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Achieving stable trajectory tracking in complex environments using an adaptive PID control strategy-based quadcopter drone

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Abstract. Stable trajectory tracking of unmanned aerial vehicles (UAVs) in complex environments is of paramount importance for achieving high precision and robustness in flight missions. In this paper, we address the attitude control problem of quadrotor UAVs and propose an optimization method based on adaptive PID control strategy. This text first presents an overview of the current status of UAVs both domestically and internationally, followed by the establishment of a mathematical model for quadrotor UAVs. Next, analysing the application of the traditional PID algorithm in UAV attitude control and provide a detailed description of the principles behind genetic algorithms and simulated annealing algorithms, along with their application in optimizing PID parameters. Through simulation experiments conducted in strong wind conditions, we compare the performance of the traditional PID algorithm with the optimization algorithm in stable trajectory tracking tasks. The experimental results demonstrate that the optimization algorithm significantly enhances the flight stability and accuracy of UAVs. Finally, this text summarizes the research findings and provide an outlook on future development directions.

Keywords: Quadrotor UAV, Stable Trajectory Tracking, Adaptive PID Control, Genetic Algorithm, Simulated Annealing Algorithm, Complex Environment.

1. Introduction

With the continuous advancement of technology, Unmanned Aerial Vehicles (UAVs), also known as drones, have been widely utilized in military, civilian, and research fields [1-4]. UAVs offer advantages such as high flexibility, low cost, and absence of human casualties, enabling them to perform various tasks such as aerial photography, surveillance, and search and rescue operations. However, stable trajectory tracking of UAVs in complex environments still poses challenges.

Stable trajectory tracking is a critical issue in UAV flight control. In complex environments, UAVs need to accurately and stably follow predetermined trajectories to cope with influences from factors like wind, obstacles, and other uncertainties. Researching and optimizing trajectory tracking techniques are of significant importance for enhancing UAV flight performance and expanding their applications.

2. Current Status of Unmanned Aerial Vehicles (UAVs) Internationally and Domestically

The research on UAV attitude control algorithms both internationally and domestically encompasses several directions, including traditional PID control, fuzzy control, genetic algorithms, and more.

The conventional Proportional-Integral-Derivative (PID) control algorithm is commonly used in UAV flight control [4]. The PID controller adjusts the control commands of the UAV based on proportional, integral, and derivative information of the current error, aiming to maintain stability on the desired trajectory. However, the traditional PID algorithm has limitations in complex environments, such as difficulties in parameter tuning and insensitivity to nonlinear and time-varying conditions.

To overcome the limitations of the traditional PID algorithm, researchers have proposed various optimized PID algorithms [1-3]. These algorithms optimize and adaptively adjust the parameters of the PID controller through techniques such as adaptivity, model prediction, and fuzzy logic, aiming to improve the performance and stability of the flight control system. Optimized PID algorithms can better meet the requirements of stable trajectory tracking in complex environments.

The latest research advancements in the field of unmanned aerial vehicles (UAVs) encompass two main areas:

Autonomous navigation and obstacle avoidance are key research focuses in the UAV domain, aiming to develop more intelligent and autonomous UAV navigation systems. By leveraging technologies like deep learning and computer vision, UAVs can autonomously plan paths in complex environments and avoid collisions with obstacles, thereby achieving more accurate and reliable obstacle avoidance capabilities. One common application involves utilizing Convolutional Neural Networks (CNNs) to process sensor data, such as images or video streams, for tasks like target detection, tracking, and obstacle avoidance. Training CNN models enables automatic extraction and recognition of features such as targets, obstacles, and terrain within complex environments. The development of these technologies is crucial for enhancing the safety and efficiency of UAVs across various application domains, laying the foundation for improved UAV navigation and obstacle avoidance capabilities.[5]

Autonomous formation flight is an important research direction in the UAV field, aiming to achieve cooperative work and autonomous formation control among multiple UAVs. By strategically planning and optimizing the structure and motion strategies of formations, safety, efficiency, and flexibility during formation flight can be enhanced, providing greater potential for UAV applications. Additionally, models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory networks (LSTMs) have seen extensive use in dynamic modeling and motion prediction. These models can be applied to dynamic trajectory planning and control of UAVs, enabling more intelligent and adaptive flight control in diverse scenarios. [6] With these research advancements, the application prospects for UAV formation flight become broader, offering new possibilities for achieving collaborative tasks and efficient operations among multiple UAVs.

