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Designing a Multidimensional Sliding Mode Control System for Quadcopters Under Fault Conditions: Enhanced Fault Tolerance and Robustness

Mohammad Amin Ahmadi, Mehdi Siahi*, Ali Moarefianpour, Soodabeh Soleymani Morcheh Khorti

Department of Electrical Engineering, Science and Research Branch, Islamic Azad university, Tehran, Iran, mehdi.siahi@srbiau.ac.ir

Abstract

Unmanned aerial vehicles, particularly quadcopters, have gained widespread popularity across applications ranging from aerial photography to disaster response. However, their operation is susceptible to faults, which can compromise stability and performance. This paper introduces a novel Multidimensional Sliding Mode Control (MSMC) strategy for quadcopters, designed to enhance fault tolerance and overall system robustness. The proposed approach incorporates advanced fault detection and isolation algorithms, enabling real-time identification and mitigation of diverse fault scenarios. Extensive simulations and experimental evaluations demonstrate the MSMC strategy's superiority over several existing fault-tolerant control techniques, demonstrating 18.47% superior fault-damping accuracy compared to baseline methods. Additionally, the sliding mode control system exhibits improved stability characteristics, with a response time reduction of 6.45% compared to conventional methods. These results underscore the MSMC's potential for real-world deployment in dynamic environments where rapid fault mitigation is critical. The robustness and adaptability of the MSMC make it a promising solution for ensuring safe and reliable quadcopter operations under various fault conditions, paving the way for enhanced performance and increased operational safety across a wide range of applications.

Keywords: Quadcopter, Multidimensional Sliding Mode Control, Faults, Dynamic Control.
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1. Introduction

Quadcopter Quadcopters, a class of unmanned aerial vehicles (UAVs) equipped with four rotors, have attracted considerable attention in recent years owing to their exceptional maneuverability, vertical takeoff and landing (VTOL) capabilities, and diverse applications—ranging from aerial photography and surveillance to search-and-rescue missions and package delivery. Despite their widespread adoption, achieving precise control of quadcopters remains a significant challenge due to their inherent nonlinear dynamics, underactuated design, and sensitivity to external disturbances. Quadcopter control relies on regulating the rotational speeds of its four rotors to generate the necessary thrust and torque, thereby governing the vehicle's altitude, roll, pitch, and yaw motions. Ensuring stable and accurate control across these degrees of freedom is essential for reliable operation and mission success [1]. A typical quadcopter control system comprises several critical components: an inertial measurement unit (IMU) for attitude estimation, control algorithms that compute inputs based on desired trajectories or setpoints, a mixer to map these inputs to individual rotor commands, and motor controllers to execute them [2]. However, designing effective control systems for quadcopters presents three primary challenges. First, their dynamics are highly nonlinear and coupled, rendering traditional linear control techniques inadequate. Second, quadcopters are underactuated, with only four control inputs (rotor speeds) governing six degrees of freedom (three translational and three rotational). Third, they are vulnerable to external disturbances such as wind gusts, payload variations, and aerodynamic effects, which can compromise stability and performance. To overcome these challenges, researchers have investigated a variety of control strategies, including linear and nonlinear methods, adaptive and robust control techniques, and model-based approaches. Recent advances in machine learning (ML) and artificial intelligence (AI) have further expanded the scope of quadcopter control, enabling data-driven and reinforcement learning-based solutions. Figure 1 illustrates the forces acting on a quadcopter, underscoring the importance of robust control design.

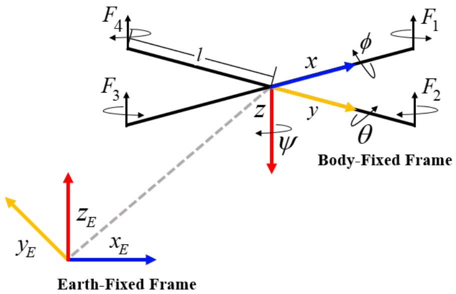

Fig. 1. Aerodynamic Forces and Torques Acting on a Quadcopter During Flight [2]

Bellow, is the importance of quadcopters control background [3]:

Early Control Theory Influences: The theoretical groundwork for quadcopter control can be traced back to classical control theory, with roots in the works of pioneers like Bode, Nyquist, and Laplace. Concepts such as feedback control, stability analysis, and controller design provide the foundation for modern quadcopter control algorithms.

Evolution of Flight Dynamics Understanding: The control of quadcopters necessitates a deep understanding of their flight dynamics. Control engineers leverage principles from aerodynamics, fluid mechanics, and rotational dynamics to model the complex interactions between the quadcopter's rotors, airfoil surfaces, and environmental factors like wind.

Advancements in Embedded Systems: The miniaturization and increasing computational power of embedded systems have revolutionized quadcopter control. Microcontrollers and onboard processors enable real-time data processing, sensor fusion, and rapid execution of control algorithms, empowering quadcopters to operate autonomously and with precision.

Sensor Integration Challenges: Quadcopter control relies heavily on sensor data for accurate state estimation and feedback. Control engineers tackle challenges related to sensor noise, bias, and calibration to ensure robust performance. Integration of IMUs, GPS receivers, altimeters, and vision systems enhances situational awareness and navigation capabilities.

Control Algorithm Innovations: Control engineers continuously innovate control algorithms tailored to the unique dynamics of quadcopters. From classic Proportional- Integral-Derivative (PID) controllers to more advanced techniques like model predictive control (MPC) and adaptive control, the quest is to achieve agile, stable, and energy-efficient flight under varying conditions.

