivity, which easily cause rapid disease spread and restrict high-quality development of aquaculture industry[1],[2].

With the advantages of low-altitude flight, flexible maneuverability, wide coverage and low operation cost, UAV technology has become a core carrier of low-altitude economy industrial applications[3]. Its mature applications in agricultural plant protection, environmental monitoring and resource exploration provide new technical approaches for intelligent aquaculture monitoring. Meanwhile, the rapid development of deep learning lays a technical foundation for automatic and accurate fish disease identification, making machine vision-based intelligent fish disease diagnosis feasible[4]. At present, UAV applications in fishery monitoring remain at simple aerial photography level, failing to achieve integrated integration of autonomous cruise, intelligent identification and data management[5]. Existing studies seldom adapt to the development demands of low-altitude economy, and lack specialized and industrial UAV schemes for fishery water environments, accompanied by poor path planning adaptability and low software-hardware integration, which cannot meet actual daily operation requirements of fishery farms.

As an emerging economic form, low-altitude economy relies on low-altitude aircraft to carry out production and operation activities in ultra-low airspace, emphasizing industry-technology integration, software-hardware coordination and scenario-demand matching[6],[7]. Combining UAV autonomous cruise technology and intelligent fish disease identification into low-altitude economy system is not only the internal demand for intelligent upgrading of aquaculture, but also an important expansion direction of low-altitude economy in agricultural industry[8]. Raspberry Pi 5, with high computing power and low power consumption, can simultaneously run path planning algorithms and lightweight deep learning models to realize edge-side data processing. The UAV platform composed of Pixhawk 2.4.8 flight controller and F450 quadrotor frame features stable low-altitude flight and waypoint cruise, adapting to complex low-altitude water environments of fishery farms.

Accordingly, combined with industrial application scenarios of low-altitude economy, this paper designs an autonomous cruise fish disease identification system based on UAV platform. A three-layer technical framework is constructed to realize software-hardware coordination, autonomous cruise and intelligent recognition. Path planning algorithms suitable for fishery environments are compared and selected, and visual development of fish disease recognition model is completed. The system realizes autonomous and intelligent monitoring in fishery low-altitude airspace, promotes practical application of low-altitude economy technology in aquaculture, and provides new scenarios and technical support for agricultural low-altitude economy development.

2. Overall System Architecture

Oriented to industrial application of low-altitude economy and actual operation demands of aquaculture farms, the system builds an integrated three-layer technical framework including management subsystem, cruise subsystem and identification subsystem. All subsystems cooperate with each other and share data, realizing the whole process from UAV autonomous cruise, image acquisition, fish disease identification to data management. Centering on deep software-hardware integration, the system integrates path planning, machine vision, deep learning and data management technologies based on UAV flight platform and Raspberry Pi embedded hardware. It meets intelligent daily maintenance requirements of fishery farms, and conforms to low-altitude economy requirements of autonomy, lightweight and industrialization for low-altitude aircraft[9],[10]. Technical positioning and functional coordination of the three subsystems are as follows:

2.1 Management Subsystem

As the core control and data center of the whole system, it undertakes overall software-hardware coordination, comprehensive data management and human-computer interaction, acting as a bridge between cruise subsystem and identification subsystem. Integrating hardware control and software management, the subsystem takes Raspberry Pi 5 as the core to connect and monitor flight controller, camera and communication module. On the software side, visual management interface supports cruise task configuration, real-time flight status monitoring, recognition result display, data storage and export. It also transmits instructions and interactive data among subsystems to ensure stable system operation.

2.2 Cruise Subsystem

As the mobile operation unit, it mainly realizes autonomous cruise and fixed-point image acquisition in breeding areas, serving as the perception and execution module and core embodiment of UAV application in low-altitude economy. Taking PIX quadrotor UAV as flight platform, combined with positioning and cruise functions of Pixhawk 2.4.8 flight controller, the subsystem executes path planning for complex fishery water areas. Through software-hardware collaboration between Raspberry Pi and flight controller, the UAV completes autonomous takeoff, fixed-point hovering, image capture and automatic return according to preset waypoints, ensuring efficient cruise tasks under complex low-altitude fishery environments.

2.3 Identification Subsystem

As the intelligent analysis core of the system, it realizes edge-side fish disease identification and result output, determining practical application value of the system. With Raspberry Pi 5 as hardware carrier and high-definition camera for real-time fish image acquisition on water surface, the subsystem adopts image preprocessing to standardize images for model input. Lightweight deep learning model outputs disease categories and confidence values. Visual front-end interface realizes hierarchical display of recognition results, abnormal early warning and data export, providing accurate decision basis for fishery disease prevention and control.

The three-layer architecture forms a closed workflow of instruction issuance, autonomous execution, intelligent analysis and data feedback. The management subsystem sends cruise and identification tasks, the cruise subsystem performs flight and image collection, and the identification subsystem feeds back diagnosis results, achieving fully automatic and intelligent whole-process monitoring. The overall architecture adapts to agricultural low-altitude economy applications, featuring lightweight deployment, easy installation and strong environmental adaptability.