3. Quadrotor UAV Model

In order to conduct the research on attitude control, this paper established a simulation model for a quadrotor unmanned aerial vehicle (UAV).

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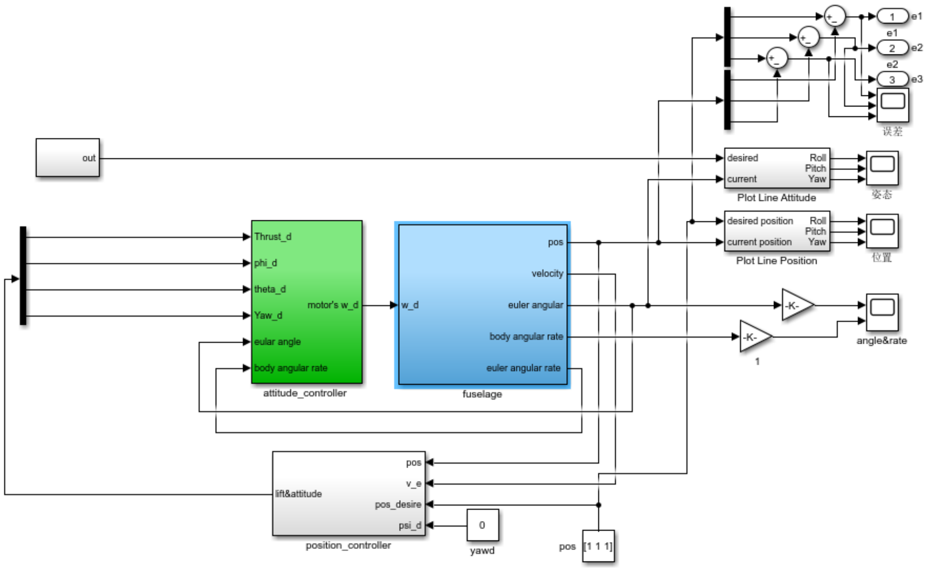

Figure 1. Overall Model of the UAV.

The UAV's disturbance unit manages and optimizes the stability of UAV flight by perceiving and adjusting its flight attitude.

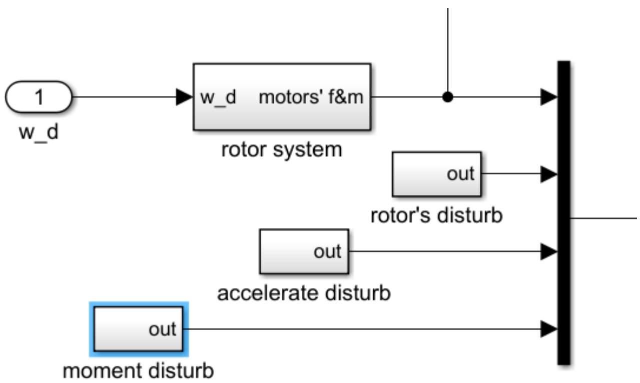

Figure 2. Disturbance Unit of the UAV.

The unmanned aerial vehicle attitude control model is a mathematical model based on rigid body dynamics and control theory. It describes and predicts the attitude of the UAV during flight and utilizes real-time feedback and adjustment based on sensor measurements.

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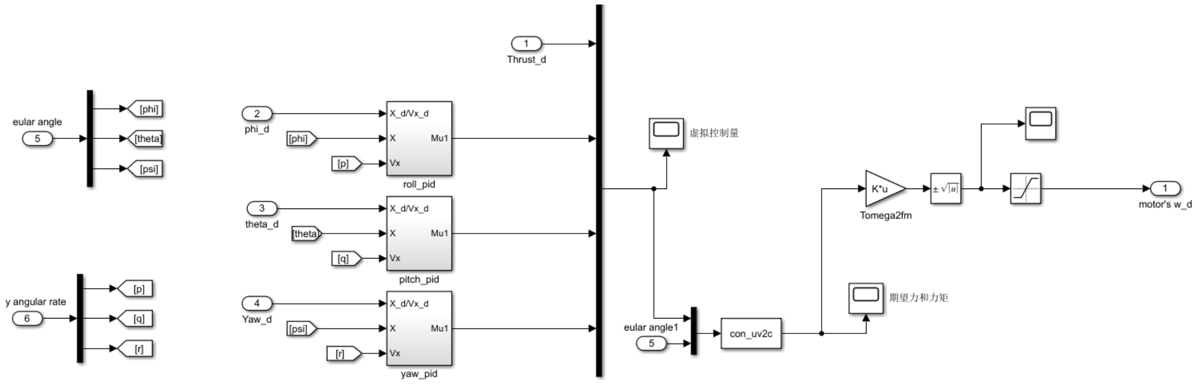