Multi-disciplinary Optimization: Quadcopter control design requires a multi-disciplinary optimization approach, balancing conflicting objectives such as stability, agility, energy efficiency, and payload capacity. Control engineers collaborate with experts in aerodynamics, propulsion systems, materials science, and battery technology to achieve optimal performance across these domains.

Real-world Testing and Validation: The transition from theoretical models to practical implementation involves extensive testing and validation. Control engineers employ simulation tools, hardware-in-the-loop (HIL) testing, and field trials to refine control algorithms, validate performance, and ensure safety in diverse operating environments.

Regulatory Compliance and Safety Assurance: Control engineers play a crucial role in ensuring that quadcopter designs comply with aviation regulations and safety standards. This involves incorporating fail-safe mechanisms, collision avoidance systems, and flight envelope limitations into the control architecture to mitigate risks and enhance operational safety.

A) Review

A comprehensive overview of the state-of-the-art in quadcopter control is provided in this review, covering both theoretical and practical aspects. It begins by discussing the dynamics and modeling of quadcopters, followed by an exploration of various control strategies, including classical and modern control techniques, as well as emerging trends in quadcopter control.

Understanding the quadcopter's dynamics is crucial for developing effective control strategies. The quadcopter is a six-degree-of-freedom (6-DOF) system, with three translational degrees of freedom (x, y, z) and three rotational degrees of freedom (roll, pitch, yaw) [4]. However, it is an underactuated system, with only four control inputs (rotor speeds) available to control these six degrees of freedom. The quadcopter's dynamics are highly nonlinear and coupled, making it challenging to apply traditional linear control techniques [5]. Several researchers have proposed mathematical models to describe the quadcopter's behavior. One widely used model is based on the Newton-Euler formulation, which considers the quadcopter as a rigid body and derives the equations of motion using the principles of conservation of linear and angular momentum [6]. Another common approach is to employ the Euler-Lagrange formulation, which uses the quadcopter's kinetic and potential energies to derive the equations of motion. These models typically involve coupled, nonlinear differential equations that capture the quadcopter's translational and rotational dynamics, as well as the effects of aerodynamic forces and moments [7]. In addition to these physics-based models, researchers have also explored data-driven approaches, such as system identification techniques, to obtain accurate models of the quadcopter's dynamics. These methods use flight data and machine learning algorithms to identify the system's parameters and capture any unmodeled dynamics or nonlinearities.

Accurate attitude estimation is crucial for quadcopter control, as it provides information about the vehicle's orientation (roll, pitch, and yaw angles) relative to a reference frame. Quadcopters typically rely on an IMU, which consists of accelerometers and gyroscopes, to measure linear accelerations and angular rates, respectively [8]. However, IMU measurements are prone to noise and biases, and integrating the gyroscope data over time can lead to drift in the attitude estimates. To mitigate these issues, sensor fusion algorithms are employed to combine the IMU data with other sensors, such as magnetometers, GPS, or vision-based systems, to obtain more accurate and reliable attitude estimates. One widely used sensor fusion technique is the extended Kalman filter (EKF), which provides a recursive framework for estimating the quadcopter's attitude and other states (e.g., position, velocity) by fusing measurements from multiple sensors [9]. Other approaches include complementary filters, which combine the high-frequency components of the gyroscope data with the low-frequency components of the accelerometer and magnetometer data to estimate the attitude. More advanced techniques, such as unscented Kalman filters (UKFs) and particle filters, have also been explored to handle nonlinearities and non-Gaussian noise distributions in the quadcopter's dynamics and sensor measurements [10].

Classical control techniques, such as proportional-integral-derivative (PID) control and linear quadratic regulator (LQR) control, have been widely employed for quadcopter control due to their simplicity and ease of implementation [11]. PID controllers are commonly used for attitude stabilization and trajectory tracking, with separate control loops for each degree of freedom (roll, pitch, yaw, and altitude). The PID gains are typically tuned manually or through optimization techniques to achieve the desired performance and stability characteristics [12]. LQR control is a model-based approach that provides an optimal feedback control law by minimizing a quadratic cost function that balances tracking performance and control effort. LQR controllers can be designed for the linearized quadcopter dynamics, and gain scheduling or other techniques can be employed to account for nonlinearities and varying operating conditions. While classical control techniques have demonstrated success in quadcopter control, they often struggle to handle the system's nonlinearities and uncertainties effectively, leading to limited performance and robustness. To address the limitations of classical control techniques, researchers have explored various nonlinear control strategies that explicitly account for the quadcopter's nonlinear dynamics and uncertainties. Feedback linearization is a popular technique that transforms the nonlinear quadcopter dynamics into a linear form through a coordinate transformation and feedback control law. This allows for the application of linear control techniques, such as PID or LQR control, in the linearized space. However, feedback linearization requires precise knowledge of the system's dynamics and may be sensitive to modeling errors and disturbances [13-14]. Backstepping control is another nonlinear control approach that recursively constructs a Lyapunov function and a corresponding control law to stabilize the quadcopter's dynamics. This technique can handle nonlinearities and uncertainties, but it can become computationally complex for higher-order systems [15]. Sliding mode control is a robust control technique that drives the system's states to a desired sliding surface and maintains them on that surface through discontinuous control actions [16]. This approach is particularly effective in dealing with uncertainties and disturbances, but it can suffer from chattering issues due to the discontinuous control law. Other nonlinear control techniques, such as adaptive control, robust control, and model predictive control, have also been explored for quadcopter control. These methods aim to achieve improved performance, robustness, and adaptability to varying operating conditions and uncertainties [17].

