

Research Article

Mode-Scheduled RBF-PID Control for Attitude Stabilization of an Unmanned Aerial Manipulator Under Wall-Collision Disturbance

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ABSTRACT

During high-rise building exterior wall crack inspection, an unmanned aerial manipulator (UAM) equipped with a 0-degree-of-freedom (0-DOF) manipulator suffers from attitude instability caused by transient wall collision disturbances. To address this problem, this study develops a dedicated flight control strategy. We first established a full rigid-body dynamic model with a non-diagonal inertia matrix for the asymmetric UAM platform. A mode-scheduled RBF neural network PID control strategy (RBF-PID-MS) was then proposed, which integrates an improved double-momentum gradient descent algorithm to improve online convergence of the RBF network. Based on the impulse theorem, we constructed a transient collision disturbance model for wall impact scenarios and calibrated the -20° pitch angle disturbance threshold. Simulation experiments were conducted under steady translational flight and wall collision scenarios, with conventional PID as the benchmark controller, while response speed, attitude overshoot, and anti-disturbance robustness were used as core evaluation metrics. Simulation results indicate that the proposed RBF-PID-MS controller improves disturbance rejection and reduces post-collision attitude overshoot relative to a conventional PID controller. This study provides a practical reference for controller design of aerial operation platforms subjected to transient collision disturbances. The proposed approach contributes to safer and more sustainable urban infrastructure inspection.

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1. Introduction

High-rise building structures have become the mainstream form of urban construction worldwide amid accelerating global urbanization. However, long-term environmental erosion, cyclic thermal stress, and structural load variations inevitably induce wall cracks, which directly threaten the long-term structural safety and service life of these buildings [1]. Traditional exterior wall inspection relies heavily on on-site manual assessment with professional tools, which has inherent limitations including high safety risks, low efficiency, and limited detection range. Although camera-equipped UAVs are now widely used for remote non-contact inspection, such platforms only support image collection and cannot perform contact verification of suspected cracks to confirm defect authenticity [2-4].

To fill this technical gap, we designed and fabricated an Unmanned Aerial Manipulator (UAM) integrated with a 0-DOF manipulator, which can widen suspected cracks

through controlled wall impact to enable on-site defect verification. The instantaneous rigid-body impact during wall crack verification introduces high-magnitude, ultra-short-duration disturbances to the UAM system, which can easily cause attitude divergence, instability, and even platform crashes. Therefore, this study focused on developing a dedicated flight control strategy to enhance the UAM's attitude stability and disturbance rejection during impact operations.

Notably, the wall collision during crack verification introduces an ultra-short (0.1 s) high-magnitude transient disturbance, within which the onboard flight controller can only complete 4–5 control cycles. Conventional RBF-PID employs global continuous adaptation, which cannot guarantee parameter convergence in such an extremely narrow time window and may even destabilize the system. Meanwhile, traditional gain-scheduled PID only switches fixed gain groups, lacking the online adaptive capability for the complex nonlinear disturbance of UAM systems. To this end, this study proposes a regime-constrained RBF-PID-MS control strategy to solve the above problems.

2. Related Works

2.1. UAM Dynamic Modeling Methods

Accurate dynamic modeling is the foundation of high-precision UAM control, and mainstream modeling methods are divided into independent modeling and holistic modeling [5]. The independent method models the UAV and manipulator separately, treats their coupling effects as external disturbances, and enables the direct reuse of mature UAV control algorithms [6]. The holistic method regards the UAM as a single integrated system, enabling the accurate characterization of coupling dynamics and higher modeling precision [7]. Ollervides-Vazquez et al. [8] established the dynamic model of an Octorotor UAM via the recursive Newton-Euler method, but most existing studies simplified the inertia matrix of the carrying platform to a diagonal form based on the assumption of a symmetrical UAV fuselage. For the asymmetric UAM with a 0-DOF impact manipulator in this study, the non-diagonal terms of the inertia matrix cannot be ignored, which renders traditional simplified models unable to accurately characterize its dynamic.

2.2. Control Strategies for UAM Contact and Collision Operations

Contact and collision between the UAM and building walls introduce large transient disturbances, which is a core challenge to system stability. For contact operation control, researchers proposed impedance, robust, and adaptive control methods: Malczyk et al. [9] developed accurate estimation of interaction force and disturbances via an extended Kalman filter; Zhang et al. [10] designed a learning-based variable impedance control strategy for aerial sliding on uneven surfaces; Xu et al. [11] proposed an image-based visual impedance force control method for contact manipulation.

For collision-induced transient disturbances, existing studies focused on multi-mode and gain scheduling control: Orsag et al. [12] adopted different adaptive algorithms for different UAM operation stages; Nava et al. [13] achieved online control strategy optimization via multi-task constrained quadratic programming; Chen et al. [14] developed a robust control scheme for composite disturbances. However, UAM wall collision for crack inspection features an ultra-short 0.1 s duration and large instantaneous disturbances, in which traditional continuous adaptive control cannot achieve parameter convergence within such a narrow time window and may even induce system instability.

2.3. RBF Neural Network-based Adaptive PID Control

PID control is widely used in UAV flight control due to its simple structure and strong robustness, but fixed-parameter PID cannot meet the control requirements of nonlinear, strongly coupled UAM systems under collision disturbances [15]. RBF neural network-based adaptive PID became a research hotspot due to its excellent nonlinear approximation capability and rapid local

learning performance, which enables online PID parameter tuning via real-time system dynamic identification [16]. Shi et al. [17] applied RBF-based adaptive robust control to a coupled gantry stage system; Ullah et al. [15] combined an improved RBF network with an extended state observer for quadrotor anti-disturbance control; Su et al. [18] applied an RBF-based control scheme to satellite attitude stability control; Lin et al. [19] proposed a data-driven RBF-PID method for PMSM speed control. The control objects of these papers are shown in Table 1.

