Design Concept of Angular Controller for Quadrotor UAV Based on Improved Particle Swarm Optimization Algorithm PID Control

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Abstract. The control of unmanned aerial vehicles (UAVs) is a key research problem in the field of UAVs. PID control is currently one of the most widely used methods for this issue. However, the classical PID control structure suffers from difficulty tuning control parameters, resulting in poor control performance for UAVs. Therefore, this paper proposes a Gaussian mutation-enhanced PSO-PID algorithm for UAV control. The proposed method is built upon classical PID control and PSO optimization algorithms. Firstly, the dynamic model of UAV is constructed using Euler's method and Newton's laws of motion. Then, single-loop PID control is applied to control the UAV, and the PSO algorithm is introduced to solve the parameter tuning problem. To overcome the drawback of PSO algorithm being prone to local optima, Gaussian mutation is introduced to enhance the ability to escape from local optima. The algorithm theoretically offers faster response and better control performance compared to the classical PID structure, and it can be used as a flight control algorithm for commercial UAVs in the future.

Keywords: UAV Control; PID Control; PSO Algorithm; PSO-PID Control.

1. Introduction

Unmanned aerial vehicles (UAVs) are planes that can carry out missions without the need for human assistance. Unlike traditional aircraft, UAVs offer higher flexibility, lower cost, wider application areas, lower safety risks, and environmental friendliness. Therefore, UAVs have been utilized extensively and developed in many fields, such as military surveillance, agricultural irrigation, and disaster relief [1,2].

According to their different uses, designs, and technical characteristics, UAVs can be divided into various types, such as Multirotor UAVs, Fixed-wing UAVs, Hybrid UAVs, etc. Among them, quadcopter UAVs have become the mainstream model due to their high flexibility, simple structure, and strong stability. With the development of UAV technology and the continuous expansion of application scenarios, the demand for UAV control performance is also increasing. Unstable control structures may lead to dangerous situations such as landing errors, crashes, or collisions with buildings or crowds. Therefore, there is a need to design efficient and stable flight control algorithms, making UAV control issues a hot research topic in this field.

The control system of UAVs is a typical underactuated nonlinear system [3]. Standard UAV control algorithms include classical PID control: Proportional-Integral-Derivative (PID), Model Predictive Control (MPC), Adaptive Control, Robust Control, etc. Due to its simplicity, robustness, and high reliability, PID control has become widely adopted by commercial UAV companies as a control method [4]. However, classical PID control often faces the problem of difficult parameter tuning and may not adapt well to various control scenarios, thus having certain limitations. Therefore, optimization of classical PID control algorithms is needed. Common optimization algorithms for control systems include nature-inspired algorithms, algorithms resembling animal behavior such as (PSO), and algorithms inspired by ants. Among them, PSO is preferred for its quick convergence time, low number of parameters, and straightforward implementation, which makes it a popular choice for controller optimization.

The tuning of PID control parameters often relies heavily on empirical methods, leading to deficiencies in precision. Therefore, using the PSO algorithm for parameter tuning in PID controllers,

known as PSO-PID, effectively addresses this issue. There have been some studies on PSO-PID, such as implementing PID control for agricultural spraying UAVs based on the PSO optimization algorithm, effectively improving spraying efficiency [1]. Among them, PSO is preferred for its quick convergence time, low number of parameters, and straightforward implementation, which makes it a popular choice for controller optimization. Choosing inappropriate parameter values may result in slow convergence speed or premature oscillation.

Furthermore, some studies have employed multi-objective PSO optimization PID algorithms by selecting four different cost functions combining different factors to achieve optimal performance. However, the limitation of this method is that multi-objective optimization problems often involve a large number of objective functions and constraints, leading to high computational complexity. Especially in real-time control systems, parameter optimization needs to be completed within a limited time frame, and high computational complexity may limit the practicality of the algorithm.

Additionally, studies are focusing on utilizing PSO optimization algorithms under the conditions of cascade fuzzy PID control to maintain optimal control parameters at all times [5]. One limitation of this method is that in cascade fuzzy PID control, there may be strong coupling between parameters in different modules, making it difficult for the PSO algorithm to handle the complex coupling relationships between parameters, which may result in unstable or non-convergent optimization results.