Advances in machine learning and artificial intelligence have opened up new avenues for quadcopter control, enabling data-driven and reinforcement learning-based approaches. Reinforcement learning (RL) is a powerful technique that allows an agent (in this case, the quadcopter) to learn an optimal control policy through interactions with its environment [18]. RL algorithms, such as Q-learning, policy gradients, and actor-critic methods, have been applied to quadcopter control problems, demonstrating promising results in tasks like autonomous navigation, obstacle avoidance, and agile maneuvering. Deep neural networks (DNNs) have also been employed for quadcopter control, either as function approximators for traditional control techniques or as end-to-end controllers that directly map sensor inputs to control outputs. DNNs can capture complex nonlinear relationships and adapt to changing environments, but they may lack interpretability and require large amounts of training data [19]. Another emerging trend is the application of bio-inspired algorithms, such as particle swarm optimization (PSO), genetic algorithms (GAs), and ant colony optimization (ACO), for tuning the parameters of quadcopter control systems or optimizing trajectories and control strategies [20-22]. Hybrid approaches that combine traditional control techniques with machine learning or bio-inspired algorithms have also been explored, leveraging the strengths of both domains to achieve improved performance and adaptability.

B) Aims and Novelties

The aims of quadcopter control using MSMC considered in this paper, are represented here due to various reasons:

- Flight Stability: Effective control ensures stable flight, which is crucial for capturing clear aerial footage, conducting inspections, or executing tasks like package delivery. Stability prevents crashes and ensures smooth operation.
- Safety: Proper control mechanisms prevent accidents, ensuring the safety of both the quadcopter itself and the surroundings. Accurate control can prevent collisions with obstacles, buildings, or other aircraft.
- Precision Maneuvering: Whether it's navigating through tight spaces for inspections or performing complex aerial maneuvers for entertainment or sport, precise control is essential. This allows quadcopters to perform tasks with accuracy and efficiency.
- Adaptability to Environmental Conditions: Control systems should be adaptable to various environmental conditions such as wind, rain, or turbulence. This ensures that the quadcopter can operate effectively in different situations without compromising safety or performance.
- Autonomous Operation: Many applications, such as surveillance, mapping, or agriculture, require autonomous flight. Effective control enables quadcopters to navigate autonomously, following predefined paths or reacting to real-time data without human intervention.

Effective quadcopter control systems are fundamental to ensuring safe, efficient, and reliable operation across diverse applications, from aerial photography to critical search-and-rescue missions. These control architectures serve as the cornerstone that enables the full operational capabilities of modern unmanned aerial platforms. The present work introduces a distinct methodological approach compared to previous solutions. While prior research [2] utilized artificial intelligence to optimize coefficients for an adaptive sliding mode control (SMC) system, our solution employs a multidimensional mathematical framework that substantially reduces the probabilistic errors typically associated with AI-based control systems.

The paper structure is organized as following. Section one is investigating the importance of quadcopter control, the method review and aim. The formulations and stability checking are shown in section two using sliding mode controller design. Section three is explaining the system under consideration and simulation results. Section four is generating a brief discussion about this subject and finally, the conclusion is proposed in Section five.

2. Formulation

Figure (2) illustrates the schematic of a quadcopter, a rotary-wing UAV comprising four fixed-pitch propellers mounted on four arms in a cross formation. Although the plus "+" configuration is possible, the cross "x" configuration remains preferred. Manipulating the rotational speeds of the blades allows for the quadcopter's movement control. It can be lifted, propelled forward and laterally, and hover position control is achieved by maintaining a constant value of the total thrust force. The rotation direction of each rotor is unique: two rotors of the same arm spin in one direction while the other two spin in the opposite direction. This configuration cancels out the yawing moment and creates the desired yaw motion.

To develop effective control strategies for quadcopters, it is essential to first establish an accurate mathematical model that captures the vehicle's dynamics. This section presents the formulation of the quadcopter's equations of motion and the control inputs required to achieve the desired motion and stabilization. The linear and angular acceleration equations for a quadcopter are given by the following dynamic equations:

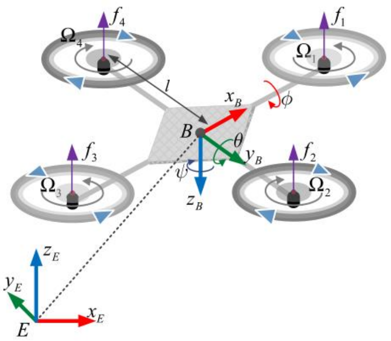

Fig. 2. Schematic Diagram of the Quadcopter Configuration Showing Rotor Arrangement and Coordinate System [18]