Nevertheless, existing RBF-PID methods adopt a continuous adaptive mechanism throughout the full flight envelope, and implicitly assume a consistent control objective across all working conditions. During a UAM collision event, the RBF network can only complete 4 to 5 learning iterations in the short time window, which cannot guarantee parameter convergence and may even lead to system instability.

2.4. Research Gaps

To clearly identify the research gaps, a detailed comparison of existing studies is presented in Table 1. Analyzing Table 1 reveals that, despite significant progress in UAM research, several critical gaps remain for active impact-based crack detection on high-rise building facades:

Accurate dynamic modeling that accounts for the non-diagonal terms of the inertia matrix is lacking for asymmetric UAMs equipped with a 0-DOF impact manipulator;

Existing contact control strategies mainly target steady and sustained contact, with no dedicated design for transient impact disturbances lasting about 0.1 seconds;

Current RBF-PID methods employ global unconstrained optimization, which struggles to reconcile the different control objectives of steady flight and collision transients, and lack a mode-scheduling mechanism to handle regime switching.

In order to address the aforementioned research gap, this study makes the following core contributions:

A 0-DOF manipulator-equipped UAM platform for high-rise wall crack inspection and impact verification is designed, and a full rigid-body dynamic model with a non-diagonal inertia matrix is established for its asymmetric structure.

A mode-scheduled RBFPID-MS control strategy is proposed to suppress UAM attitude divergence during wall collision, which divides the flight envelope into two regimes via supervisory logic and constrains RBF optimization to mode-specific manifolds, addressing the limitation of slow convergence and poor adaptability of traditional adaptive PID in ultra-short collision windows.

An improved double-momentum gradient descent algorithm is designed for RBF online training, which

improves network convergence efficiency and closed-loop system stability under transient disturbances.

A collision disturbance model based on the impulse theorem is established, the -20° pitch angle disturbance

threshold for mode switching is calibrated, and the performance of the proposed strategy is verified via systematic MATLAB/Simulink simulation.

Table 1 Comparative Analysis of Related Studies on Anti-Disturbance Control for Aerial Manipulators

Reference	Inertia Matrix of the body	Control Strategy	Impact	Mode Scheduling	Manipulator Type
Liu & Huang [6]	Diagonal	DDPG adaptive robust	No	No	Multi-DOF.
Lippiello & Ruggiero [7]	Diagonal	Cartesian impedance control	No	No	Multi-DOF.
Ollervides-Vazquez et al. [8]	Diagonal	PID	No	No	Multi-DOF.
Malczyk et al. [9]	Diagonal	EKF disturbance estimation + interaction force control	Yes (contact)	No	Multi-DOF (with 0-DOF test).
Zhang et al. [10]	Diagonal	Learning variable impedance	Yes (contact sliding)	No	Multi-DOF.
Xu et al. [11]	Diagonal	Visual impedance force control	Yes (contact)	No	Multi-DOF.
Orsag et al. [12]	Diagonal	Model reference adaptive	Yes (staged)	Yes (task phase)	Multi-DOF.
Nava et al. [13]	Diagonal	Multi-task QP optimization	No	No	1-DOF.
Chen et al. [14]	Diagonal	Sliding mode + disturbance observer	Yes (general disturbance)	No	Multi-DOF.
Ullah et al. [15]	Diagonal	RBF + sliding mode	No	No	None (UAV only).
Liu et al. [16]	—	RBF adaptive	No	No	Robotic arm (non-UAM).
Shi et al. [17]	—	RBF adaptive robust synchronization	No	No	Gantry (non-UAM).
Su et al. [18]	—	RBF neural network	No	No	Satellite (non-UAM).
Lin et al. [19]	—	RBF data-driven	No	No	PMSM (non-UAM).

3. Mathematical Model of UAM

To clearly elaborate the UAM mathematical model, the North-East-Down (NED) frame is adopted as the global Earth-fixed coordinate system, and the body-fixed coordinate system is defined as follows: the origin is fixed at the UAM's center of mass (CoM); the x_b -axis points forward along the fuselage longitudinal axis; the y_b -axis points rightward along the fuselage transverse axis; the z_b -axis points downward along the fuselage vertical axis; the pitch angle θ is defined as the rotation angle of the fuselage around the y_b -axis. The general dynamic model of a UAV is shown in Eq. (1):

$$\begin{aligned}
 \dot{\mathbf{P}}_e &= \mathbf{V}_e \\
 \dot{\mathbf{V}}_e &= \mathbf{g} - \mathbf{R}_b^e \frac{\mathbf{f}_b}{m} \\
 \dot{\mathbf{q}}_e^b &= \frac{1}{2} \mathbf{q}_e^b \otimes \boldsymbol{\omega}_b \\
 \mathbf{G}_a + \boldsymbol{\tau} + \mathbf{M}_d &= \mathbf{J} \dot{\boldsymbol{\omega}}_b + \boldsymbol{\omega}_b \times \mathbf{J} \boldsymbol{\omega}_b
 \end{aligned} \tag{1}$$

Where $\mathbf{P}$ is the position vector of the UAV in the Earth-fixed frame; $\mathbf{V}$ is the velocity, $\mathbf{g}$ is the gravitational acceleration; $\mathbf{R}_b^e$ is the rotation matrix from the body frame to the Earth frame, $\mathbf{f}_b$ is the total force; m is the total mass; $\mathbf{q}_b^e$ is the attitude quaternion; $\boldsymbol{\omega}$ is the angular velocity; $\mathbf{G}_a$ is the gyroscopic moment; $\boldsymbol{\tau}$ is the total control torque, $\mathbf{M}_d$ is the aerodynamic drag moment; subscript e represents the Earth-fixed frame, and subscript b represents the body-fixed frame.

