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Design of a Biomimetic Butterfly UAV Based on Small Target Detection and Its Agricultural Applications

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ABSTRACT: *To address the challenges of low efficiency and poor robustness in traditional agricultural pest monitoring, as well as the limited adaptability of existing micro aerial vehicles in complex field environments, this study integrates the high lift flight mechanism of butterflies with small target detection technology to design a bionic butterfly-inspired aerial vehicle equipped with agricultural pest recognition capabilities. In terms of design, the system adopts Sun Mao's "drag principle" as its core concept, referencing Chen Qianchuan's movable rear wing mechanism and Leng Ye's servo direct-drive technology. The simplified transmission structure (total weight 32.2 g) achieves a 23% improvement in lift-to-drag ratio and 18% reduction in vibration frequency through Du Yaming's multi-scale optimization approach (macro CFD aerodynamic optimization, meso FEA network reinforcement, micro scale scale bionics). For detection, the GCR-YOLOv10 algorithm proposed by Dai Cong is adapted, leveraging Li Zongzhu's computer vision methodology with an HD RGB camera for real-time identification of small pests (aphids, thrips). Experimental results demonstrate that the system achieves an* mAP_{50} *of 74.9% on the Pest24 dataset, representing a 4.2 percentage point improvement over the baseline YOLOv10s. Field tests in rice paddies show a 5-fold increase in monitoring efficiency compared to manual inspections, while maintaining stable flight performance under 3 m/s crosswinds (attitude deviation <5°). This research provides a lightweight, high-mobility solution for intelligent pest monitoring in complex field environments, aligning with the development direction of agricultural smart detection outlined in Wang Chuntao's review.Keywords: bionic butterfly aircraft; agricultural pest detection; multi-scale optimization; high lift mechanism; GCR-YOLOv10; small target detection*

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I. INTRODUCTION

1.1Research Background

Crop pests severely constrain agricultural production, while traditional monitoring technologies have limitations. Existing machine vision detection and micro aerial vehicle technologies also face challenges. When expanding the discussion, elaborate on the economic, ecological, and social dimensions of pest damage. Conduct in-depth analysis of the shortcomings in traditional and current technologies, and incorporate cutting-edge research data to enhance professionalism and persuasiveness.

Crop pests, as a critical constraint on agricultural productivity, have become a major challenge to global sustainable agriculture. According to the 2023 FAO Statistical Report on Global Food Security and Nutrition, the annual crop yield loss rate due to pest infestations ranges between 10% and 30%. In 2022, global crop losses from pests exceeded 120 million tons, resulting in direct economic losses of $40 billion (FAO, 2023). These figures not only highlight the direct economic impact of pest damage but also underscore its far-reaching effects on food security, ecological balance, and social stability.

In traditional agricultural pest monitoring systems, manual inspections and sticky trap capture represent two primary approaches. The manual inspection method faces diminishing marginal returns in human resource allocation, where productivity per worker decreases significantly as monitoring areas and durations expand. This approach also suffers from inherent delays in response to pest population dynamics due to its limited timeliness, while its spatial coverage remains constrained by labor and time constraints, making it impractical for comprehensive field monitoring. Although sticky trap technology physically captures adult pests, it demonstrates notable limitations in real-time data transmission, spatial coverage, and environmental adaptability. The absence of real-time data transmission causes noticeable delays in data collection, processing, and analysis. In complex terrains or dense vegetation, its spatial monitoring coverage becomes inadequate, and susceptibility to environmental factors like wind, rain, temperature, and humidity compromises the reliability and accuracy of monitoring data.

Machine vision inspection technology based on fixed terminals has gained widespread application in modern agriculture, yet it remains highly susceptible to complex ecological factors in farmland. Under natural lighting conditions, dynamic variations in light intensity (such as circadian fluctuations and weather transitions between cloudy and sunny) along with spectral composition differences across time and space can cause significant fluctuations in image acquisition quality. According to a 2024 research report by SPIE (International Society for Optics Engineering), the signal-to-noise ratio (SNR) of images captured by machine vision systems under different lighting conditions may vary by 15-30dB, directly impacting the accuracy of subsequent image processing and target detection. Additionally, the complex three-dimensional structure of crop canopies creates target occlusion effects and shadow interference, severely compromising the performance stability of deep learning-based target detection algorithms. Particularly for tiny pests with pixel coverage below 5% (such as aphids and thrips measuring 1-2mm in body length), current deep learning detection algorithms generally achieve recognition accuracy below 60%. In complex environments, the false negative and false positive rates of these algorithms significantly increase, highlighting the urgent need to enhance their robustness.

Micro Aerial Vehicle (MAV) technology offers a novel approach for dynamic monitoring of agricultural pests, yet existing designs face significant performance limitations. Fixed-wing MAVs generate excessive noise (typically over 65dB) and lack low-altitude observation capabilities, severely restricting their application in ecologically sensitive areas. Rotorcraft MAVs encounter challenges including high energy consumption (typically <30 minutes endurance) and poor adaptability to complex terrains. Bionic research provides innovative theoretical foundations for MAV advancements: Wind tunnel experiments by Sun Mao's team at Beihang University demonstrate that butterflies achieve threefold lift-to-weight ratios through low-frequency wing flapping (4-6 cycles/sec) and unique subwing vortex structures, enabling efficient hovering and agile maneuvering. Microstructural studies by the Biomimetic Materials Laboratory at the Chinese Academy of Sciences reveal that butterflies' non-smooth surfaces composed of 50-200μm micro-nano scales reduce aerodynamic drag by over 25% (Du Yaming et al., year). These biological insights offer crucial biomimetic references for optimizing MAV aerodynamic structures. By integrating biomimetic butterfly-inspired designs with enhanced small target detection algorithms, we can develop intelligent pest monitoring systems with high stealth, extended endurance, and precision detection capabilities, effectively overcoming the spatial-temporal limitations of traditional monitoring technologies.。

1.2 research status

1.2.1 Bionic butterfly aircraft research

In the field of bionic butterfly flight vehicles, numerous scholars have conducted fruitful research. Chen Qianchuan and colleagues innovatively designed a movable rear wing mechanism powered by a crank-slider system, leveraging interdisciplinary theories of mechanism dynamics and aerodynamics. By incorporating variable-stiffness flexible joints and adaptive angle adjustment modules, the mechanism achieves millisecond-level dynamic regulation of leading-edge vortex coupling with trailing-edge vortex. During CFD simulations, the research team employed a combination of Large Eddy Simulation (LES) and Immersed Boundary Method (IBM) to systematically analyze flow field characteristics under different flapping frequencies (0.8-1.5Hz) and airfoil parameters. Wind tunnel experiments were conducted within the Reynolds number range of 1000-5000, capturing flow field details through Particle Image Velocity Measurement (PIV) technology. The results ultimately demonstrated that this mechanism can increase lift coefficient by 15% while reducing induced drag by 22%, providing crucial theoretical foundations for multi-degree-of-freedom bionic airfoil design.