Based on the research background mentioned above, this paper proposes using Gaussian mutation enhanced PSO algorithm applied to PID control for adjusting the control parameters of quadcopter UAVs. By comparing with basic PID control and PID control using PSO algorithm, this paper aims to demonstrate that the proposed improvement measures can achieve better control performance.

The proposed method leverages the Gaussian mutation enhanced PSO algorithm to optimize the PID control parameters of quadcopter UAVs. The Gaussian mutation introduces randomness into the PSO algorithm, enhancing its ability to escape local optima and improving parameter optimization's convergence speed and stability. By integrating Gaussian mutation into the PSO algorithm, the proposed method aims to overcome the limitations of traditional PID control and standard PSO algorithm in parameter tuning and achieve better control performance.

Comparative experiments with basic PID control and PSO algorithm based PID control demonstrate the effectiveness of the proposed Gaussian mutation enhanced PSO algorithm for PID control of quadcopter UAVs. The comparison can be conducted based on various performance metrics such as control accuracy, stability, convergence speed, and robustness. The results of the comparison will provide empirical evidence to support the superiority of the proposed method in achieving better control effects for quadcopter UAVs.

2. Modeling

2.1. Mathematical Modeling of Quadcopter UAVs- Angular Controller

To better describe the dynamics equation model of the UAV, it is necessary to choose appropriate coordinate systems. Considering that the UAV has two types of motion, translational motion and angular motion, this paper treats it as a symmetric rigid body with its center at the geometric center [6]. The EI-xyz inertial coordinate system and EB-xByBzB body-fixed coordinate system are chosen to describe the UAV's motion. The Euler angles describing the rotation of the UAV about the xB axis, yB axis, and zB axis are defined as φ (roll angle), θ (pitch angle), and ψ (yaw angle), respectively, with angular velocities p, q, and r. Additionally, the moments of inertia of the UAV about the xB, yB, and zB axes are defined as Ix, Iy, and Iz. The distance from each motor to the center of the UAV is denoted as l [7], as shown in Fig.1.

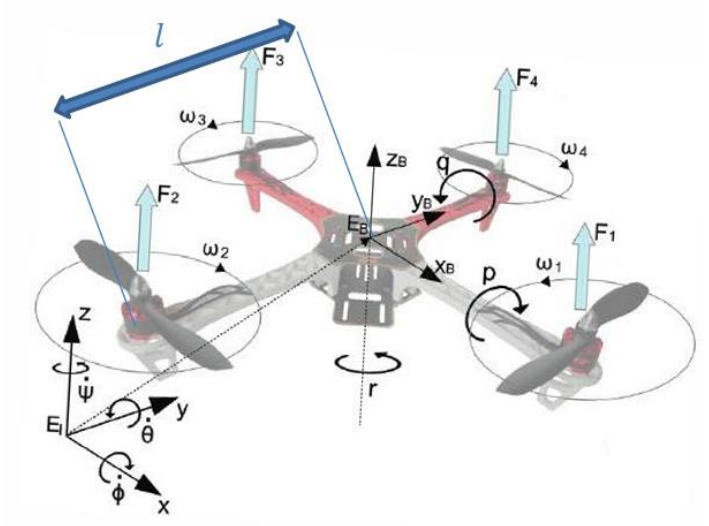


Fig. 1 A Quadcopter UAV Model

The UAV has four typical flight modes: vertical, roll, pitch, and yaw. Therefore, with four input parameters, it is possible to achieve separate control inputs for the four flight modes of the nonlinear control system of the UAV [8]. Let the four input values be Ft, τp, τq, and τr, and consider the resistance of the UAV as directly proportional to the velocity [7]. The dynamics model of the UAV can be obtained as follows:

$$\begin{cases} \dot{x} = v_x \\ \dot{y} = v_y \\ \dot{z} = v_z \end{cases} \tag{1}$$

$$\begin{cases} m\dot{v}_x = F_t(\cos\varphi\cos\psi\sin\theta + \sin\varphi\sin\psi) \\ m\dot{v}_y = F_t(\cos\varphi\sin\theta\sin\psi + \cos\psi\sin\psi) \\ m\dot{v}_z = -mg + F_t\cos\varphi\cos\theta \end{cases} \tag{2}$$