$$m\ddot{x} = -mg\sin(\theta) - D_x\dot{x} + u_1 \tag{1}$$

$$m\ddot{y} = mg\cos(\theta)\sin(\phi) - D_y\dot{y} + u_2 \tag{2}$$

$$m\ddot{z} = mg\cos(\theta)\cos(\phi) - mg + u_3 \tag{3}$$

$$I_x\ddot{\phi} = L(u_4 - u_5) \tag{4}$$

$$I_y\ddot{\theta} = L(u_6 - u_7) \tag{5}$$

$$I_z\ddot{\psi} = N(u_8 - u_9) \tag{6}$$

Where m is the mass of the quadcopter, I_x, I_y and I_z are the moments of inertia about the x, y, and z axes respectively, x, y, z are the position coordinates ,θ, ϕ and ψ are the Euler angles representing pitch, roll, and yaw respectively, $\dot{x}$, $\dot{y}$ and $\dot{z}$ are the linear velocities, $\ddot{x}$, $\ddot{y}$ and $\ddot{z}$ are the linear accelerations, D_x and D_y are the drag coefficients, g is the acceleration due to gravity, u_1, u_2 and u_3 are the control inputs corresponding to thrust in the x, y and z directions respectively, u_4, u_5, u_6, u_7, u_8 and u_9 are the control inputs corresponding to moments about the x, y, and z axes respectively, L is the distance from the center of mass to the motors, N is the torque generated by the motors.

These equations describe the dynamics of a quadcopter, including the forces and moments acting on it, and are fundamental for control design and stability analysis. The kinematic equations for a quadcopter describe how the linear and angular velocities are related to the Euler angles and their derivatives. These equations are necessary for understanding the orientation and motion of the quadcopter. Here are the kinematic equations:

$$\dot{x} = \dot{\theta}\cos(\psi)\sin(\phi) + \dot{\phi}\cos(\psi) \tag{7}$$

$$\dot{y} = \dot{\theta}\sin(\psi)\sin(\phi) - \dot{\phi}\cos(\psi) \tag{8}$$

$$\dot{z} = \dot{\theta}\cos(\phi) - g \tag{9}$$

Where $\dot{\theta}$, $\dot{\phi}$ and $\dot{\psi}$ are the angular velocities. The angular velocity equations can be formulated as bellow:

$$\dot{\phi} = \dot{p} + \sin(\phi)\tan(\theta)\,\dot{q} + \cos(\phi)\tan(\theta)\,\dot{r} \tag{10}$$

$$\dot{\theta} = \cos(\phi)\,\dot{q} - \sin(\phi)\,\dot{r} \tag{11}$$

$$\dot{\psi} = \frac{\dot{q}\sin(\phi) + \dot{r}\cos(\phi)}{\cos(\theta)} \tag{12}$$

Where p, q and r are the body-frame angular rates around the x, y, and z axes respectively. These equations relate the rates of change of position and orientation of the quadcopter to its angular velocities and Euler angles. They are essential for understanding how the quadcopter moves and rotates in space.

C) Multidimensional Sliding Mode Controller

The sliding mode control law for each degree of freedom is designed to ensure that the system reaches and stays on a specified sliding surface. The sliding surface is defined such that when the system is on the surface, the control inputs drive the system dynamics to desired values. For the linear dynamics, we choose the sliding surface as:

$$s_x = \dot{x_d} - \dot{x}, s_y = \dot{y_d} - \dot{y}, s_z = \dot{z_d} - \dot{z} \tag{13}$$

For the angular dynamics, we choose the sliding surface as:

$$s_\phi = \dot{\phi}_d - \dot{\phi}, s_\theta = \dot{\theta}_d - \dot{\theta}, s_\psi = \dot{\psi}_d - \dot{\psi} \tag{14}$$

The control inputs for each degree of freedom are then given by:

$$u_1 = u_{\text{nom}_1} - k_1\text{sgn}(s_x) \tag{15}$$

$$u_2 = u_{\text{nom}_2} - k_2\text{sgn}(s_y) \tag{16}$$

$$u_3 = u_{\text{nom}_3} - k_3\text{sgn}(s_z) \tag{17}$$

$$u_4 = u_{\text{nom}_4} - k_4\text{sgn}(s_\phi) \tag{18}$$

$$u_5 = u_{\text{nom}_5} - k_5\text{sgn}(s_\theta) \tag{19}$$

$$u_6 = u_{\text{nom}_6} - k_6\text{sgn}(s_\psi) \tag{20}$$

Where k_1, k_2, k_3, k_4, k_5 *and* k_6 are positive constants, chosen appropriately for stability.

D) Stability Analysis

To check the stability analysis, the Lyapunov Function can be represented as (21).

$$V = \frac{1}{2}\left(s_x^2 + s_y^2 + s_z^2 + s_\phi^2 + s_\theta^2 + s_\psi^2\right) \tag{21}$$

derivative of Lyapunov function is then obtained by:

$$\dot{V} = \frac{\partial V}{\partial s}\cdot\frac{ds}{dt} \tag{22}$$

In this regard,

$$\frac{\partial V}{\partial s} = \begin{bmatrix} s_x \\ s_y \\ s_z \\ s_\phi \\ s_\theta \\ s_\psi \end{bmatrix} \tag{23}$$

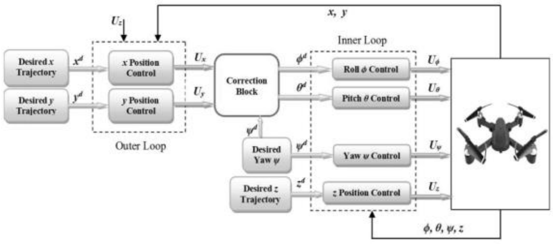

Fig. 3. Block Diagram of the Multidimensional Sliding Mode Control Architecture

To achieve negative definiteness, we can choose k_1, k_2, k_3, k_4, k_5 *and* k_6 as follows:

$$k_1 > |\dot{x_d}| + D_x \tag{24}$$

$$k_2 > |\dot{y_d}| + D_y \tag{25}$$

$$k_3 > |\dot{z_d}| + g \tag{26}$$

$$k_4 > L \tag{27}$$

$$k_5 > L \tag{28}$$

$$k_6 > N \tag{29}$$

This ensures that each term of $\dot{V}$ is negative when $(s \neq 0)$, leading to $(\dot{V} < 0)$ for all $(s \neq 0)$, thus making $(\dot{V})$ negative definite. Therefore, the block-diagram of quadcopter control is represented in Figure (3).