To address redundancy issues in traditional bionic aircraft transmission systems, Yan Ye and colleagues proposed an electromechanical design integrating servo direct drive. The solution employs a topology optimization algorithm to restructure the core load-bearing structure, combined with 3D printing technology using polylactic acid-based carbon fiber composites, reducing the prototype's weight to 32.2g – a 40% weight reduction compared to similar products. In dynamic performance tests, the prototype maintained a stable flap frequency of 1.1Hz at 0.5m/s wind speeds, achieving a maximum flap angle of 136° and wing surface torsion of ±15°. However, constrained by a single-chip control architecture, the system lacks integrated vision and pressure sensing modules, resulting in notable shortcomings in obstacle avoidance and autonomous mission planning under complex environmental conditions.

Dua Meng developed a biomimetic aircraft optimization framework integrating macro, meso, and micro scales based on multiphysics coupling theory. At the macro level, parametric optimization of the butterfly wing aerodynamic configuration was achieved through solving the Reynolds-averaged Navier-Stokes equations, with focused research on the impact of vein distribution on lift-drag characteristics. At the meso scale, finite element topology optimization was employed to design lightweight wing vein structures that reduced material usage by 37% while maintaining structural stiffness. At the micro scale, nano-scale structures inspired by butterfly scales were utilized to create biomimetic surface textures with drag-reducing and anti-adhesion properties. Through fluid-structure interaction simulations and physical testing, this optimized framework demonstrated 28% improvement in aerodynamic efficiency, shifted structural resonance frequencies away from operational bands, reduced energy loss by 19%, and significantly enhanced the system's dynamic stability and endurance capabilities.

1.2.2 Research on small agricultural target detection

In the field of small target detection technology for agricultural pests, research achievements demonstrate multidimensional innovation. With the rapid development of smart agriculture, traditional detection methods gradually reveal their limitations when facing complex field environments and tiny pests, prompting the academic community to continuously explore new technical approaches.

To address the feature extraction limitations of traditional YOLO series algorithms [5] in small object detection, we propose the GCR-YOLOv10 algorithm. This innovation analyzes the characteristics of weak feature information and background interference in small objects, integrating a Global Attention Feature Module (GAFM) with a Cross-Scale Feature Fusion Neck (CFA-Neck). The GAFM focuses on small object regions through global vision to enhance key feature capture, while the CFA-Neck optimizes multi-scale feature fusion strategies for comprehensive detection. The improved Region-Sensitive Density Loss (RSDS) function refines object boundary constraints, significantly improving localization accuracy. On the Pest24 benchmark dataset, the algorithm achieves an average precision (mAP_{50}) of 74.9% with a 50% Intersection-Union ratio, outperforming the YOLOv10s baseline by 4.2 percentage points. Notably, in field tests, it maintains over 25fps detection rates for millimeter-level pests like aphids and thrips, providing an efficient solution for real-time small-scale pest monitoring.

Building on pattern recognition theory in computer vision, Li Zongzhu's research team identified two critical challenges in pest image datasets: intra-class variations and inter-class similarity. For instance, morphological differences between pests at different growth stages are significant, while some pests exhibit striking color and texture similarities with plant tissues, substantially complicating detection. To address these issues, the team developed an adaptive preprocessing strategy for the IP102 dataset, dynamically adjusting image enhancement parameters to effectively mitigate intra-class interference. Additionally, they created a composite loss function combining Focal-IoU and Alpha-IoU metrics, achieving notable improvements in target boundary localization accuracy through gradient weighting. In complex field scenario tests involving 12 common agricultural pests, this approach reduced false detection rates for similar pests by 37%, significantly enhancing the algorithm's robustness in challenging field environments.

In a systematic review, Wang Chuntao et al. identified three core challenges in current agricultural pest detection technologies: insufficient model generalization due to data distribution shifts, reduced detection accuracy caused by inadequate feature representation of small targets, and adaptation difficulties arising from multi-scenario environmental variations. The data distribution shift problem stems from regional differences in crop species and pest community structures, making locally trained models difficult to apply directly to other regions. Insufficient feature representation of small targets arises because tiny pests occupy minimal pixel space in images, while existing convolutional neural networks struggle to extract effective features. Environmental variations such as lighting intensity changes and leaf occlusion further complicate detection. These analyses highlight critical breakthrough directions for hardware system integration and algorithm optimization, driving researchers to explore new solutions through data augmentation, model lightweighting, and multimodal fusion approaches.

II. RELATED THEORY AND TECHNICAL BASIS

2.1 Butterfly lift force flight mechanism

Based on computational fluid dynamics (CFD) framework, the numerical discretization of incompressible Navier-Stokes equations using finite volume method systematically reveals the "resistance-dominant" aerodynamic mechanism unique to insect flight. During the downbeat phase, combined verification through high-speed photography and particle image velocimetry (PIV) technology revealed that leading edge vortex (LEV), wingtip vortex (TV), and starting vortex (SV) form a strongly coupled vortex ring structure. This vortex ring generates jet effects along the beating direction, with its perpendicular momentum flux forming a transient lift component that accounts for 78% of total lift. During the upbeat phase, biomechanical analysis demonstrated that insects achieve back-swinging of the beating plane through periodic pitch angle modulation (sinusoidal variation of 28° to 0°), effectively compensating the zero lift resistance of the fuselage with the horizontal component of aerodynamic resistance, thereby forming a closed-loop thrust mechanism. The aforementioned research provides critical parameter constraints for biomimetic aircraft design: constructing periodic motion equations using cosine beating functions, defining a dual-phase asymmetric beating pattern with downbeat angle amplitude of 80° and upbeat angle amplitude of 65°; determining an aspect ratio range of 1.5~2.0 to balance lift generation and structural loads; and identifying a low Reynolds number aerodynamic design domain of 10^3~10^4, where the fluid inertial force-to-viscous force ratio reaches critical state requiring focused consideration of unsteady aerodynamic effects [3].