For a symmetrical UAV fuselage, the inertia matrix $\mathbf{J}$ is usually simplified to a diagonal form as Eq. (2):

$$\mathbf{J} = \begin{bmatrix} I_{xx} & 0 & 0 \\ 0 & I_{yy} & 0 \\ 0 & 0 & I_{zz} \end{bmatrix} \tag{2}$$

Where I_{xx} , I_{yy} , I_{zz} are the rotational inertia of the UAM around the x, y, z axes of the body-fixed frame, respectively. In order for the above dynamics Eq (1) to be

appropriately applicable to this study, the following assumptions are necessary.

The UAM is regarded as a rigid body, and the structural flexibility of the fuselage and manipulator is neglected;

The 0-DOF manipulator is rigidly fixed to the fuselage, with no relative motion between the manipulator and the UAV body during flight and collision;

Motor dynamics, sensor noise, and unmodeled high-frequency dynamics of the propulsion system are neglected in the modeling process;

Collision disturbance is mainly concentrated in the pitch axis, and the coupling effects of collision on the roll and yaw axes are neglected in disturbance modeling and simulation analysis.

For the asymmetric UAM in this study, the complete non-diagonal inertia matrix is adopted as Eq. (3):

$$\mathbf{J} = \begin{bmatrix} I_{xx} & -I_{xy} & -I_{xz} \\ -I_{yx} & I_{yy} & -I_{yz} \\ -I_{zx} & -I_{zy} & I_{zz} \end{bmatrix} \quad (3)$$

where $I_{xz} = I_{zx}, I_{yz} = I_{zy}, I_{xy} = I_{yx}$ are the inertial product terms of the UAM. The full set of rotational inertia parameters of the UAM were obtained via a 1:1 3D model built in SolidWorks 2024. The body-fixed coordinate system defined in this Section was used as the reference coordinate system for mass attribute calculation, with the origin coinciding with the UAM's center of mass. The 3D assembly fully includes the core components of the UAM: fuselage frame, flight controller, battery, propulsion system (motors, propellers, ESCs), 0-DOF impact manipulator, and an intelligent small cabin. The inertia parameters were calculated using the built-in mass attribute analysis module of SolidWorks, with the results shown in Table 2.

4. Proposed RBFPID-MS Control Strategy

Conventional cascade PID control delivers acceptable performance in routine UAM flight scenarios, yet short-duration, large-magnitude external disturbances from sudden wall collisions can easily exceed the regulation capability of standard PID controllers and lead to UAM crashes. To enhance the UAM's disturbance rejection performance and collision stability with limited onboard flight controller computational resources, we propose a cascade control architecture with outer-loop position control and inner-loop attitude control, and introduce an RBF neural network for online PID parameter tuning only in the roll and pitch angular velocity loops that are critical to flight stability, as shown in Figure 1.

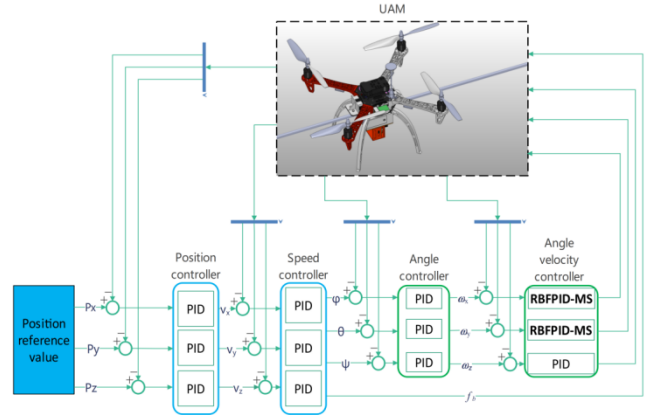


Figure 1 Overall Controller Structure Diagram

The control system adopts a cascade architecture, including an outer-loop position controller and an inner-loop attitude controller. The outer loop consists of a position PID controller and a speed PID controller, which outputs the desired attitude angle for the inner loop. The inner loop is divided into an angle PID controller and an angular velocity controller; the roll and pitch angular velocity loops adopt the proposed RBFPID-MS controller, and the rest loops adopt conventional PID controllers. The error between the desired and actual angular velocity is used as the input of the RBF neural network, which realizes online PID parameter update in the mode-specific manifold, and outputs the final control torque to the UAM dynamic model. Compared with traditional RBFPID, the proposed RBFPID-MS features active mode-scheduled optimization capabilities, which renders it more suitable for the varying optimization requirements of the controlled system across different scenarios.

4.1. RBF Neural Network Model

The RBF neural network is a three-layer feedforward network whose structure is shown in Figure 2, which supports general multi-input multi-output mapping.