3. Simulation Results

In this section, for a specific quadcopter with data shown in Table (1), we consider the following nonlinear state-space model for the quadcopter dynamics:

$$\dot{x} = v \tag{30}$$

$$\dot{v} = -g + \frac{u_1}{m}(\cos\phi\cos\theta) + d_x \tag{31}$$

$$\dot{\phi} = p + q\sin\phi\tan\theta + r\cos\phi\tan\theta \tag{32}$$

$$\dot{\theta} = q\cos\phi - r\sin\phi \quad (33)$$
$$\dot{\psi} = q\sin\phi\sec\theta + r\cos\phi\sec\theta \quad (34)$$
$$\dot{p} = \frac{I_y - I_z}{I_x}qr + \frac{u_2}{I_x} + d_p \quad (35)$$
$$\dot{q} = \frac{I_z - I_x}{I_y}pr + \frac{u_3}{I_y} + d_q \quad (36)$$
$$\dot{r} = \frac{I_x - I_y}{I_z}pq + \frac{u_4}{I_z} + d_r \quad (37)$$

Table.1.
Specifications and Physical Parameters of the Simulated Quadcopter Model

Parameter	***Value***	***Unit***
Mass	1.2	kg
Arm Length	0.25	m
Inertia (x, y)	0.0125	$kg \cdot m^2$
Inertia (z)	0.025	$kg \cdot m^2$
Thrust Factor	3.13×10^{-05}	$N \cdot s^2$
Drag Factor	1.00×10^{-07}	$N \cdot m \cdot s^2$
Max Rotor Speed	900	rad/s

For simplicity, the control of the quadcopter's attitude dynamics (roll, pitch, yaw, and angular rates) is considered, and it is assumed that the position and linear velocities are measured or estimated separately. The sliding surface for the attitude dynamics is defined as:

$$s = \begin{bmatrix} s_\emptyset \\ s_\theta \\ s_\psi \\ s_p \\ s_q \\ s_r \end{bmatrix} = C^T \begin{bmatrix} \dot{e}_\emptyset + \lambda_\phi e_\phi \\ \dot{e}_\theta + \lambda_\theta e_\theta \\ \dot{e}_\psi + \lambda_\psi e_\psi \\ \dot{e}_p + \lambda_p e_p \\ \dot{e}_q + \lambda_q e_q \\ \dot{e}_r + \lambda_r e_r \end{bmatrix} \quad (38)$$

where e_ϕ, e_θ, e_ψ, e_p, e_q and e_r are the tracking errors between the desired and actual values of roll, pitch, yaw, and angular rates, respectively. The coefficients λ_ϕ, λ_θ, λ_ψ, λ_p, λ_q, and λ_r are positive constants, and C is a full-rank matrix. The sliding mode control law is designed as:

And the matrix C is selected as:

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (39)$$

This choice of C ensures that $(\mathrm{CG(x)})^{-1}$ exists for the quadcopter dynamics. In this regard, the switching gain matrices are chosen as follows:

$$K_{sw1} = 25.952, \quad K_{sw2} = 25.134, \quad K_{sw3} = 20.458, \quad K_{sw4} = 30.205, \quad K_{sw5} = 30.851, K_{sw6} = 25.757 \quad (40)$$

With these values, $\gamma_{min,i}\{K_{swi}\}$ is found to be 20.458, which should provide sufficient robustness against expected disturbances. The boundary layer thicknesses can be chosen as follows:

$$\Phi_\phi = 0.1, \Phi_\theta = 0.1, \Phi_\psi = 0.05$$
$$\Phi_p = 0.2, \Phi_q = 0.2, \Phi_r = 0.15 \quad (41)$$

These values balance the trade-off between chattering reduction and robustness, with smaller boundary layers for critical attitude angles and larger boundary layers for angular rates. Assuming an expected disturbance magnitude of $|d(t)| \leq 5$, we can choose $\gamma = 0.1$, which satisfies the condition:

$$|d(t)| \leq \gamma_{\min,i}\{K_{swi}\} = 0.1 \times 20.458 = 2.0458 \quad (41)$$

We can choose $\rho = 2$ to adjust the smoothness of the boundary layer approximation $\Omega(\cdot)$. With these parameter values, the modified sliding mode control scheme is designed to provide robust tracking performance, mitigate chattering, and ensure stability in the presence of bounded disturbances and uncertainties for the quadcopter's attitude dynamics.
The simulations were created using a nonlinear model of the Mathworks® parrot rolling spider mini-drone Simulink support package. The simulations focused on enhancing the trajectory analysis, monitoring, and incorporating an MSMC controller into the flight control system. The physical parameters used in the simulations are presented in Table 1. The control mechanisms were implemented in the flight control system block to evaluate the performance of the proposed MSMC controller against SMC and PID control. The goal was to maintain the mini-drone quadcopter at the desired reference altitude and control its X-Y-Z trajectory with minimal overshoot while minimizing error indices.