Figure 3. UAV Attitude Control.

The unmanned aerial vehicle position control model is a mathematical model that describes and predicts the position of the UAV during flight, utilizing real-time feedback and adjustment based on sensor measurements and control algorithms.

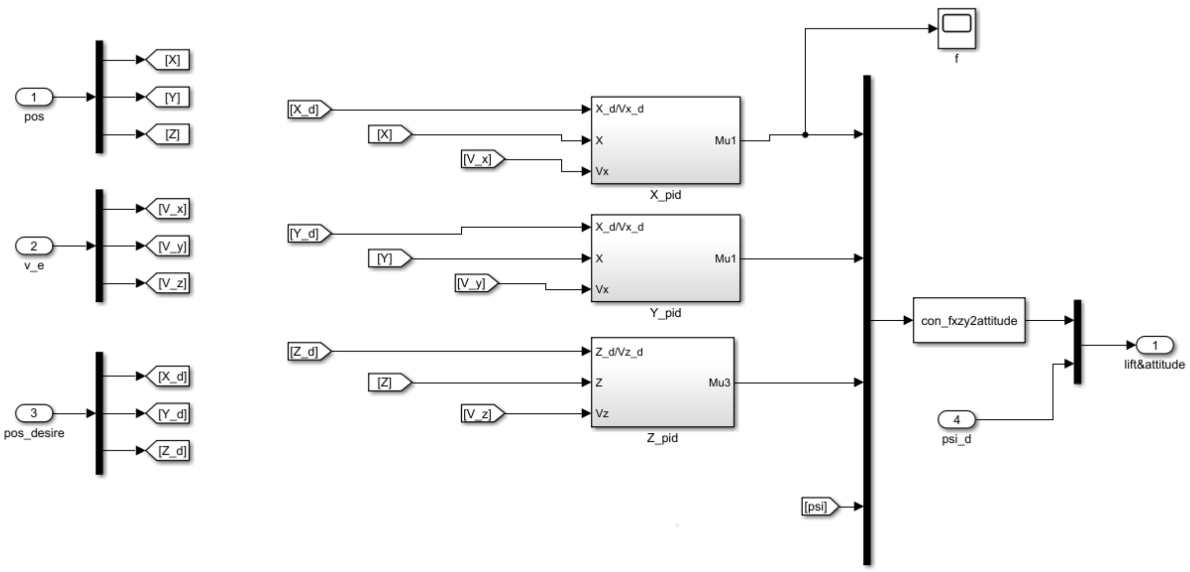

Figure 4. UAV Position Control.

4. Application of Traditional PID Algorithm in UAVs

The traditional PID control algorithm employs three control components - proportional, integral, and derivative - to adjust the controller output based on the magnitude of the error signal. The specific expression of the controller is as follows:

$$u(t) = Kp * e(t) + Ki * \int e(t)dt + Kd * dtde(t)$$

Where, e(t) represents the error between the desired value and the actual value. And proportional term: The purpose of proportional control is to generate an output corresponding to the current error. The proportional gain parameter Kp is used to adjust the magnitude of this output. Therefore, the expression for the proportional term is $Kp * e(t)$. As for integral term: The purpose of integral control is to generate an output based on the accumulation of error, which helps eliminate steady-state error. The integral gain parameter Ki is used to adjust the magnitude of the integral output, which is generated only when the error is nonzero. The expression for the integral term is $Ki * \int e(t)dt$. The derivative term: The purpose of derivative control is to generate an output based on the rate of change of error, which aids in quick response and compensates for system changes. The derivative gain parameter Kd is used to adjust the magnitude of the derivative output. The expression for the derivative term is $Kd * dtde(t)$.