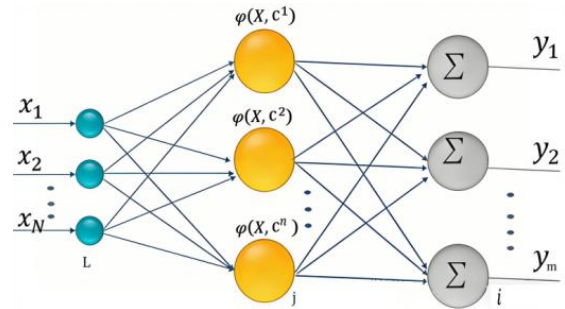


Figure 2 RBF Neural Network Structure

As shown in Figure 2, the hidden layer uses a radial basis function as the activation function. This study uses the Gaussian form shown in Eq. (4):

$$\varphi(\mathbf{X}, \mathbf{C}_j) = e^{-\frac{\|\mathbf{X} - \mathbf{C}_j\|^2}{2\sigma^2}} \quad (4)$$

where $\mathbf{X}=[x_1, x_2, \dots, x_N]^T$ is the network input vector; $\mathbf{C}_j=[C_{1j}, C_{2j}, \dots, C_{qj}]$ is the center vector of the j -th hidden layer neuron; n is the number of hidden layer neurons; σ is the width parameter of the Gaussian kernel function; and $\|\mathbf{X}-\mathbf{C}_j\|$ is the Euclidean distance from the input sample $\mathbf{X}$ to the center point $\mathbf{C}_j$. The mathematical description of the single output y_m is shown in Eq. (5).

$$y_m = \omega \phi(\mathbf{X}, \mathbf{C}_j) = \sum_{j=1}^q \omega_j \cdot \phi(\mathbf{X}, \mathbf{C}_j) \quad (5)$$

where $\omega=[\omega_1, \omega_2, \dots, \omega_q]^T$ is the network weight vector, and ω_j is the output layer weight corresponding to the j -th hidden layer neuron.

In this study, the specific architecture and parameter settings of the RBF neural network are as follows:

I. Input vector: $\mathbf{X}=[e(k), \Delta e(k), u(k-1)]^T$, where $e(k)$ is the angular velocity tracking error at the k -th iteration, $\Delta e(k)$ is the error change rate, and $u(k-1)$ is the control output of the previous step; input dimension is 3.

II. Output scalar: y_m used to calculate the adjustment quantity of the three parameters of PID.

III. Hidden layer configuration: The number of hidden layer neurons is set to 6; the Gaussian kernel center vector $\mathbf{C}_j$ is set to matrix $\begin{bmatrix} -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 1 \end{bmatrix}$, and the kernel width σ_j is initialized by random sampling within the input variation range

IV. Normalization: The input vector is normalized to $[-1, 1]$ before being fed into the network, to avoid Gaussian activation function saturation and improve network learning efficiency.

4.2. Training Method for RBF Neural Networks

Traditional gradient descent only uses the gradient of the current step to update parameters, which suffers from slow convergence and is easy to fall into local optima when dealing with abrupt collision disturbance. The single-momentum gradient descent only introduces first-order historical momentum, which has a limited effect on smoothing parameter oscillation under abrupt transients. To this end, an improved double-momentum gradient descent algorithm is proposed, which introduces both first-order and second-order historical momentum terms. This design accelerates network convergence by accumulating historical gradient information, and smooths parameter abrupt changes during collision transients, thus improving closed-loop system stability.

The error function of the network is defined as shown in Eq. (6):

$$\begin{aligned} E &= \frac{1}{2m} \sum_{i=1}^m e_i^2(k) = \frac{1}{2m} \sum_{i=1}^m (f(\mathbf{X}) - y)^2 \\ &= \frac{1}{2m} \sum_{i=1}^m \left(\sum_{j=1}^q \omega_j \cdot \phi(\mathbf{X}, \mathbf{C}_j) - y \right)^2 \end{aligned} \quad (6)$$

where m is the number of network outputs, and $e_i(k)$ is the error of the i -th output of the neural network at the k -th iteration.

I. Update equation for the linear weights, as shown in Eqs. (7) and (8)

$$\begin{aligned} \Delta w &= \frac{\partial E}{\partial \omega} = \frac{1}{m} \sum_{i=1}^m (f(\mathbf{X}) - y) \cdot \phi(\mathbf{X}, \mathbf{C}_j) \\ &= \frac{1}{m} \sum_{i=1}^m e_i \cdot \phi(\mathbf{X}, \mathbf{C}_j) \end{aligned} \quad (7)$$

$$w_{k+1} = w_k - \eta \Delta w_k - \alpha \Delta w_{k-1} - \beta \Delta w_{k-2} \quad (8)$$

Where η is the learning rate; α and β are the first-order and second-order momentum coefficients, respectively; Δw_{k-1} and Δw_{k-2} are the weight adjustment amounts of the $(k-1)$ -th and $(k-2)$ -th iterations.

II. Update equation for the center vectors of the hidden layer neurons, as shown in Eqs. (9) and (10):

$$\begin{aligned} \Delta C_j &= \frac{\partial E}{\partial C_j} = \frac{\partial E}{\partial \phi(X, C_j)} \cdot \frac{\partial \phi(X, C_j)}{\partial C_j} \\ &= \frac{1}{m \cdot \sigma_j^2} \sum_{i=1}^m (f(X) - y) \omega \cdot \phi(X, C_j) \cdot \|X - C_j\| \end{aligned} \quad (9)$$

$$c_{j \cdot k+1} = c_{j \cdot k} - \eta \Delta c_{j \cdot k} - \alpha \Delta c_{j \cdot k-1} - \beta \Delta c_{j \cdot k-2} \quad (10)$$

Where $c_{j \cdot k+1}$ is the i -th element of the center vector of the j -th hidden layer neuron, and other parameters are consistent with Eq. (8).