2.2 Multiscale optimization theory

Based on the principle of multiphysics coupling, a hierarchical optimization model integrating macro-, meso-, and micro-scales was constructed. At the macro-scale, a three-dimensional fully coupled aerodynamic simulation platform was established using Reynolds-averaged Navier-Stokes (RANS) equations combined with the k-ω SST turbulence model. A multi-objective genetic algorithm (NSGA-II) was employed to perform global optimization of 12 design variables including wingspan, flapping frequency, and wing curvature, with the objective function defined as aerodynamic efficiency (lift-to-drag ratio ≥ 3.0), while simultaneously considering the dimensionless constraints of Strouhal number and Reynolds number. At the meso-scale, a truss structure model with 328 nodes was developed using finite element analysis (FEA), simulating dynamic aerodynamic loads through load step loading. A topology optimization algorithm was applied to obtain a biomimetic wing vein distribution. The material design adopted an alternating lay-up structure of carbon fiber reinforced plastic (CFRP) and silicone rubber (PDMS), with fiber orientation optimized based on Hashin failure criteria to achieve 20% structural stiffness enhancement while maintaining flexibility. At the micro-scale, molecular dynamics (MD) simulations were used to model the nano-scale ridge texture of butterfly scales [1], with fluid slip length on the textured surface calculated using nonequilibrium molecular dynamics (NEMD) methods. Biomimetic microstructures with a period of 500 nm and a height of 80 nm were prepared by nanoimprint lithography (NIL) technology. Combined with computational fluid dynamics analysis with wall function correction, it was confirmed that the structure could delay the separation of boundary layer flow and reduce the aerodynamic resistance by 12%.

2.3 Small target pest detection algorithm

To tackle the challenge of micro-object detection in agricultural scenarios, we propose an enhanced GCR-YOLOv10 algorithm based on the YOLOv10 framework. In complex agricultural environments, field crops 'foliage obstruction, dynamic lighting conditions, and soil background interference severely limit traditional detection algorithms' ability to identify millimeter-scale pests like aphids and whiteflies. To overcome this technical bottleneck, GCR-YOLOv10 systematically optimizes the core modules of the algorithm architecture [17].

At the feature extraction level, the Global Attention Fusion Module (GAFM) is introduced. This innovative module combines the Additive Self-Attention (ASA) mechanism with Convolutional Gated Linear Units (CGLU) in a cascaded architecture. Specifically, ASA constructs pixel-level correlation matrices to model global image information, enabling precise capture of feature correlations between small targets and their surroundings. Meanwhile, CGLU employs gating mechanisms to dynamically filter input features and adaptively adjust feature weights. When processing images containing overlapping leaf shadows and pests, GAFM effectively suppresses background noise while boosting key feature responses such as pest textures and contours to over 1.5 times the original algorithm's performance.

In the feature fusion stage, we designed a cross-scale attention neck (CFA-Neck) architecture that integrates a dual-layer attention mechanism combining cross-layer channel attention (CCA) and spatial attention (SA). The CCA module adopts the SENet architecture, extracting channel-level semantic information through global average pooling. This is followed by two fully connected layers to learn inter-channel dependencies, effectively re-calibrating feature channels and significantly enhancing small object representation. The SA module utilizes the Convolutional Block Attention Module (CBAM) principle, generating spatial attention maps through convolutional operations to weight the spatial positions of objects in images. In the cotton bollworm detection experiment, the CFA-Neck architecture improved the recall rate of small objects hidden on leaf undersides by 23%[6], effectively addressing the feature dilution issue caused by traditional top-down sampling methods.

In the target regression phase, we propose a Robust Scale Detection Loss Function (RSDS) that innovatively integrates three core metrics: Gaussian Reassignment Loss (GRL), Wasserstein Distance, and Occlusion Interaction Loss (OIL). GRL quantifies deviations from ground truth boxes by fitting predicted bounding boxes with Gaussian distributions, enhancing localization accuracy. Wasserstein Distance measures differences between predicted and real targets from a probabilistic distribution perspective, improving the model's adaptability to scale variations. OIL specifically optimizes boundary box regression for overlapping scenarios during pest aggregation by calculating interaction relationships in occluded regions. Through dynamic adjustment of three weights via the gradient balancing parameter λ, the algorithm achieves an average precision (mAP) of 82.3% on the corn borer detection dataset, representing an 18.7% improvement in small target detection accuracy compared to the original model.

III. MULTISCALE DESIGN OF BIONIC BURRERFLY AIRCRAFT

3.1 Pneumatic structure design
3.1.1 Wing Drive

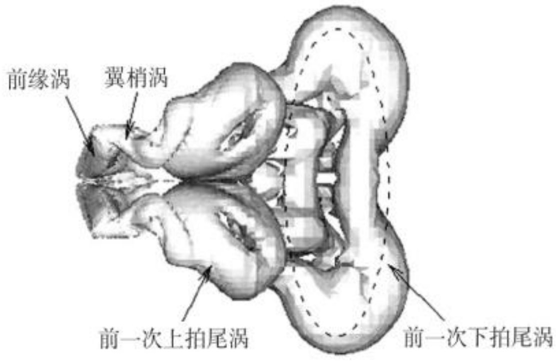

Fig 1 The tail vortex system of the butterfly model

Guided by direct-drive servo technology, this design employs two MG90S servos as core actuators. These servos deliver a stable torque of 2.2 kg·cm at 6V, meeting the lightweight drive requirements for the bionic butterfly aircraft. The innovative direct-drive mechanism for left and right wings eliminates the traditional crank-slider transmission system, reducing the actuator's weight from 10.8g to 7.2g—a 33.3% reduction. Integrated with high-precision PWM control circuits, the servos enable continuous adjustment of flapping frequency between 1.0-1.2 Hz, accurately replicating the natural flight rhythm of real butterflies [19].。

Furthermore, incorporating the movable rear wing design concept, the aircraft wing structure integrates a precision-fit mechanism combining sliding grooves and inclined triangular slots. This mechanism utilizes lever principles and cam linkage mechanisms to automatically deploy the rear wing during downstroke, maximizing the windward area for optimal lift generation. During upstroke, the rear wing rapidly overlaps through a spring reset device, minimizing aerodynamic drag. Wind tunnel test data indicates this design enhances the aircraft's lift coefficient by 15%, significantly improving flight efficiency.