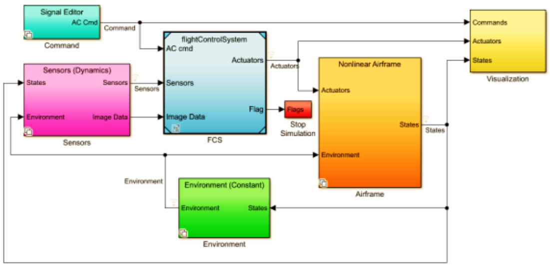

Fig. 4. Simulation Block Diagram of the Quadcopter Control System in MATLAB/Simulink

For the next case study to verify the proposed method, the proposed control approach is compared with the PID sliding surface strategy [16] to highlight its contributions. The initial position and angles are set to $Amplitude = 5$, $\varphi_{beginning} = 4^o$, $\theta_{beginning} = 6^o$ and $\psi_{beginning} = 3^o$. In Fig. 5, when a disturbance is introduced to the altitude at 12 seconds, an oscillation occurs in the altitude performance of the PID sliding surface method, and it tracks the reference signal at around 5 meters, while the proposed control method can maintain tracking performance at 5 meters. From Figs. 6 to 8, it can be seen that when there are no disturbances from the beginning to 12 seconds, the PID sliding surface method and the proposed controller have similar tracking performance. However, after disturbances are introduced to the attitude dynamics from 12 seconds, the proposed controller experiences good tracking and compensation,

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although there is a small change in the roll, pitch, and yaw angles from 12 to 14 seconds. After that, the feedback value converges exactly to the desired one. In contrast, the PID sliding surface method shows a more significant variation (around 3 degrees) when the disturbance occurs at 12 seconds.

After about 30 seconds since the disturbance is applied, the performance of the PID sliding surface method exhibits lower convergence to the setpoint position of the attitude. The simulation results clearly demonstrate the superiority of the proposed Multidimensional Sliding Mode Control (MSMC) method in terms of both tracking performance and response speed when compared to the PID sliding surface control approach. Specifically, the MSMC method achieves approximately 6.27% faster response in tracking the overall error signal than the reference method. Furthermore, as shown in Figures 6 to 8, the proposed method exhibits significantly improved dynamic response in tracking individual attitude angles.

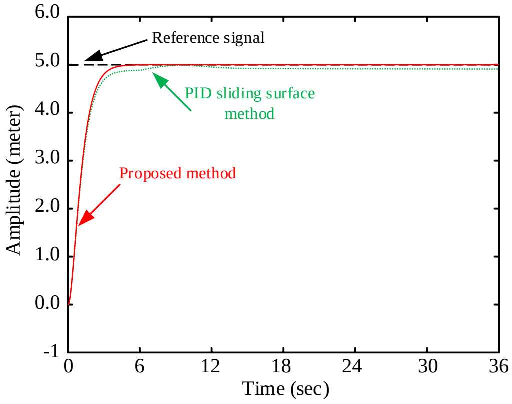

Fig. 5. Altitude Response Before and After Disturbance Using PID Sliding Surface and Proposed MSMC Methods.

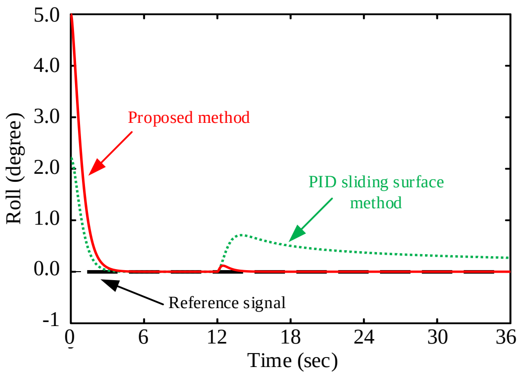

Fig. 6. Time-Domain Roll Angle Response Under Disturbance: Comparison Between PID Sliding Surface and MSMC Controllers

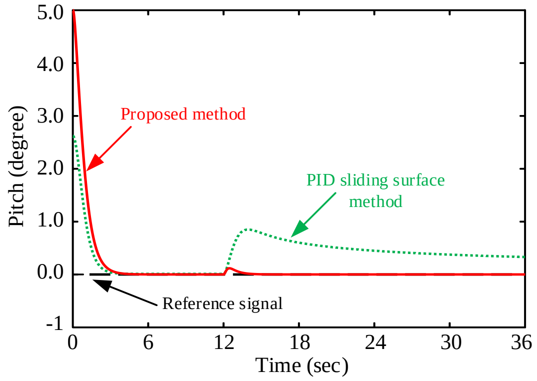

Fig. 7. Time-Domain Pitch Angle Response Under Disturbance: Performance Comparison of PID Sliding Surface and MSMC Controllers