III. Update equation for the Gaussian kernel width parameters of the hidden layer, as shown in Eqs. (11) and (12):

$$\begin{aligned} \Delta \sigma_j &= \frac{\partial E}{\partial \sigma_j} = \frac{\partial E}{\partial \phi(X, C_j)} \cdot \frac{\partial \phi(X, C_j)}{\partial \sigma_j} \\ &= \frac{1}{m \cdot \sigma_j^3} \sum_{i=1}^m (f(X) - y) \omega \cdot \phi(X, C_j) \cdot \|X - C_j\|^2 \end{aligned} \quad (11)$$

$$\sigma_{j \cdot k+1} = \sigma_{j \cdot k} - \eta \Delta \sigma_{j \cdot k} - \alpha \Delta \sigma_{j \cdot k-1} - \beta \Delta \sigma_{j \cdot k-2} \quad (12)$$

Where $\sigma_{j,k+1}$ is the width parameter of the j -th hidden layer neuron, and other parameters are consistent with Eq. (8).

4.3. RBFPID-MS Controller

The traditional RBFPID architecture implicitly assumes a consistent control objective throughout the entire flight envelope, an assumption that fails completely during highly dynamic impact events. A typical wall collision event lasts only 0.1 s, and with a 20 ms control cycle of the flight controller, the RBF network can only complete 4 to 5 learning iterations in this window. Gradient-based parameter convergence cannot be guaranteed in such an ultra-short timeframe, and the standard continuous adaptation mechanism may even destabilize the system.

4.3.1. Supervisory Logic and Operating Regime Decomposition

To overcome this challenge, we propose an RBFPID-MS architecture as shown in Figure 3. This framework redefines the control problem as a hybrid system control task, which requires the controller to switch seamlessly between pre-identified operational modes rather than relying solely on continuous adaptation.

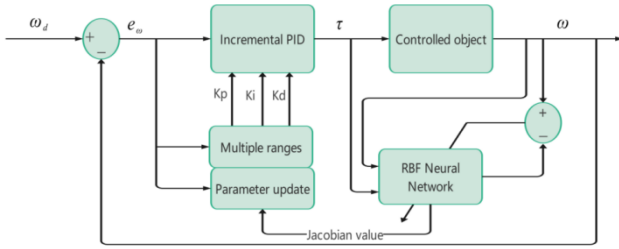


Figure 3 The Structure of RBFPID-MS

The core innovation of the architecture is the introduction of high-level supervisory logic for real-time operating regime decomposition. Based on the instantaneous system error $e(\omega)$ (which directly reflects the deviation between the actual state and the desired state), the supervisor discretizes the continuous operating space into distinct dynamic regimes. This approach is theoretically grounded in multiple-model switching control theory, where a set of sub-controllers, each optimized for a specific regime, are governed by a logic-based switching law.

The supervisory logic adopts the angular velocity tracking error $e(k) = \omega_d(k) - \omega(k)$ as the switching criterion, where $\omega_d(k)$ is the desired angular velocity, and $\omega(k)$ is the actual angular velocity. A hysteresis band is introduced to avoid mode chattering caused by frequent crossings of the threshold. The numerical switching law is defined as shown in Eq. (13).

$$\begin{cases} \text{Switch to Regime II:} & |e(k)| \geq \varepsilon_{\text{high}} \\ \text{Maintain current regime:} & \varepsilon_{\text{low}} \leq |e(k)| \leq \varepsilon_{\text{high}} \\ \text{Switch to Regime I:} & |e(k)| \leq \varepsilon_{\text{low}} \end{cases} \quad (13)$$

Where $\varepsilon_{\text{high}}$ is the upper threshold of the hysteresis band, and ε_{low} is the lower threshold. However, actual simulation tests show that at a threshold of $\varepsilon = 0.2$ rad/s, no chattering occurs and mode switching is reliably triggered. Therefore, the hysteresis band is effectively reduced to a single threshold, i.e., $\varepsilon_{\text{high}} = \varepsilon_{\text{low}}$. A 20° collision disturbance causes the angular velocity error to exceed 0.2 rad/s significantly, which can trigger the switching of the mode.

Based on the above switching law, the flight envelope is divided into two regimes:

I. Regime I: Quiescent Operation (Small-Signal Model): defined by $|e(k)| \leq \varepsilon_{\text{low}}$, corresponding to hovering or steady unperturbed flight. The control objective prioritizes robust stability, noise immunity, and steady-state disturbance rejection.

II. Regime II: Transient/Agile Operation (Large-Signal Model): defined by $|e(k)| \geq \varepsilon_{\text{high}}$, triggered by collision-induced impulsive disturbances. The control objective shifts to prioritize rapid recovery, high control bandwidth, and transient performance.

This regime decomposition is not merely a heuristic rule, but a necessary architectural response to the stability requirements of multiple scenarios.

4.3.2. Constrained Parameter Manifold and Mode Scheduling

In standard RBFPID, the RBF network searches the unconstrained global parameter space $\Omega \in \mathbb{R}^3$ for optimal PID parameters. In the proposed RBFPID-MS, the global parameter space is decomposed into two mutually exclusive mode-specific parameter manifolds, and RBF optimization is strictly projected onto the corresponding manifold according to the supervisory switching logic.

The PID parameter update law with a mode-dependent projection operator $\text{Proj}_i(\cdot)$ is designed as shown in Eq. (14):

$$\theta(k) = \text{Proj}_i(\theta(k-1) + \Delta\theta(k)) \quad (14)$$

Where $\theta = [K_p, K_i, K_d]^T$ is the PID parameter vector; $i \in 1, 2$ is the regime index (1 for Regime I, 2 for Regime II); $\Delta\theta(k)$ is the parameter adjustment amount output by the RBF network; $\text{Proj}_i(\cdot)$ is the projection operator, which constrains the updated parameters within the i -th parameter manifold Ω_i .