Applying the traditional PID controller to UAV attitude control allows us to obtain the corresponding control inputs.

5. Application of Optimization Algorithms in UAVs

5.1. Genetic Algorithm

Genetic Algorithm [7] is an optimization algorithm that simulates the process of biological evolution. It is well-suited for global search and optimization problems, possessing strong global search capabilities and adaptability to complex issues. It has evolved into a practical, efficient, and robust optimization technique, widely applied in controller design and optimization. In the context of UAV attitude control, Genetic Algorithm can be used to optimize PID parameters to enhance the performance of the controller.

The optimization process of a genetic algorithm typically involves the following steps. First, the population size is initialized, usually with 100 randomly generated individuals. Next, the fitness function is computed to measure the performance of each individual in solving the problem. Then, the top 10 individuals with the highest fitness are selected as elite individuals to preserve their superior genetic information.

Before further operations, crossover is performed on the parent individuals. This means that with a certain probability (e.g., 0.4), two individuals are selected from the parent population, and some of their genes are exchanged to create new offspring individuals. This crossover operation helps introduce diversity and explore new solution spaces.

Next is the mutation operation, which applies a certain probability (e.g., 0.1) to mutate the offspring individuals. Mutation typically introduces new genetic information, increasing the population's diversity and helping to avoid getting stuck in local optima.

Then, the parent individuals and offspring individuals are merged to form the new generation population. This new population will include the elite individuals with good performance, as well as the offspring individuals generated through crossover and mutation.

The entire process is iterated repeatedly, performing steps 2 to 6 to evolve through multiple generations. Each generation evaluates the individuals' performance based on the fitness function and selects new elite individuals for crossover and mutation.

When a predetermined number of generations (e.g., 20 generations) is reached, the evolution process stops, and the individual with the optimal PID parameters is obtained. This optimal individual exhibits better adaptiveness in solving a given problem. Through this optimization process, genetic algorithms are able to search for better solutions in the solution space.

5.2. Genetic Algorithm Design

In the implementation of this genetic algorithm, the population size is set to 100 individuals, out of which 10 elite individuals are selected. After 20 generations of evolution, each generation undergoes crossover and mutation operations. The crossover probability is set to 0.4, indicating a 40% probability of crossover operation in each generation. The mutation probability is set to 0.1, indicating a 10% probability of mutation operation in each generation. The goal of this genetic algorithm is to solve a function problem with 4 independent variables. Through continuous evolution, the genetic algorithm can search for optimal solutions to meet the specified problem requirements.

The attitude range for the variable is set between -10 and 10.

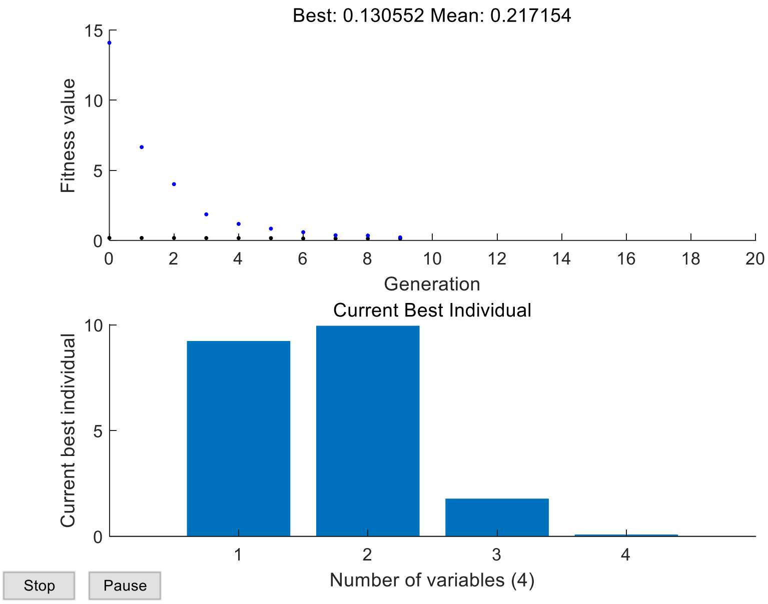

Figure 5. UAV Attitude with Genetic Algorithm.