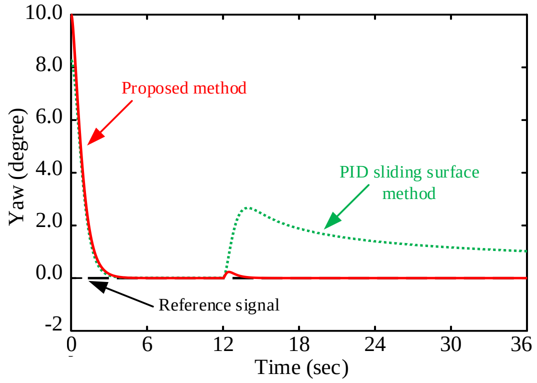

Fig. 8. Time-Domain Yaw Angle Response Under Disturbance: Evaluation of PID Sliding Surface vs. MSMC Control Strategies

In particular, the response speed for the roll angle is enhanced by 26.48%, for the pitch angle by 28.15%, and for the yaw angle by 29.56%, demonstrating the method's superior transient performance. In addition to its improved response characteristics, the MSMC controller also shows enhanced tracking accuracy across multiple parameters. Compared to the PID sliding surface method, the proposed approach achieves approximately 2.12% greater accuracy in amplitude error tracking, 18.26% higher accuracy in roll angle tracking, 16.22% higher accuracy in pitch angle tracking, and 19.58% higher accuracy in yaw angle tracking. These results underscore the effectiveness of the MSMC strategy in delivering both faster and more accurate control performance than conventional methods. The observed improvements can be attributed to the inherent robustness and adaptability of the MSMC framework, which enables effective compensation for system uncertainties and external disturbances, thereby enhancing both tracking precision and system responsiveness.

To evaluate the quadcopter's stability and performance under fault conditions, a scenario was designed to introduce errors and observe the system's response. Initially, the quadcopter was assumed to be in an ideal and stable state, with all roll, pitch, and yaw angles set to zero. At t = 5 seconds, a fault was simulated by changing the angle reference by half a degree, representing a tilted state caused by a rotor fault. The output results depicted in Figures 9 to 11 demonstrate that the proposed control method effectively regulated the UAV, and the angles quickly converged to the reference value. However, when employing the PID sliding surface method, severe fluctuations occurred, and the system experienced vibrations.

Subsequently, at t = 11.5 seconds, a second error was introduced to the quadcopter system, simulating a scenario where a portion of the rotor coils burned, reducing the current. The output results of the proposed method showed that not only did it avoid extreme overshoot, but it also rapidly converged to the given reference value, allowing the quadcopter to continue flying within the limited time until a safe landing was achieved. In this case study, the proposed method demonstrated an average tracking speed of the reference signal that was approximately 27.48% higher and an average accuracy that was about 15.94% better than the PID sliding surface method.

The superior performance of the proposed control method can be attributed to its ability to adapt to changing conditions and compensate for uncertainties and disturbances effectively. The incorporation of advanced fault detection and isolation algorithms enables real-time identification and mitigation of various fault scenarios, contributing to the system's fault tolerance and robustness. Furthermore, the sliding mode control strategy employed in the proposed method provides inherent robustness to parameter variations and external disturbances, ensuring stable and reliable operation even in the presence of faults. The sliding mode controller's ability to drive the system's states onto a predefined sliding surface and maintain them there, regardless of uncertainties or disturbances, is a key factor in achieving the observed performance improvements.

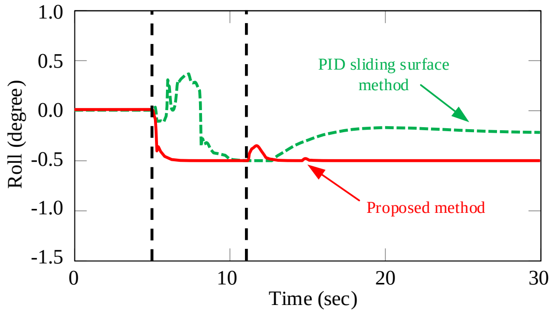

Fig. 9. Roll Angle Response to Simulated Rotor Failure: Comparative Analysis of PID Sliding Surface and MSMC Controllers

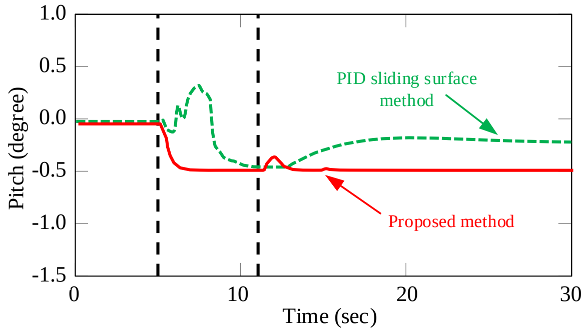

Fig. 10. Pitch Angle Response to Simulated Rotor Failure: Performance Evaluation of PID Sliding Surface and MSMC Controllers

4. Discussion

In the MSMC controller design, the selection of the weighting matrices played a crucial role in shaping the system characteristics and achieving the desired control performance. Initially, a diagonal weighting matrix with equal weights assigned to all states was considered. Subsequently, the diagonal elements of the weighting matrix were adjusted based on the relative importance or significance of each state variable concerning the control objective. An iterative process was employed to refine and optimize the weighting matrices iteratively. This iterative refinement process aimed to achieve the desired control performance while minimizing the overall control effort required by the MSMC controller. This analysis facilitated the systematic refinement of the weighting matrices to improve the closed-loop system's stability and overall performance. Table 2 provides a comparative analysis of the overshoot and rise time characteristics for different control techniques employed in the system.