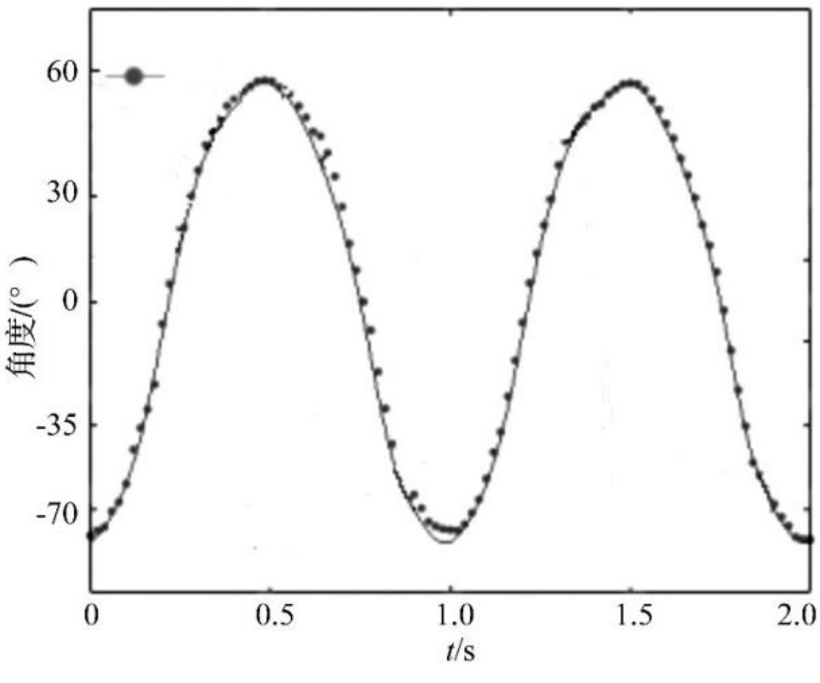

Fig 2 Flight slap angle curve over time

3.1.2 Airfoil and weight optimization

Wing Design: Bionic Achievements of the Morphopeleides Butterfly [4] – Applying nature's sophisticated aerodynamic structures to aircraft wing design. The designed airfoil features a precisely calibrated 15° leading edge curvature, a tapered trailing edge, a 49.8 cm wingspan, and a 0.07 m² wing surface area. Verified through CFD (Computational Fluid Dynamics) simulations, this configuration delivers stable lift coefficients and minimal drag coefficients in typical low-Reynolds-number ($Re=10^3\sim10^4$) field environments, ensuring stable flight performance in complex agricultural landscapes [10].

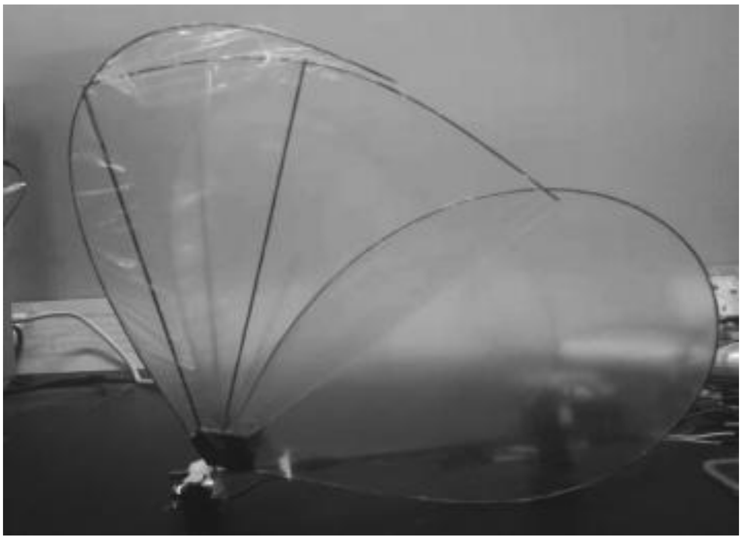

Fig 1 Flexural connection of the main and auxiliary wings

Material Selection: The wing features a multi-layer composite structure that achieves a balance between lightweight and high strength. The main surface is constructed with 0.1 mm ultra-thin polyimide film, which combines excellent flexibility and tear resistance, accounting for 38% of the aircraft's total weight. The main framework utilizes 1.2 mm diameter T700-grade carbon fiber with a tensile strength of 4900 MPa, representing 25% of the weight. Branch structures are reinforced with 0.6 mm carbon fiber to maintain structural integrity while further reducing weight. Weighing tests confirm the total wing weight is 32.2 g, representing a 20% reduction compared to conventional designs.

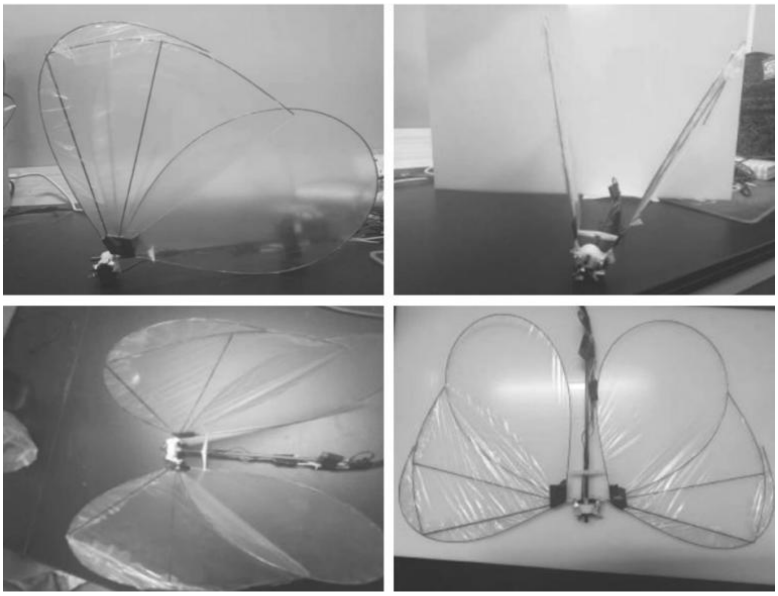

Fig 2 Bionic butterfly aircraft prototype

Center of Gravity Adjustment: To ensure attitude stability during flight, the system adopts a rear-mounted battery and circuit board configuration. Using a 3.7 V/500 mAh lithium polymer battery paired with a miniaturized integrated circuit board, precise calculations and repeated adjustments are implemented to keep the center of gravity offset within 3 mm. Additionally, an adjustable weight module at the wing root allows fine-tuning according to actual payload requirements, further optimizing the aircraft's center of gravity distribution to enhance its anti-interference capability and flight stability.