3. Design and Implementation of Autonomous Cruise Path Planning Algorithm

3.1 Comparison and Selection of UAV Path Planning Algorithms for Water Areas

Path planning for surface unmanned systems is the core technology of autonomous operation, directly affecting cruise efficiency, positioning accuracy and flight safety. Aiming at characteristics of aquaculture water such as wide open water, grid-distributed breeding areas, static obstacles including cages and complex low-altitude airflow, path planning needs to balance four indicators: full-area coverage, fixed-point hovering precision, embedded real-time performance and flight controller compatibility. Existing path planning methods for aquatic robots are divided into global search algorithms, local real-time algorithms and coverage patrol algorithms, represented by improved A* algorithm, artificial potential field method and grid-waypoint planning method respectively. They differ greatly in modeling mode, optimization objective and engineering adaptability.

Improved A* algorithm is mainstream global path planning method for unmanned surface vehicles (USVs). Zhang et al. (2023) proposed an improved A* algorithm with bidirectional search and optimized heuristic function for inland water environments. Grid modeling, 8-neighborhood search and B-spline curve smoothing reduce path inflection points and improve search efficiency. Aiming at shortest path optimization, it generates optimal trajectories under obstacle conditions. However, high computational complexity and frequent node traversal cause obvious delay on embedded platforms such as Raspberry Pi, failing to meet high-frequency fixed-point cruise and real-time control demands. Besides, targeting point-to-point optimal paths, A* algorithm cannot match full-area patrol tasks of fishery farms.

Artificial Potential Field (APF) is a typical local real-time planning algorithm, realizing dynamic obstacle avoidance through target attraction force and obstacle repulsion force. According to USV path planning review by Zhang et al. (2025), APF has simple structure and low computation load, suitable for dynamic obstacle avoidance. Nevertheless, it has inherent defects including local optimum, unreachable target and flight oscillation. Position drift increases under low-texture water surfaces and weak airflow disturbances, failing to guarantee hovering precision required for disease identification. Moreover, APF cannot achieve full regional coverage and orderly multi-point cruise.

Grid-waypoint integrated planning is a special scheme for water patrol tasks, especially suitable for regularly distributed breeding ponds. Davis et al. (2022) pointed out in UAV fishery patrol research that dividing breeding areas into grids and taking grid centers as cruise waypoints can achieve 100% area coverage in sequence. Waypoint instructions are natively compatible with flight controllers. Instead of pursuing shortest paths, this algorithm focuses on full coverage, fixed-point sampling and low computing consumption. With simple environmental modeling and stable operation, it rapidly generates flight routes on embedded terminals and converts routes into MAVLink instructions, perfectly adapting to airborne deployment with limited computing resources.

Considering algorithm performance, water environment characteristics and hardware conditions, grid-waypoint planning is the most suitable for fishery disease cruise tasks. Improved A* algorithm has high path optimality but excessive computing demand, while APF features good real-time performance but poor stability. Neither can satisfy coverage accuracy, positioning precision and embedded deployment simultaneously. Grid-waypoint algorithm enjoys simple modeling, reliable operation and high compatibility with Pixhawk flight controller. It generates waypoints at microsecond level on Raspberry Pi 5, ensuring cruise positioning error ≤ 0.5 m and fully matching lightweight, autonomous and industrial design goals of the system.

3.2 Software and Hardware Collaborative Implementation of Grid-Waypoint Fusion Algorithm

The autonomous cruise adopts grid environmental modeling and sequential waypoint navigation, building a three-level collaborative architecture: ground terminal, Raspberry Pi 5 and Pixhawk flight controller. The whole process operates autonomously via SSH remote control and MAVLink communication.

In environmental modeling, fishery water areas are divided into uniform grids, and centers of each grid are taken as monitoring waypoints to form full-coverage waypoint sequences. Complex map construction is unnecessary, and routes can be generated rapidly by inputting farm boundaries and grid spacing, adapting to outdoor scenarios without high-precision electronic maps.

On airborne computing side, Raspberry Pi 5 undertakes path analysis and instruction conversion. It communicates with Pixhawk 2.4.8 flight controller through USB serial port (/dev/ttyACM0) at 115200 baud rate for stable data transmission. Raspberry Pi loads pre-stored waypoint lists, and encapsulates longitude, latitude and relative altitude into MAVLink instructions to schedule flight controller sequentially.

In flight execution mode, the flight controller works in GUIDED mode. After receiving waypoint commands, it autonomously completes takeoff, cruise, fixed hovering and attitude stabilization. When the UAV reaches the target waypoint and maintains stable hovering, the flight controller feeds position data back to Raspberry Pi and triggers image capture, forming a closed logic of arrival-shooting-next waypoint.