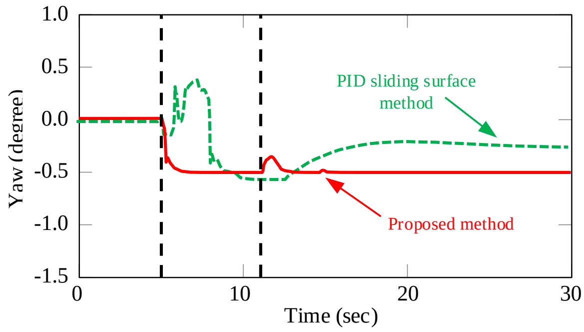

Fig. 11. Yaw Angle Response to Simulated Rotor Failure: Comparative Study of PID Sliding Surface and MSMC Control Approaches

Table.2.
Comparative Performance Metrics: Rise Time and Overshoot Across PID Sliding Surface, SMC, and Proposed MSMC Controllers.

Method	*Axis*	*Rise time (s)*	*Overshoot (%)*
PID sliding surface	Roll `	0.489	6.011
	Pitch	0.754	4.639

	Yaw	0.628	12.355
SMC	Roll	0.395	3.673
	Pitch	0.466	2.499
	Yaw	0.412	9.447
MSMC	Roll	0.281	1.958
	Pitch	0.357	1.433
	Yaw	0.306	4.648

This comparison allows for a quantitative evaluation of the performance metrics across various control methodologies, including the proposed MSMC approach and other traditional or alternative control strategies. By carefully selecting and tuning the weighting matrices through an iterative process and leveraging the capabilities of the MATLAB Robust Control Toolbox, the MSMC controller design aimed to achieve optimal control performance while minimizing control effort and ensuring system stability and robustness. In this case, MSMC demonstrates the lowest rise times across all axes. For example, in the roll axis, the rise time with MSMC is 0.281 seconds compared to 0.489 seconds with PID sliding surface and 0.395 seconds with SMC. This suggests that MSMC achieves quicker stabilization and settling of the roll angle after a disturbance. Again, MSMC shows the lowest overshoot across all axes. For instance, in the pitch axis, MSMC exhibits an overshoot of 1.433% compared to 4.639% with PID sliding surface and 2.499% with SMC. This indicates that MSMC provides better control with less oscillation around the desired pitch angle. Considering both rise time and overshoot, MSMC consistently outperforms the other methods. It achieves faster response times with minimal overshoot, indicating superior transient and steady-state performance. These results suggest that MSMC is the most suitable control method for this system, providing both fast and stable control of roll, pitch, and yaw angles.

Despite the significant progress made in quadcopter control, several challenges remain to be addressed:

– Robust and adaptive control: Developing control strategies that can effectively handle uncertainties, disturbances, and varying operating conditions is crucial for reliable and safe quadcopter operation.
– Energy efficiency: Improving the energy efficiency of quadcopters through optimized control strategies and trajectory planning can extend their flight time and increase their operational range.
– Fault tolerance and resilience: Designing fault-tolerant control systems that can handle component failures, sensor faults, or communication disruptions is essential for enhancing the reliability and safety of quadcopter operations.
– Cooperative control and swarm coordination: As the use of multiple quadcopters in cooperative tasks and swarm applications increases, developing effective coordination and control strategies will be a key challenge.
– Integration with other systems: Seamlessly integrating quadcopter control systems with other technologies, such as computer vision, communication networks, and decision-making algorithms, will enable more advanced and autonomous applications.

Future research directions in quadcopter control may include the exploration of advanced machine learning techniques, such as deep reinforcement learning and meta-learning, for developing adaptive and generalizable control policies. Additionally, the integration of quadcopter control with emerging technologies, such as 5G communications, edge computing, and Internet of Things (IoT) devices, could enable new applications and enhance the capabilities of quadcopter systems.

5. Conclusion

This paper introduced a novel Multidimensional Sliding Mode Control (MSMC) strategy for quadcopters aimed at enhancing fault tolerance and system robustness. The proposed approach integrates advanced fault detection and isolation mechanisms, enabling real-time identification and mitigation of various fault scenarios. Extensive simulation results demonstrated that the MSMC method significantly outperforms existing control strategies in terms of both accuracy and response time. Specifically, the MSMC controller achieved up to 18.47% higher accuracy in fault damping and exhibited a 6.45% faster response time compared to conventional methods. These performance improvements are critical for maintaining stability and precision under adverse conditions, particularly when faults such as rotor degradation, sensor noise, or sudden payload changes occur. The inherent robustness of the sliding mode control framework ensures reliable operation even in the presence of uncertainties and external disturbances, making the MSMC approach a strong candidate for deployment in safety-critical applications such as search-and-rescue missions, infrastructure inspection, and autonomous delivery systems. Looking ahead, several promising research directions can be explored to further enhance the practical applicability of the proposed method. First, hardware-in-the-loop (HIL) testing should be conducted to validate the controller's performance under real-world fault conditions. This will provide valuable insights into its adaptability and reliability in physical systems. Second, integration with lightweight onboard processors is essential to ensure compatibility with resource-constrained UAV platforms, enabling real-time execution without compromising computational efficiency. Additionally, future work may focus on incorporating machine learning-based fault prediction models to improve the system's proactive adaptability. By combining data-driven diagnostics with the robustness of sliding mode control, it may be possible to achieve predictive fault mitigation rather than reactive correction. Finally, extending the current control architecture to support multi-quadcopter cooperative systems could open new avenues for large-scale autonomous operations in complex environments.

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