$$\begin{cases} \dot{\varphi} = p + (r\cos\varphi + q\sin\varphi)\tan\theta \\ \dot{\theta} = q\cos\varphi - r\sin\varphi \\ \dot{\psi} = \frac{1}{\cos\theta}(r\cos\varphi + q\sin\varphi) \end{cases} \tag{3}$$

$$\begin{cases} I_x\dot{p} = (I_y - I_z)qr + \tau_p \\ I_y\dot{q} = (I_z - I_x)pr + \tau_q \\ I_z\dot{r} = (I_x - I_x)pq + \tau_r \end{cases} \tag{4}$$

Assuming the input quantities Ft, τp, τq, and τr are denoted as U1, U2, U3, and U4, respectively, and the output quantities are x, y, z, φ, θ, and ψ, it can be observed that the UAV control system is a multi-input, multi-output, nonlinear control system. Consequently, directly deriving the transfer function of the system is challenging.

2.2. Several control methods

Fig.2 illustrates the typical control system of the UAV.

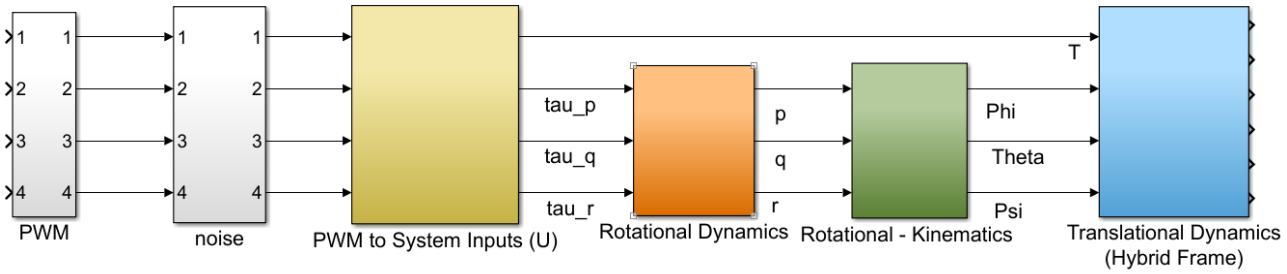


Fig. 2 A UAV Dynamics Control System

Next, this paper will design UAV attitude angle controllers using three different control methods: single-loop PID, PSO-PID, and Gaussian mutation enhanced PSO-PID.

In the UAV control scenario described, the desired position (xd, yd, zd) is known, and sensor data is collected to determine the current position (x, y, z) of the UAV. First, the position controller and attitude controller of the UAV computes the input quantities Ft, τp, τq, and τr, which are then transmitted to the UAV flight controller via the PWM module. The flight controller provides feedback on the desired Euler angles about the x-axis (φd), about the y-axis (θd), and about the z-axis (ψd). Next, the sensor collects the current attitude angles (φ, θ, ψ) of the UAV, and the collected information is compared with the feedback from the flight controller to determine the adjustments required. Finally, the adjustments are transmitted back to the PWM module, which adjusts the motor speeds accordingly. The motor adjusts its speed to alter the three-dimensional coordinates of the drone in physical space and the degree of tilt of its body, continuously approaching the desired position [8].

2.1.1 Single-loop PID controller

The traditional single-loop PID controller achieves control through three components: proportional, integral, and derivative control, as described in Equation (5) and illustrated in Fig.3.