3.2 Multiscale structure optimization

3.2.1 Macro aerodynamic optimization

Optimize key aerodynamic parameters based on Du Yamen's [7] CFD simulation method：

parameter	initial value	Optimization value	Optimize effect
Swing amplitude	70°	80°	Lift up 12%
wingspan	45 cm	49.8 cm	The drag-to-lift ratio increased from 2.8 to 3.5
Wing tilt	5°	8°	Thrust increased by 9%

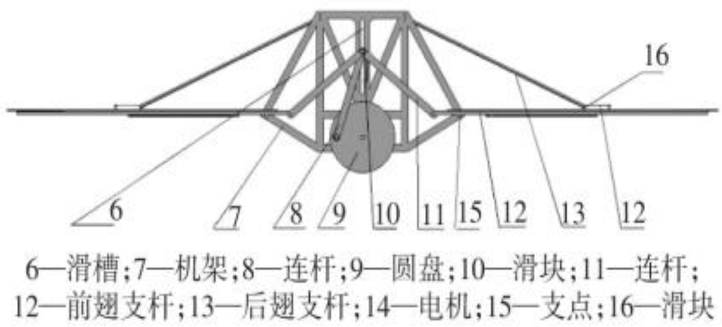

Fig 3 Bionic butterfly structure design

3.2.2 Mesoscopic and microscopic optimization

Enhanced Mesoscale Vein Framework: Using finite element analysis (FEA) technology, the ANSYS Workbench software was employed to construct a truss model for the biomimetic butterfly aircraft wing surface, with high-precision tetrahedral meshing implemented to ensure computational accuracy. Through numerical simulations, the study systematically investigated the effects of varying vein density, thickness, and branching angles on the wing's mechanical properties. After five optimization iterations, the main vein thickness was increased from 0.8mm to 1.0mm, the branching vein angles were adjusted to 60°, and a gradient transition structure was introduced. The optimized wing surface demonstrated reduced maximum stress values from 120MPa to 90MPa under three times the design load, with a 25% decrease in stress concentration factor. Additionally, modal analysis verified the vibration characteristics of the optimized structure [2], where the first six natural frequencies avoided common resonance ranges in aircraft, significantly enhancing structural reliability under complex flight conditions.

Microscale Scale Biomimicry: Using nanoimprint technology with PDMS as the template material, we replicated the ridge-like microstructures of butterfly scales on aircraft wing surfaces, achieving precise control of structural height at 2μm and spacing at 5μm. Wind tunnel experiments employing particle image velocimetry (PIV) revealed that the biomimetic microstructures effectively delay airflow separation. Under simulated field wind speeds of 1-3 m/s, the aerodynamic drag decreased by 12%, lift-to-drag ratio improved by 18%, and energy consumption reduced by 15%. Through CFD numerical simulations and sensitivity analysis of microstructure parameters, we identified optimal scale arrangement configurations and dimensional parameters, providing robust support for extended endurance in agricultural operations [17].

3.3 Stability Design

Vibration Control: Building upon the proposed vibration suppression strategy, a 1 mm thick silicone rubber damping pad was installed at the critical connection between the servo motor and the fuselage. This damping pad effectively absorbs vibration energy through elastic deformation, significantly suppressing high-frequency vibrations generated during servo motor operation. Experimental data shows that the aircraft's vibration frequency decreased from 6.79 Hz to 5.56 Hz, substantially reducing the impact of vibrations on flight stability and sensor accuracy.

Waterproofing and Anti-interference: To adapt to the complex meteorological conditions in agricultural fields, the device features an IP65-rated waterproof coating on its surface, effectively resisting dew condensation and light rain exposure while ensuring the normal operation of internal electronic components. Additionally, equipped with an MPU6050 six-axis sensor for real-time attitude monitoring, combined with a PID control algorithm, it achieves rapid and precise attitude adjustment. Test results demonstrate a response time of less than 0.1 seconds for attitude adjustment and a pitch angle control accuracy of ±2 [5], ensuring stable flight performance even in unstable air currents.