For human-computer interaction, ground computer connects to Raspberry Pi via WiFi and SSH, supporting remote program startup, real-time log viewing and flight status monitoring. Manual intervention in flight control is unnecessary, and operators only need task initiation and abnormal monitoring, realizing unattended autonomous patrol.

Through the above collaborative design, the whole link of path planning, instruction transmission, flight execution and status feedback is interconnected, providing stable, efficient and full-coverage image acquisition for fish disease detection.

4. Design and Implementation of Intelligent Fish Disease Identification System

Intelligent fish disease identification is the core functional module of the system, automatically judging fish health status and disease types according to actual fishery monitoring requirements. A deep learning identification model is constructed from model design, system implementation and function verification. Web-based system under B/S architecture is developed to support image import, batch recognition, visual display and report export, serving as a practical tool for rapid fishery disease screening.

4.1 Design of Fish Disease Identification Model

4.1.1 Network Structure Selection

ResNet50 is selected as the basic network to construct fish disease classification model. Its residual structure effectively alleviates gradient disappearance in deep network training, with excellent feature extraction ability and generalization performance for fine-grained image classification. Combined with transfer learning strategy, pre-trained weights on public datasets are adopted to initialize the network, accelerating model convergence and improving recognition accuracy under small sample conditions.

4.1.2 Dataset Construction

The experimental dataset consists of on-site fishery images, open-source fish disease datasets and supplemented compliant images, covering 7 categories: healthy fish, bacterial red spot disease, aeromonasis, bacterial gill rot disease, fungal saprolegniasis, parasitosis and viral white tail disease. The total dataset contains 14,000 images, divided into training set and test set at a ratio of 8:2. Data augmentation methods including random cropping, horizontal flipping, rotation and brightness adjustment are applied to enhance model robustness and adaptability to complex scenes.

4.1.3 Model Training and Optimization

Cross entropy loss function is adopted as optimization objective, and adaptive optimizer is used for model training. Dropout layers and label smoothing are introduced to suppress overfitting. Learning rate adopts combined scheduling of warm-up and cosine annealing to improve training stability and convergence speed. Experimental results show that the optimized model achieves 92.3% recognition accuracy and 91.6% macro-average F1 score on the test set, meeting practical fishery disease identification requirements.

4.2 Implementation of Web-Based Fish Disease Identification System

4.2.1 System Architecture

The system adopts B/S architecture, with Flask framework building back-end services and HTML, CSS, JavaScript realizing front-end interactive interface. Lightweight and easy to deploy, the system can be accessed by browsers on computers, tablets, mobile phones and other terminals, suitable for on-site and remote fishery monitoring.

4.2.2 Core Functional Modules

Five modules are included: multi-source image import, image preprocessing, deep learning inference, result visualization and data report export. It supports single-image, batch-image, folder upload and drag-and-drop upload. The back-end automatically completes size normalization, central cropping and standardization. After model inference, results are displayed hierarchically by confidence, and high-confidence diseases are highlighted automatically. The system exports CSV diagnosis records including file name, recognition category, confidence and processing time, facilitating data management and traceability.

4.2.3 System Working Process

Users access the system via browsers, upload images and start identification. The system completes asynchronous batch inference and displays real-time progress and results. After detection, disease types and confidence values can be viewed, and complete diagnostic reports can be exported. With simple operation and no professional operation requirements, the system is suitable for direct use by breeding staff. It meets fishery monitoring demands in recognition accuracy, operation efficiency and usability, providing reliable diagnosis support for UAV cruise images.

5. Conclusion

Aiming at low efficiency, limited coverage and lagging monitoring of traditional fish disease detection in aquaculture, combined with industrial development of low-altitude economy, this paper designs an autonomous cruise fish disease identification system based on UAV platform. A three-layer framework of management, cruise and identification is established to integrate autonomous fishery cruise, edge-side disease recognition and data management. By comparing A* algorithm, artificial potential field and grid path planning schemes, the grid-waypoint cruise algorithm is selected. Software-hardware collaboration with Pixhawk 2.4.8 flight controller and Raspberry Pi 5 is completed, realizing precise autonomous cruise with positioning error ≤0.5 m. Lightweight ResNet50 model is deployed on Raspberry Pi, achieving 92.3% fish disease recognition accuracy and single-image inference time ≤1 s. Matching visual front-end realizes hierarchical result display, abnormal early warning and data export.

Experimental verification proves that the system runs stably and operates conveniently, which can replace manual daily fishery monitoring and provide feasible scheme for intelligent upgrading of aquaculture. The research promotes deep integration between low-altitude economy and aquaculture industry, expands application scenarios of low-altitude economy, and has broad practical application value and industrial popularization prospects.

Acknowledgement

This work was supported by Project Funds from the National College Students' Innovation and Entrepreneurship Training Program of Shenzhen Technology University 2025.

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