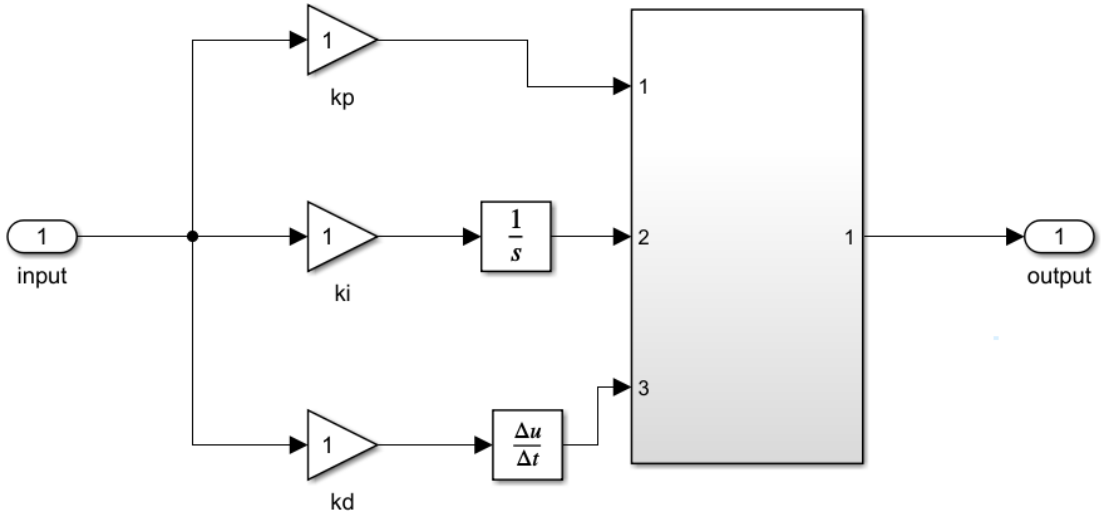


Fig. 3 A Typical PID Controller

The proportional component accelerates the system's response speed, where kp represents the gain parameter of the proportional controller. The integral component eliminates steady-state error, where ki represents the gain parameter of the integral controller. The derivative component suppresses system oscillation, where kd represents the gain parameter of the derivative controller [9].

$$C(s) = k_p + \frac{k_i}{s} + k_d s \tag{5}$$

2.1.2 PSO Algorithm

PSO is a mature algorithm that draws inspiration from the coordinated movements observed in social groups like bird flocks and schools of fish. It is a method of evolutionary computation used to find the optimal solution to a multi-dimensional problem. In 1995, an American social psychologist and an electrical engineer collaboratively devised the Particle Swarm Optimization (PSO) algorithm after conducting extensive research.

In PSO, the potential solutions to the problem are treated as points in a multi-dimensional space. These points are referred to as particles and move within the solution space, with each particle having a velocity and position. The various information of particles, such as velocity and coordinates, are adjusted based on the evaluation of the fitness of the current solution. The algorithm's central premise is to simulate information sharing and cooperation among individuals in a population, enabling the entire population to converge towards potential optimal solutions in the solution space quickly.

Assuming there is an n-dimensional space with a total of particles, the ith particle's coordinate is denoted as Xin. Vin represents the velocity of the particle. A solution found within its own population, which is the best in that population, should then be represented as Pi = (Pi1, Pi2, ..., Pin). The best solutions found by individual populations are aggregated, with the best-performing solution among them referred to as Pg = (Pg1, Pg2, ..., Pgn). [9]. The global best solution is compared to each particle's individual best solution; if the latter is superior, the global best solution's position is then updated.

During the iteration process of PSO, particles continuously adjust their velocity and position [10] according to the following equations:

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 (P_{id}^{k} - X_{id}^{k}) + c_2 r_2 \left(P_{gd}^{k} - X_{id}^{k}\right) \tag{6}$$

$$X_{id}^{k+1} = X_{id}^{k} + v_{id}^{k+1} \tag{7}$$

In the Equation, where:
ω is the inertia weight,
d = 1, 2, ..., n,
i = 1, 2, ...,
a, k is the iteration number,
v_{id}^{k+1} represents the particle velocity,
X_{id}^{k+1} represents the particle position,
c_1 and c_2 are coefficients known as acceleration factors,
r_1 and r_2 are two randomly generated values between 0 and 1.

2.3. Gaussian Mutation

Gaussian Mutation is an improvement technique commonly used in optimization algorithms to enhance the exploration capability of the search algorithm in the solution space. Heuristic optimization methods like Particle Swarm Optimization and Genetic methods frequently use this augmentation technique. The main idea of Gaussian Mutation is to introduce some randomness into the search space to explore the domain of solutions more comprehensively rather than just searching near the current position.

Gaussian Mutation is typically implemented by adding random numbers from a Gaussian distribution to the current position. Specifically, given a position x, Gaussian Mutation can be represented by the following mathematical formula:

$$x_{mutated} = x + \sigma + \mathrm{N}(0,1) \tag{8}$$

Where:$x_{mutated}$ is the new position after Gaussian mutation.
x is the current position.
σ is the standard deviation of the Gaussian mutation, controlling the magnitude of the mutation.
$\mathrm{N}(0,1)$ is a random number generated from a standard normal distribution.