The parameter manifolds are defined by standard set notation:

Regime I (Quiescent Operation) parameter manifold is as shown in Eq. (15):

$$\Omega_1 = \left\{ \theta \in \mathbb{R}^3 \left| \begin{array}{l} K_{p,min,1} < K_p < K_{p,max,1} \\ K_{i,min,1} \leq K_i \leq K_{i,max,1} \\ K_{d,min,1} \leq K_d \leq K_{d,max,1} \end{array} \right. \right\} \quad (15)$$

Regime II (Transient Operation) parameter manifold is as shown in Eq. (16):

$$\Omega_2 = \left\{ \theta \in \mathbb{R}^3 \left| \begin{array}{l} K_{p,min,2} < K_p < K_{p,max,2} \\ K_{i,min,2} \leq K_i \leq K_{i,max,2} \\ K_{d,min,2} \leq K_d \leq K_{d,max,2} \end{array} \right. \right\} \quad (16)$$

Where $K_{p,min,1} < K_{p,max,1} \leq K_{p,min,2} < K_{p,max,2}$ are set to ensure the two manifolds are different, At the same time, K_i / K_d can be set to be the same as needed. The specific parameter boundaries are pre-calibrated via offline simulation, as shown in Table 3.

5. Simulation Setup and Test Scenarios

All verification experiments in this study were conducted in MATLAB/Simulink R2024a. The core simulation settings are as follows: the solver adopts the fixed-step ode3 (Bogacki-Shampine) algorithm, the fixed step size is 0.001 s, and Gaussian white noise with a mean of 0 and a variance of 0.005 is added to the angular velocity feedback signal to simulate actual sensor noise. The initial state of the UAM is set to a stable hovering state, with initial attitude angle [roll, pitch, yaw] = [0, 0, 0] rad, initial angular velocity [0, 0, 0] rad/s. Two test scenarios, steady translational flight and wall collision, are designed to verify the performance of the proposed controller.

5.1. Translational Flight Performance Experiment

This experiment was designed to verify the basic flight performance of the UAM. The UAM first ascended to a predefined altitude, then executed fixed-speed translational maneuvers along the X and Y axes. Since the yaw channel was not optimized in this study, it was not included in the experimental comparison. The expected control signal of the experiment is shown in Figure 4.

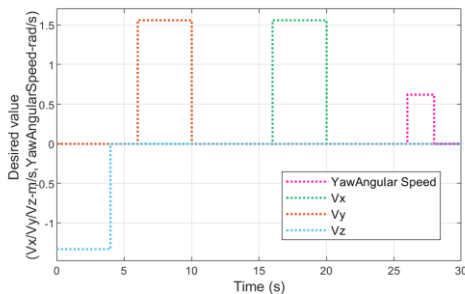


Figure 4 Desired Signals of the Translational Flight Experiment

5.2. Collision Disturbance Modeling and Analysis

During the forced crack verification operation on the wall surface, the UAM undergoes a transient rigid-body collision with the rigid wall at a preset forward velocity, which induces attitude disturbance mainly in the pitch channel. The force analysis principle is shown in Figure 5.



Figure 5 Schematic Diagram of UAM Wall Collision Force Analysis

At the moment of collision, the rigid wall exerts a transient impact reaction force F_c on the UAM fuselage. According to classical contact mechanics, collisions involving rigid bodies are characterized by large-magnitude contact forces acting over extremely short time intervals. The duration of such impacts, typically on the order of tens to hundreds of milliseconds for macroscopic objects, can be experimentally measured using high-frequency data acquisition systems [20]. Considering the physical scale and material properties of the UAM, as well as the flight controller sampling period (20 ms), the collision duration T_c is set to 0.1 s, which lies within this characteristic range.

In the body-fixed coordinate system, the impact reaction force F_c is orthogonally decomposed into a translational component F_p along the x_b -axis and a torque excitation component F_t along the z_b -axis. Of these, the translational component F_p only causes the translational position offset of the UAM, and its coupling effect on attitude stability was neglected in the present study. The torque excitation component F_t generates a pitch axis moment on the UAM's CoM, inducing a negative angular velocity of the fuselage around the y_b -axis and thus resulting in a negative offset of the pitch angle, which is the core excitation source of attitude disturbance during collision.

5.2.1. Mathematical Modeling of Collision Disturbance

To accurately reproduce the pitch attitude disturbance during collision in the simulation environment, a mathematical model of collision disturbance was constructed based on the impulse theorem. The total impulse of the collision process is defined by the integral of the impact reaction force over the collision duration as shown in Eq. (17):

$$\mathbf{J}_c = \int_0^{T_c} \mathbf{F}_c dt \quad (17)$$

Where $\mathbf{J}_c$ is the total collision impulse vector, and its component J_{c,z_b} along the z_b -axis is the core excitation impulse of pitch attitude disturbance.

Based on rigid-body rotation dynamics, the transfer function between the collision-induced pitch angle disturbance increments and the excitation impulse is derived as shown in Eq. (18), which is the core governing equation of the collision disturbance model in this paper:

$$\Delta\theta = -K_{coll} \cdot J_{c,z_b} \cdot \frac{1}{I_{yy}} \quad (18)$$

Where $\Delta\theta$ is the pitch angle disturbance increment (the negative sign represents negative offset); K_{coll} is the collision disturbance gain calibrated via offline simulation; I_{yy} is the UAM's moment of inertia around the pitch axis.

K_{coll} is a dimensionless gain, used to characterize the combined effect of the force arm between the force application point and the center of mass during the collision, the collision recovery coefficient, and the force distribution. Its value is obtained through offline simulation calibration in MATLAB/Simulink, following two core constraints: first, the generated pitch disturbance must be physically plausible for the UAM platform, without exceeding the maximum bearing capacity of the propulsion system; second, the disturbance amplitude must exceed the supervisory switching threshold, to effectively trigger the mode switching of the RBFPID-MS controller. Through iterative offline calibration, K_{coll} is set to 4.309, which can produce an approximate -20° pitch angle disturbance under the set collision duration, meeting the above two calibration constraints.