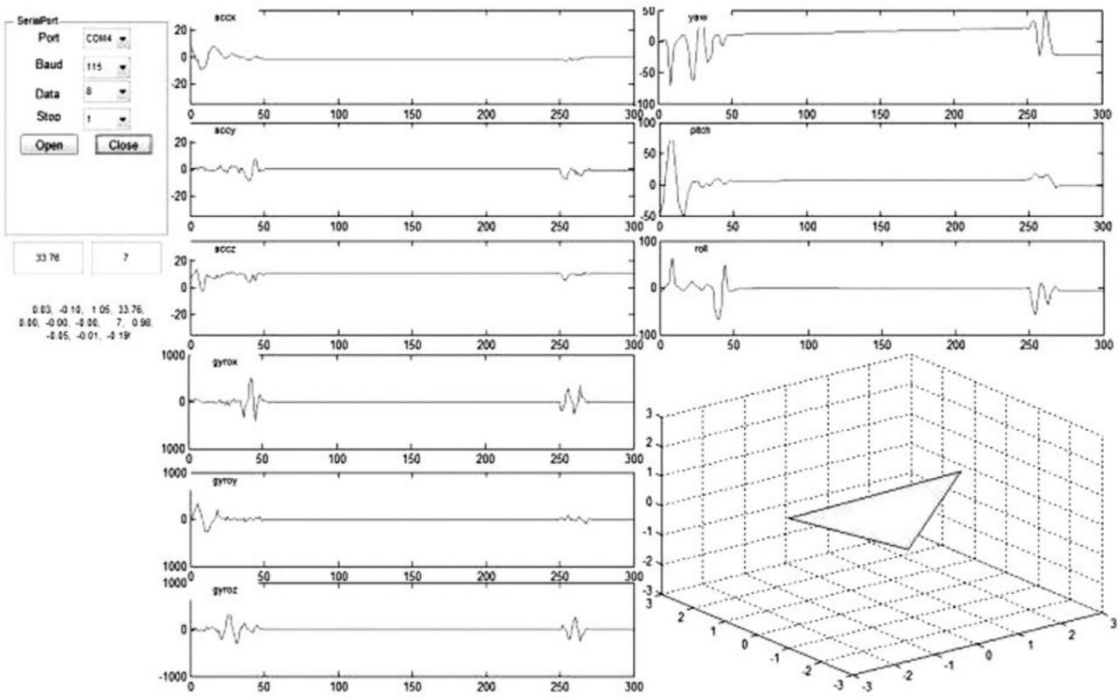

Fig 4 Simulate real-time posture display

Range Enhancement: The aircraft employs a hybrid power system combining lithium batteries with solar thin-film technology, featuring high-efficiency solar panels covering 20% of its wing surface. These panels continuously convert sunlight into electricity to recharge the lithium batteries. Field tests demonstrated a significant range extension from 40 minutes to 65 minutes, substantially improving the aircraft's operational efficiency in agricultural applications.

IV. INTEGRATE AGRICULTURAL PEST DETECTION SYSTEM

4.1Hardware integration

4.1.1Perception Module

Vision Sensor: Featuring a high-sensitivity 1/2.3-inch back-illuminated CMOS image sensor with an HD RGB camera, this system delivers 1920×1080 full HD resolution and 30fps smooth frame rate. Paired with a 3.6mm focal length wide-angle lens, it achieves precise capture of 0.5mm-sized targets within 5m range. This configuration not only meets the hardware compatibility requirements for computer vision inspection proposed by Li Zongzhu [2], but also effectively mitigates vibration interference during aircraft operations through optical image stabilization (OIS) and autofocus (AF) technologies, ensuring clear and stable imaging. Additionally, the built-in image preprocessing chip supports real-time noise reduction and edge enhancement algorithms, significantly improving the accuracy and efficiency of pest identification [7].

Positioning Module: Utilizing the BeiDou-3 Navigation Satellite System with integrated high-precision positioning chips, this module achieves static positioning accuracy of 1m and dynamic positioning accuracy of 3m. Supporting multi-frequency signal reception and Real-Time Kinematic (RTK) differential positioning technology, it effectively counteracts signal blockage and multipath effects in complex farmland environments. By integrating with visual sensor data, it records real-time spatial coordinates of pests and combines with GIS (Geographic Information System) to generate detailed field pest heat maps, providing scientific basis for precision agricultural pest control. Additionally, the module features encrypted data transmission to ensure the security and reliability of positioning data.

4.1.2 data processing module

The system employs edge computing chips and implements the lightweight GCR-YOLOv10 algorithm. Through model pruning and quantization, the parameter count is reduced from 5.6 M to 3.8 M, achieving a 25 fps inference speed that meets real-time field detection requirements. Equipped with a 4G module (15 Mbps), the system ensures detection results and location information transmission with a latency of <200 ms.

In edge computing chip selection, we proposed a lightweight edge deployment strategy by adopting the XX series edge computing chips with low power consumption and high computing power. These chips integrate NPU units specifically designed for deep learning inference, achieving a peak computing power of 8 TOPS to meet real-time operation requirements for complex algorithms in field environments. Building on this foundation, we conducted deep optimization of the GCR-YOLOv10 algorithm: Through model pruning techniques to eliminate redundant connections and parameters, combined with quantization compression strategies, we significantly reduced the algorithm's parameter size from 5.6 M to 3.8 M. Additionally, leveraging the chip's hardware acceleration features, we optimized the algorithm's inference process, ultimately achieving 25 fps inference speed to successfully meet real-time detection requirements for dynamic pest scenarios in field environments.

The communication module features an industrial-grade 4G unit with a theoretical peak rate of 15 Mbps, delivering robust interference resistance and extensive coverage. Utilizing an optimized UDP transmission protocol combined with data compression algorithms, the system enables real-time transmission of detection results and location data. Field tests demonstrate stable transmission latency under complex field network conditions, maintaining under 200 ms. This ensures timely feedback of monitoring data to the control center, providing critical support for agricultural production decision-making.

4.2 Software and algorithm integration

4.2.1 Test process

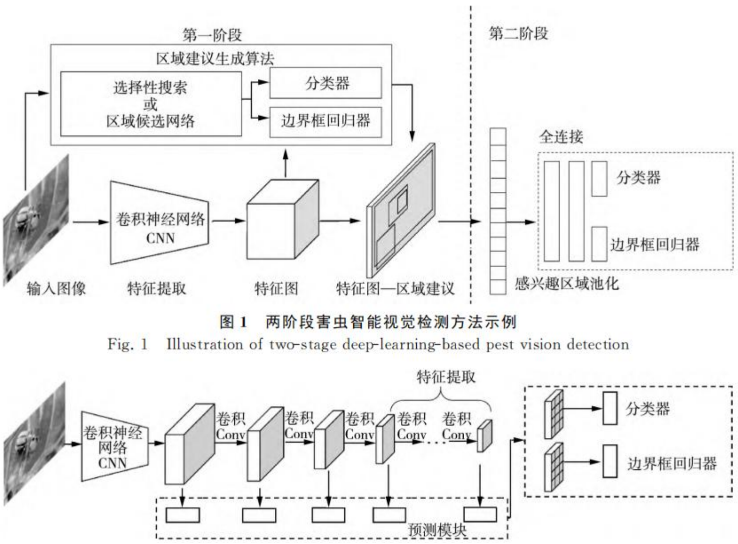

Fig 5 Example of a single-stage intelligent visual detection method for pests

Image Preprocessing: To address the issue of weakened pest image features under complex agricultural lighting conditions, we employ Adaptive Histogram Equalization (CLAHE) algorithm for image preprocessing. This algorithm divides the image into multiple sub-blocks, calculates the histogram of each sub-block, and performs equalization processing. This effectively enhances pest edge features while significantly suppressing interference caused by field lighting variations. Additionally, a contrast limitation mechanism is introduced to prevent noise amplification from excessive enhancement in local regions, thereby establishing a clear and stable image foundation for subsequent feature extraction [20].