The position range for the variable is set between -2 and 10.

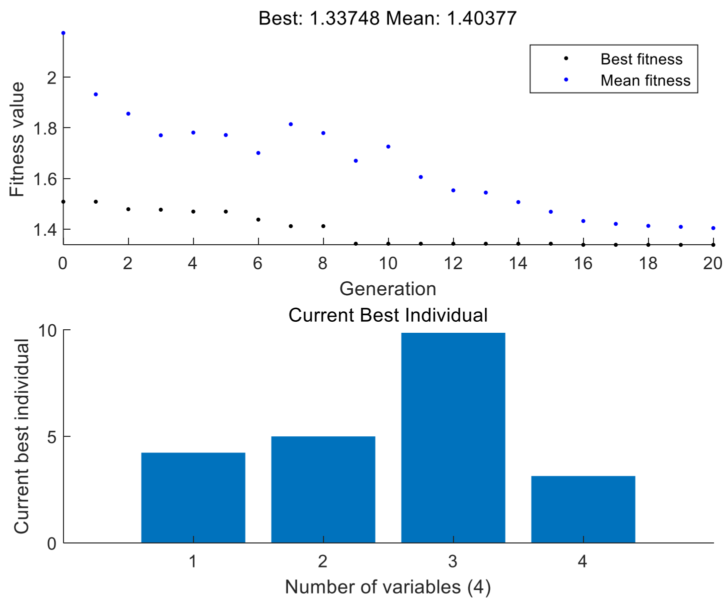

Figure 6. UAV Position with Genetic Algorithm.

5.3. Simulated Annealing Algorithm

The Simulated Annealing algorithm is a global optimization technique that simulates the molecular motion during the annealing process of solids. In the context of UAV attitude control, the Simulated Annealing algorithm can also be employed to optimize PID parameters.

According to the Metropolis criterion, the probability of a particle transitioning to a neighboring state at temperature T is given by:

$$T = e - \Delta e / kT$$

Where, P is the probability of the transition, e is the internal energy of temperature T, ΔE is its change in energy, k is the Boltzmann constant. [8]

The optimization process of the Simulated Annealing algorithm is as follows:[9]

(1) Initialize the temperature parameter with a relatively high initial value, gradually decreasing it.

(2) At the current temperature, generate a new solution randomly and calculate its fitness function value.

(3) Compute the difference between the current solution and the new solution, and decide whether to accept the new solution based on the Metropolis criterion.

(4) Reduce the temperature, lowering the probability of accepting new solutions.

(5) Repeat steps 2 to 4 until the temperature decreases to a certain level.

(6) When a certain number of iterations is reached, stop the optimization process, obtaining the optimal PID parameters for the best individual.

5.4. Simulated Annealing Algorithm Design

The more iterations, the better the parameters. However, due to limited resources, relatively optimal values will be temporarily used.The current generation can be directly read from the graph.

The upper and lower bounds are the same as the Genetic Algorithm.

Attitude:

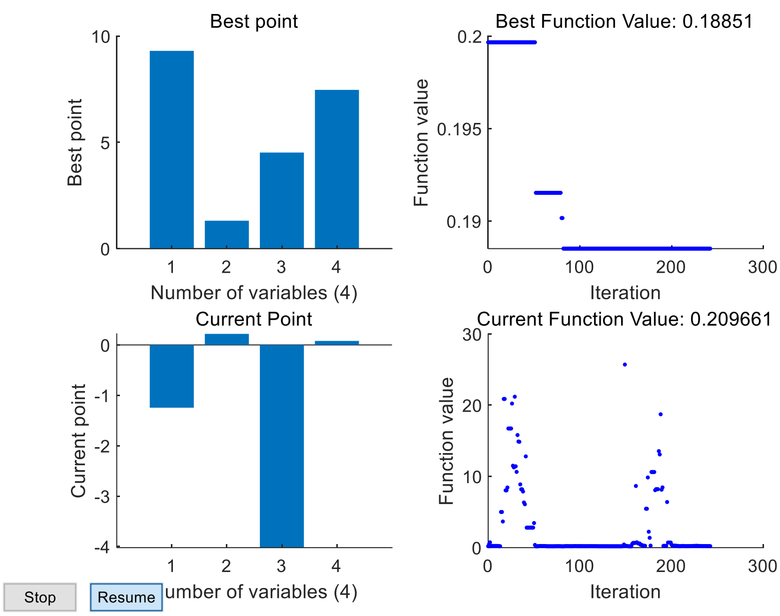

Figure 7. UAV Attitude with Simulated Annealing Algorithm.