5.2.2. Experimental Setup and Model Embedding

The constructed collision disturbance model was superimposed on the UAM angular velocity kinematics model shown in Eq. (1) including non-diagonal inertial matrix Eq. (3), to construct a closed-loop simulation verification system with collision transient disturbance. To isolate the impact of collision-induced pitch disturbance on system dynamics and eliminate coupling interference from the roll and yaw channels, the roll and yaw angles were set to 0 throughout the entire collision simulation experiment, and only the dynamic characteristics of the pitch channel were considered for control performance verification.

6. Results and Discussion

The final MATLAB/Simulink simulation model was built based on the above dynamic Eq. (1), with the UAM's physical parameters listed in Table 2, and the pre-calibrated parameter ranges of the RBFPID-MS controller listed in Table 3. To further verify the effectiveness of the mode-scheduled mechanism, the standard RBFPID controller is added as an additional benchmark.

Table 2 Physical Parameters of UAM

Variable	Description	Value	Unit
m	The total mass of UAM	1.849	kg
l	The arm's length	0.225	m
R	Propeller radius	0.127	m
I_{xx}	Rotational inertia about the x-axis	0.02162205	kg·m ²
I_{yy}	Rotational inertia about the y-axis	0.02873761	kg·m ²
I_{zz}	Rotational inertia about the z-axis	0.04287441	kg·m ²
I_{xy}	Rotational inertia about the xy-axis	-4.11×10^{-5}	kg·m ²
I_{xz}	Rotational inertia about the xz-axis	-1.695×10^{-4}	kg·m ²
I_{yz}	Rotational inertia about the yz-axis	1.371×10^{-4}	kg·m ²
T	sampling time	0.001	s

Table 3 Parameters of the RBFPID-MS Controller

Item	Value for roll angular velocity	Value for pitch angular velocity	Description
K_{p1}	(0.11, 0.18)	(0.12, 0.19)	K_{p1} range of Regime II
K_{p2}	(0.067, 0.11)	(0.07, 0.12)	K_{p2} range of Regime I
K_{i1}	(0.002, 0.003)	(0.002, 0.003)	K_{i1} range of Regime II
K_{i2}	(1×10^{-4} , 1×10^{-3})	(1×10^{-4} , 1×10^{-3})	K_{i2} range of Regime I
K_d	(1×10^{-5} , 1×10^{-4})	(1×10^{-5} , 1×10^{-4})	K_d range is the same for Regime I and Regime II

6.1. Translational Flight Performance

The aforementioned translational flight experiment was conducted. Even with identical expected speeds, the expected angular velocities and angles differ significantly among the three controllers, so comparing setpoint tracking performance is not meaningful, and the expected values are not presented in these figures.

Figure 6 presents the angular velocity comparison, where only the time periods with significant state changes are shown, and the remaining segments (with zero angular velocity) are omitted. From the attitude response comparison, the core objective of this study is to enhance the attitude stability of the UAM. The yaw channel was not optimized with the RBFPID-MS strategy, and its response results are almost completely consistent among the three controllers, so it is not listed here. The speed loop responses of the two algorithms are essentially identical, and are not presented for space reasons. The attitude angles return to zero without overshoot, so they are not presented in Table 4. All values listed in the table are absolute values. To quantitatively evaluate control performance more

comprehensively, settling time (time for the error to stabilize within $\pm 2\%$ of the steady-state value) is introduced as supplementary metric, with results shown in Table 4. All values in the table are absolute values. Because their expected values are inconsistent, the comparison effect of the Integral of Absolute Error (IAE), the Integral of Squared Error (ISE), and the Integral of Time-weighted Absolute Error (ITAE) is not so strong. Therefore, these three indicators were abandoned in this experiment.

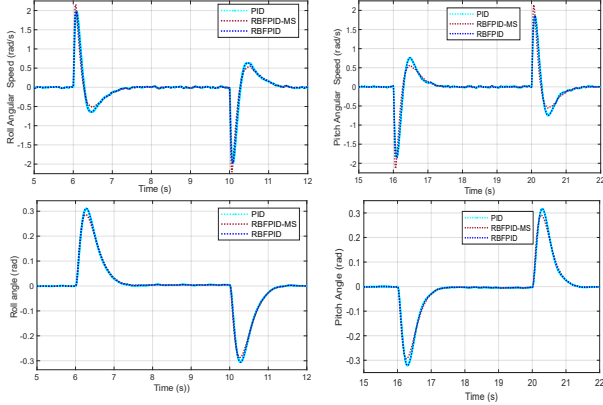


Figure 6 Attitude Response Curve of the Translational Flight Experiment

Table 4 Key Performance Metrics of the Translational Flight Experiment

Index	PID	RBFPID	RBFPID-MS
Peak roll angular velocity (rad/s)	1.961	1.983	2.208
Peak pitch angular velocity (rad/s)	1.864	1.853	2.155
Peak overshoot of roll angular velocity during recovery (rad/s)	0.646	0.644	0.519
Peak overshoot of pitch angular velocity during recovery (rad/s)	0.758	0.761	0.550
Peak Roll angle (rad)	0.309	0.310	0.290
Peak pitch angle (rad)	0.322	0.321	0.291
Roll angular velocity settling time (s)	1.157	1.157	1.155
Pitch angular velocity settling time (s)	1.168	1.166	1.163

Quantitative comparison shows these. RBFPID-MS achieves higher peak roll and pitch angular velocity than PID and RBFPID. This reflects a more aggressive initial control effort, which accelerates attitude recovery. Consequently, the overshoot during recovery is notably smaller for RBFPID-MS compared to PID and RBFPID. Settling times, however, are almost identical across all controllers (~ 1.16 s), indicating that the faster initial correction does not prolong the transient. Peak roll and pitch angles are slightly reduced by RBFPID-MS relative to PID and RBFPID. This suggests improved steady-state

stability during forward flight. In summary, RBFPID-MS provides faster and more stable regulation in conventional flight. The larger peak angular velocities represent a more energetic control action, which yields smaller recovery overshoot and marginally lower peak angles.