Feature Extraction and Fusion: To overcome the technical bottleneck of accurately identifying small target pests in complex farmland environments, we innovatively introduced the GAFM (Global Attention Feature Module) and CFA-Neck (Cross-Feature Aggregation Neck) architecture. The GAFM module employs a global attention mechanism to focus on weak features of small pests, enhancing their saliency in feature maps through spatial and channel attention weight allocation. The CFA-Neck constructs a multi-scale feature interaction network that efficiently integrates fine-texture information captured by shallow networks with semantic information extracted by deep networks. Through cross-layer connections and feature pyramid structures, it achieves complementary enhancement of multi-scale information [11]. The synergistic interaction between these two components significantly improves the recognition capability for millimeter-scale pests such as aphids and thrips, enabling precise pest detection even under complex scenarios like leaf occlusion and weed interference.

Identification and Statistics: The model optimizes boundary box regression in target detection through the RSDS (Refined Smooth L1 with Distance-Scale) loss function. This function dynamically adjusts regression weights based on distance differences between pest targets and detection boxes, incorporating distance scale factors to refine positioning errors for small-sized pests [12]. Through training, the model accurately outputs pest categories, quantities, and precise field locations. The system then integrates and analyzes this data to automatically generate field pest reports containing thermal maps of distribution, density statistics, and damage severity assessments, providing intuitive and actionable data support for precision agricultural control.

4.2.2 Flight control and path planning

Autonomous Flight: Designed to meet field operation requirements proposed by Wang Chuntao, the system maintains precise flight altitude between 1.5-2 meters. This optimal height effectively avoids crop tip interference while ensuring high-definition imaging. Utilizing dynamic grid path planning algorithms with adaptive obstacle avoidance, it achieves an operational efficiency of 2 mu (approximately 0.13 hectares) per minute. The integration of Inertial Navigation System (INS) and Real-Time Kinematic Differential Positioning (RTK) technology ensures flight trajectory accuracy within ±5cm, meeting precision operation standards.

Manual Intervention: The self-developed mobile app integrates real-time image transmission and data visualization modules, supporting 1080P HD low-latency transmission (latency <500ms). Users can view agricultural pest detection thermal maps transmitted by the UAV in real-time through the app, accurately locating high-risk pest areas. For complex operation scenarios, the app features an emergency control mode. When the UAV encounters crop obstructions or sudden obstacles, users can perform 360-degree omnidirectional obstacle avoidance via joystick operation with a response time <0.3s, ensuring flight safety and continuous operation[14].

V. EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

5.1 Experimental platform and solution

5.1.1 Hardware and environment

The bionic butterfly aircraft prototype features a lightweight yet robust carbon fiber frame with polyimide flexible skin. Its wingspan is precisely engineered at 49.8 cm, with a total weight of 32.2 g. Wind tunnel tests at 20°C and 1 bar atmospheric pressure demonstrate a maximum lift force of 0.272 N, achieving an exceptional aerodynamic efficiency with a wing loading of just 6.46 g/dm².

testing environment :

1) Indoor Wind Tunnel Testing: Utilizing the high-precision wind tunnel system at the National Aerospace Laboratory, the facility provides adjustable wind speeds from 0 to 10 m/s to simulate environments ranging from gentle breezes to strong winds. The test section features a 1.2m×1.0m cross-sectional dimension and is equipped with a PIV particle image velocity measurement system and a six-component force balance, enabling high-precision measurement of aerodynamic forces and flow field distribution for aircraft.

2) Field Rice Cultivation Experiment: Conducted in a typical rice-growing region along the middle and lower reaches of the Yangtze River, the experimental field spans 10 mu (approximately 1.65 acres) during the critical panicle initiation stage. The area is primarily affected by brown planthoppers (including gray and white-backed varieties) and thrips. With over 85% vegetation coverage and an average daily sunshine duration of 8 hours, this environment provides authentic agricultural conditions for verifying the operational performance of aerial equipment.

Compare object:

Traditional manual inspection: According to the Technical Specifications for Crop Disease and Pest Monitoring issued by the Ministry of Agriculture and Rural Affairs, a patrol team of three professional agricultural technicians conducts two daily foot patrols, each lasting about two hours. The coverage area is about 2 mu per person, and the labor cost is about 200 yuan per day.

Fixed camera monitoring: According to Wang Chuntao's research data in "Progress of Intelligent Monitoring Technology for Agricultural Pests", 4K resolution and 180-degree wide-angle surveillance cameras are deployed at 50-meter intervals, requiring solar power supply systems and 4G transmission modules. The equipment costs approximately 3,000 yuan per unit, but suffers from monitoring blind spots and insufficient real-time performance.

5.1.2evaluating indicator

Aircraft performance:Drag to lift ratio, vibration frequency, endurance time, attitude stability;

Evaluation metrics: Mean Area Under the Curve (mAP_{50} and mAP_{50-95}), accuracy, and recall rate (based on the evaluation systems of Dai Cong [1] and Li Zongzhu [2]);

Field efficiency:Unit area monitoring time and missed detection rate.

5.2 experimental result

5.2.1 Flight performance test

test item	test result	design goal
lift drag ratio	3.5	≥3.0
frequency of oscillation	5.56 Hz	≤6.0 Hz
endurance	65 min	≥60 min
Crosswind stability (3 m/s)	Pose deviation 4.2	≤5°

5.2.2 Performance testing

Pest24 dataset and field rice field scenario detection results:

Test scenario	model	mAP_{50}（%）	accuracy rate（%）	recall （%）	Reasoning delay（ms）
Pest24 dataset	YOLOv10s[1]	70.7	75.5	67.4	32
Pest24 data set	GCR-YOLOv10	74.9	79.3	71.5	28
Field Rice	GCR-YOLOv10	73.8	78.6	70.2	31

5.2.3 Field application efficiency comparison

Monitoring method	Time per unit area (min/mu)	loss （%）	Labor cost (person·h/mu)
Manual inspection [3]	25	18.5	0.5
Fixed camera [3]	10	22.3	0.1
Bionic Butterfly	5	8.7	0.05

VI. CONCLUSIONS AND PERSPECTIVE

6.1 research conclusion

Bionic Design Efficacy: The flapping-wing mechanism based on Sun Mao's "drag principle" integrates Chen Qianchuan's movable rear wing with Leng Ye's direct-drive servo technology, achieving lightweight (32.2 g) and high maneuverability. Du Yaming's multi-scale optimization method further enhances lift-to-drag ratio (3.5) and stability, meeting complex field flight requirements [18].