Position:

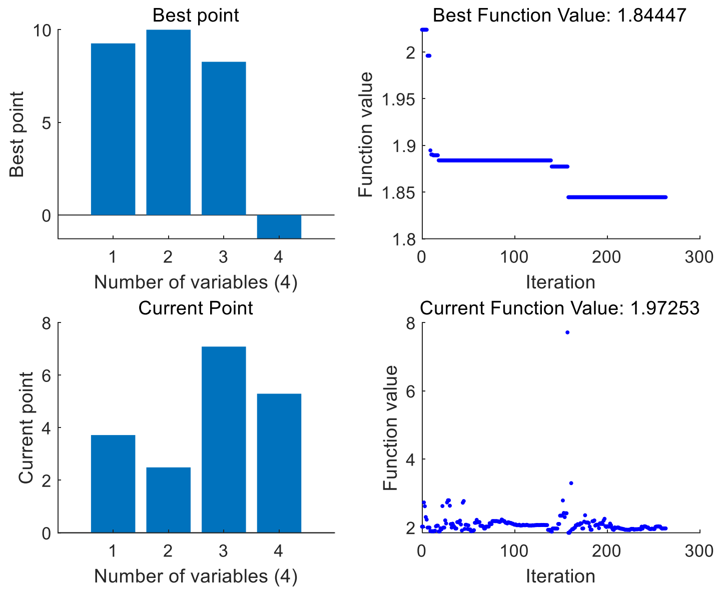

Figure 8. UAV Position with Simulated Annealing Algorithm.

6. Simulation Results (Specifically conducted in Strong Wind Environment)

In order to validate the performance of the optimization algorithm in complex flight conditions, this study conducted simulation experiments in a strong wind environment.[10] By comparing the performance of the traditional PID algorithm with the optimization algorithm in stable trajectory tracking tasks, the following results were obtained:

6.1. Traditional PID

1.1 Without Strong Wind:

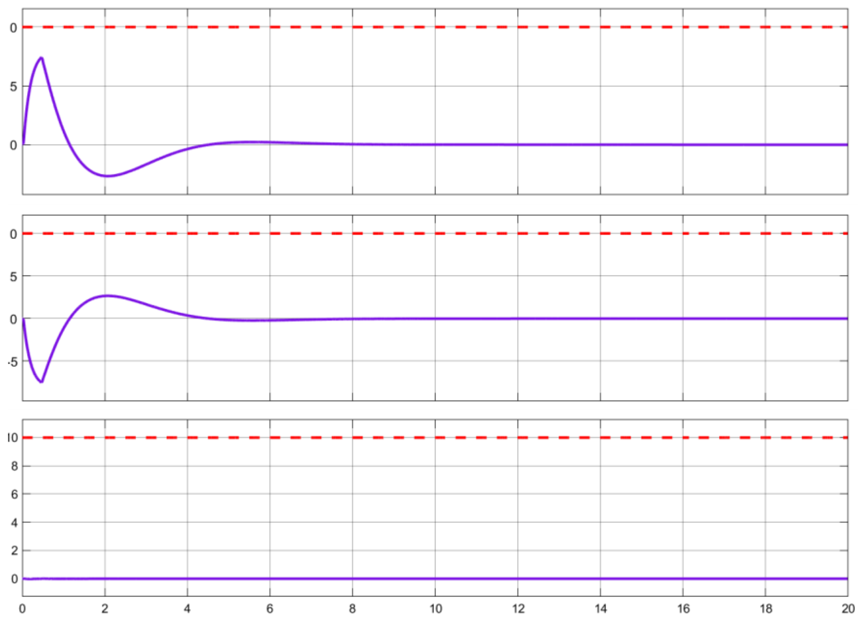

Figure 9. Attitude of UAV with Traditional PID in No Strong Wind Condition.