6.2. Collision Response Performance

The collision simulation experiment was conducted with the UAM in a controlled hovering state, to verify the attitude stabilization performance of the proposed strategy under impact disturbance. The experiment was configured according to the scheme in Section 5.2, with all CH1-CH4 inputs set to 1500 (corresponding to the UAM maintaining a hovering state). The total simulation duration was 3.5 s, with the collision event occurring at 0 s and ending at 0.1 s. The pitch channel response curve is shown in Figure 7, and the key performance indicators are shown in Table 5 (all values are absolute values).

The comparison reveals the following. RBFPID-MS produces a higher peak pitch angular velocity than PID and RBFPID, again indicating a stronger immediate reaction. This implies that during the collision the UAM continuously opposes the disturbance, and the angle begins returning to zero immediately after the impact. The pitch angular velocity overshoot after the initial rebound is slightly larger for RBFPID-MS than for PID and RBFPID. The RBFPID-MS applied a stronger initial reverse torque after the collision, resulting in a higher peak angular velocity, but it also suppressed the angle deviation more quickly, and as a result, the final angle peak was actually reduced. Conversely, the pitch angle overshoot is markedly smaller with RBFPID-MS. Hence, although the rate response overshoots a bit more, the resulting angle deviation is better contained. The most striking improvement is in settling time: RBFPID-MS reduces pitch angular velocity settling time to 0.603 s from ≈ 0.95 s for PID and RBFPID, and angle settling time to 0.499 s from ≈ 0.73 s. This confirms that the more aggressive initial torque accelerates convergence. For pitch angular velocity, RBFPID-MS has a slightly higher IAE than PID and RBFPID because of the larger rate overshoot, but its ISE is lower, meaning that large squared errors are reduced. More importantly, the angle-related integrals (IAE, ISE, ITAE) are all substantially smaller for RBFPID-MS, reflecting its superior attitude stabilization. The RBFPID-MS shows a worse angular velocity ITAE because it hits a higher peak right after the collision. However, since the angle error converges so fast, its angle-related ITAE (0.0021) is much better than the comparative controller (0.0093). Therefore, the overall attitude control performance remains superior. Overall, RBFPID-MS exhibits a more aggressive initial response to collision, leading to faster recovery and smaller angle deviations, at the cost of a slightly larger rate overshoot. This trade-off is well justified by the significantly improved settling and integral error measures.

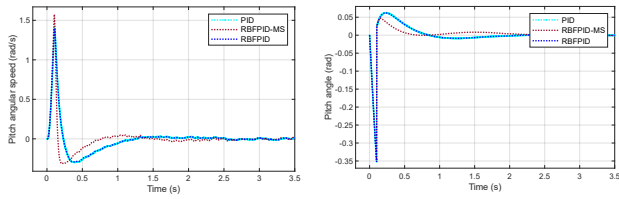


Figure 7 Pitch Channel Response Curve of the Collision Experiment

Table 5 Key Performance Metrics of the Collision Experiment

Index	PID	RBFPID	RBFPID-MS
Peak pitch angular velocity (rad/s)	1.401	1.398	1.575
Peak overshoot of pitch angular velocity during recovery (rad/s)	0.297	0.294	0.316
Peak pitch angle (rad)	0.3522	0.3524	0.349
Pitch angle overshoot during recovery (rad)	0.0623	0.0619	0.044
Pitch angular velocity settling time (s)	0.949	0.950	0.603
Pitch angle settling time (s)	0.729	0.731	0.499
IAE of pitch angular velocity	0.1962	0.1955	0.2214
ISE of pitch angular velocity	0.1626	0.1625	0.1394
ITAE of pitch angular velocity	0.0280	0.0278	0.0472
IAE of pitch angle	0.0387	0.0386	0.0221
ISE of pitch angle	0.0059	0.0059	0.0052
ITAE of pitch angle	0.0093	0.0092	0.0021

7. Conclusion

This paper presented a 0-DOF manipulator-equipped UAM for wall crack inspection and impact verification. A complete rigid-body dynamic model accounting for the asymmetric structure's non-diagonal inertia matrix was established. To cope with transient collision disturbances, a mode-scheduled RBFPID-MS control strategy was proposed, which partitions the flight envelope into two regimes and constrains RBF optimization within regime-specific parameter manifolds. An improved double-momentum gradient descent algorithm was also introduced to accelerate online RBF training. A collision disturbance model based on the impulse theorem was developed and used in simulation.

Simulation results indicate that, compared with conventional PID and standard RBFPID, the proposed RBFPID-MS strategy achieves faster attitude recovery, lower overshoot, and better disturbance rejection in both

translational flight and wall-collision scenarios. However, these findings are based solely on numerical simulations; experimental validation is required to confirm the controller's real-world effectiveness. Overall, the findings support resilient infrastructure and sustainable urban development through scalable maintenance of urban infrastructure.

Future work will focus on Hardware-In-the-Loop (HIL) testing and actual flight experiments. The study will also be extended to multi-axis collision scenarios, and the effects of sensor noise and parametric uncertainties will be investigated to further assess robustness.

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