2.4. Gaussian Mutation-based PSO-PID improvement

Using Gaussian Mutation to Improve PSO-PID as follows:

Firstly, PID parameters and Gaussian mutation parameters are initialized. Initialize the PID controller's gain, summation, and differentiation settings, along with parameters such as the probability and magnitude of Gaussian mutation. For example, set a group of parameter values: kp=0.5, ki=0.1, kd=0.05, Gaussian mutation probability of 0.1, and Gaussian mutation magnitude of 0.1.

Next, system performance indicators such as control error, stability, etc., are used as the objective function.

Then, represent PID parameters as particles, with each particle corresponding to a PID parameter combination. Initialize a group of particles, where each particle's position represents a PID parameter combination.

Each particle is mutated with a certain Gaussian mutation probability during each iteration. Evaluate the performance of the mutated particles and calculate the objective function value.
Consider global and local optima and update the position and velocity of each particle accordingly.

Compute the objective function value for each particle, assess its performance, and select the global optimal particle based on the value. Map the position of the global optimal particle to the PID controller parameters and update the controller parameters.

Repeat the iteration process until either the set number of iterations is achieved, or the stopping criteria are met.

3. Simulation Design and Expected Results

The controller designed in this paper is expected to offer superior control performance for the UAV compared to the typical PID controller. The following outlines the envisioned verification process. Simulations and result analysis of the two control methods are conducted in MATLAB/Simulink.

The input signal of the control system adopts a typical step signal, with an initial value set to 0 and an ending value set to 1. The initial settings for the typical PID control are kp = 14, ki = 0.05, and kd = 0.7.

The flight parameters of the quadcopter UAV are set as follows:

$m = 2.5kg,\ L = 0.450m,\ I_x = 3.88 \times 10^{-2}kg \cdot m^2,\ I_y = 3.88 \times 10^{-2}kg \cdot m^2,\ I_z = 7.82 \times 10^{-2}kg \cdot m^2$.

Assuming the roll channel as the controlled object, the transfer function of the roll channel is given by: $G_{(s)} = 8.70/(0.1s^2 + s)$ [7].

In ideal conditions, this control method should exhibit faster system response, smaller system oscillations, and less overshoot compared to classical PID control and other PSO-PID control methods. Additionally, system stability should be achieved faster after introducing a disturbance than with the aforementioned methods. If, at this point, the number of iterations is within the specified range and the fitness of the particle swarm algorithm remains stable, it can be concluded that the control method proposed in this paper offers superior control performance compared to the mentioned control methods.

There may be several reasons if the control performance does not meet the expected results. For instance, there could be errors in the logic of the PSO algorithm code, incorrect implementation of the Gaussian mutation operation, or improper updating of particle positions and velocities. Additionally, convergence issues may arise, where the PSO-PID algorithm fails to converge due to either slow convergence speed or premature convergence. Increasing the number of iterations, adjusting algorithm parameters, or trying other optimization algorithms can be attempted to improve convergence. Moreover, there may be modeling issues, where the UAV control system requires appropriate objective functions and constraints. Incorrect problem modeling may lead to algorithmic failure to converge correctly.

4. Conclusion

This paper proposes an improved PSO-PID control method utilizing Gaussian mutation to address the issue of PSO-PID control easily falling into local optima in UAVs, based on the classical PID controller and particle swarm optimization (PSO) algorithm. Leveraging the Euler method-established UAV dynamics model. The optimization of control parameters is achieved through the combination of PSO and PID. Additionally, Gaussian mutation is introduced to reduce the probability of PSO algorithm falling into local optima. The introduction of Gaussian mutation adds randomness to enhance the global search capability of the PSO-PID algorithm. Moreover, Gaussian mutation can dynamically adjust the mutation magnitude based on the current optimization process state, thereby enhancing the algorithm's adaptability. This approach theoretically yields better control performance than classical PID control methods and other PSO-based optimization methods. Future work will further validate its control effectiveness and promote its application as a UAV flight control algorithm.

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