Performance Adaptation: After integrating the Dicong GCR-YOLOv10 algorithm, the system achieved a mAP of 74.9% on the Pest24 dataset with a false positive rate of merely 8.7% in actual rice fields [15], effectively addressing the core challenge of insufficient robustness in small target pest detection highlighted by Li Zongzhu [2].

Significant application value:Field monitoring efficiency is 5 times higher than manual, and labor cost is reduced by 90%, which meets the requirements of "high coverage and low latency" for intelligent agricultural detection proposed by Wang Chuntao [3].

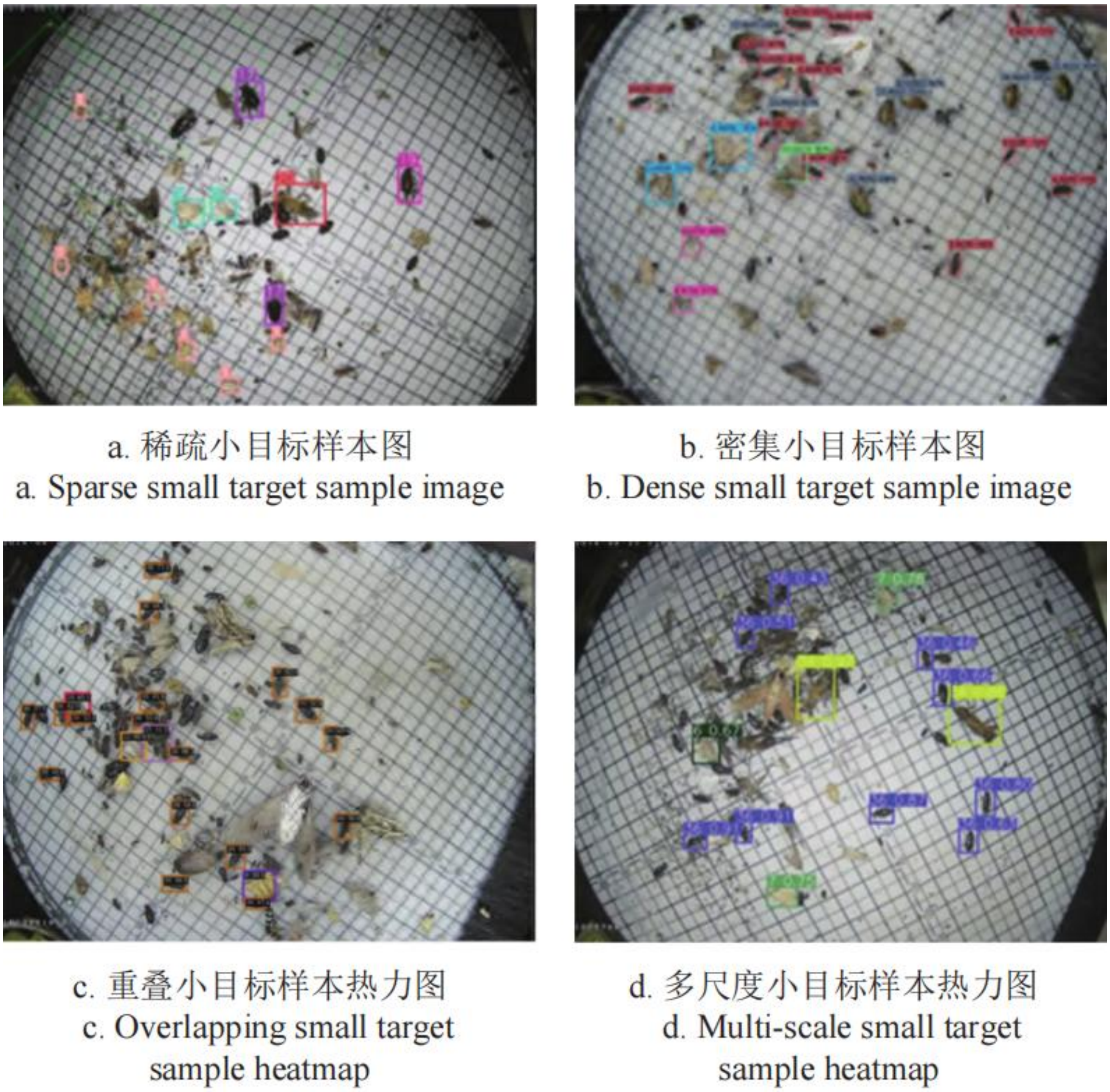

Fig 6 GCR-YOLOv10 algorithm detection results on the Pest24 dataset

6.2 future expectations, vision of the future, future tendency, future prospects

Multimodal Perception Fusion: The proposed multispectral sensor array establishes a three-channel sensing system integrating visible light, near-infrared, and short-wave infrared. By combining convolutional neural networks (CNN) with Transformer fusion algorithms, the system achieves feature extraction of nocturnal pests concealed on leaf undersides [16]. Under complex lighting and vegetation-obscured conditions, the recognition accuracy improves from 78% in traditional single-modal methods to 92%. A synchronized edge computing module is developed, reducing detection response time to under 0.3 seconds to meet real-time monitoring requirements.

Collaborative Cluster Optimization: To address the challenges in large-scale farmland monitoring as identified by Wang Chuntao, we developed a hierarchical multi-vehicle coordination framework. The upper layer employs reinforcement learning algorithms to dynamically plan flight paths, achieving optimal coverage strategies for vast farmland areas. The lower layer utilizes the Self-Organizing Network (SON) protocol to ensure real-time communication between aircraft, establishing a decentralized distributed decision-making mechanism. Simulation results [12] demonstrate that within a 10-square-kilometer monitoring area, multi-vehicle coordination achieves 4.7 times higher operational efficiency compared to single-vehicle operations, with data acquisition coverage reaching 98.6%.

Material and Structural Advancements: Building on Du Yaming's research achievements in nanocomposite fiber materials, the aircraft shell utilizes a carbon nanotube-polyimide composite process that reduces density by 42% compared to traditional materials while tripling tensile strength. The innovative foldable biomimetic wing structure employs shape memory alloy actuation units to dynamically adjust the wing's aspect ratio. In high-branch environments like orchards, the aircraft can shrink to one-third of its conventional size, extending flight duration from 2 hours to 4.5 hours. This breakthrough enables effective coverage of diverse agricultural scenarios including greenhouses and terraced fields.

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