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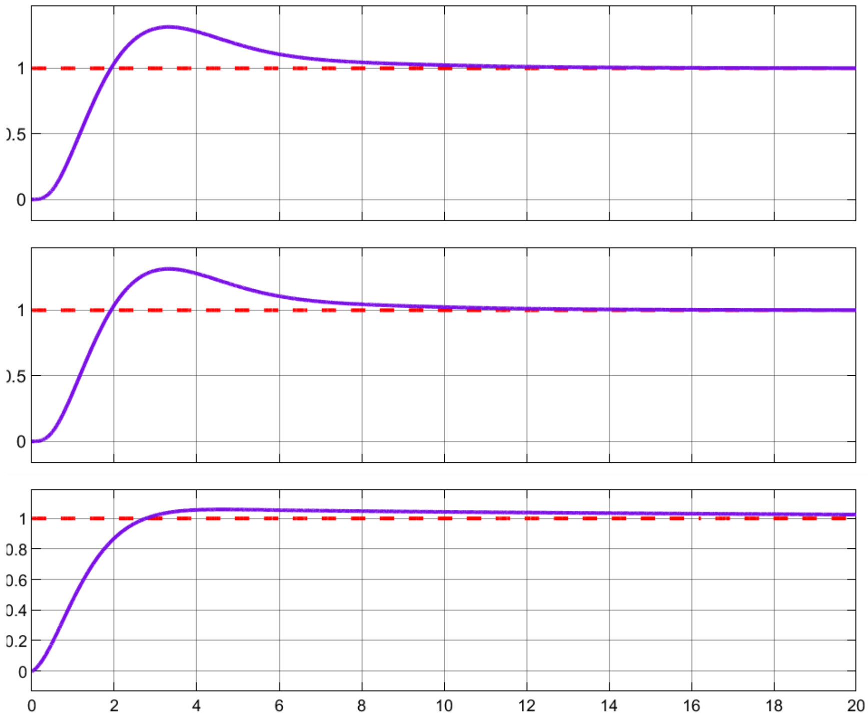

Figure 10. Position of UAV with Traditional PID in No Strong Wind Condition.

1.2 With Strong Wind:

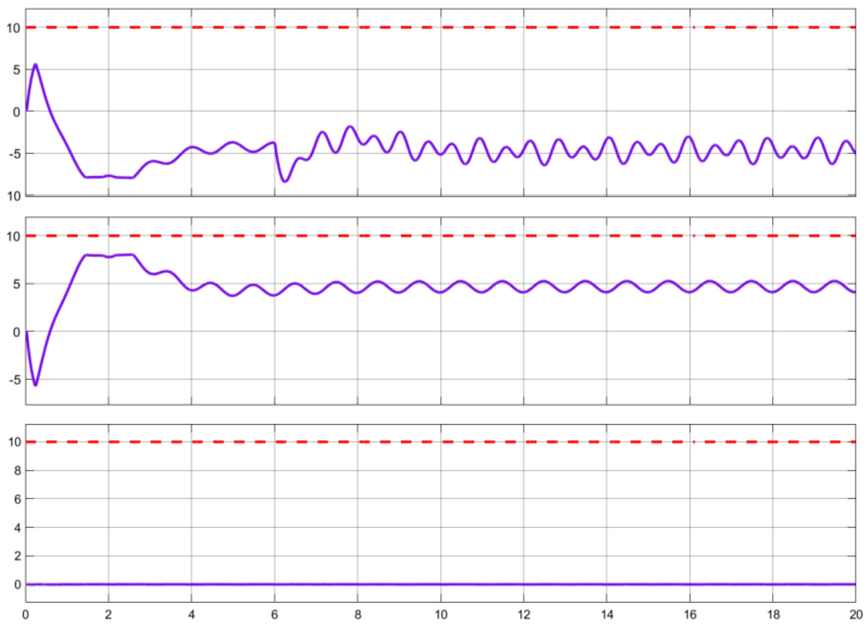

Figure 11. Attitude of UAV with Traditional PID in Strong Wind Condition.

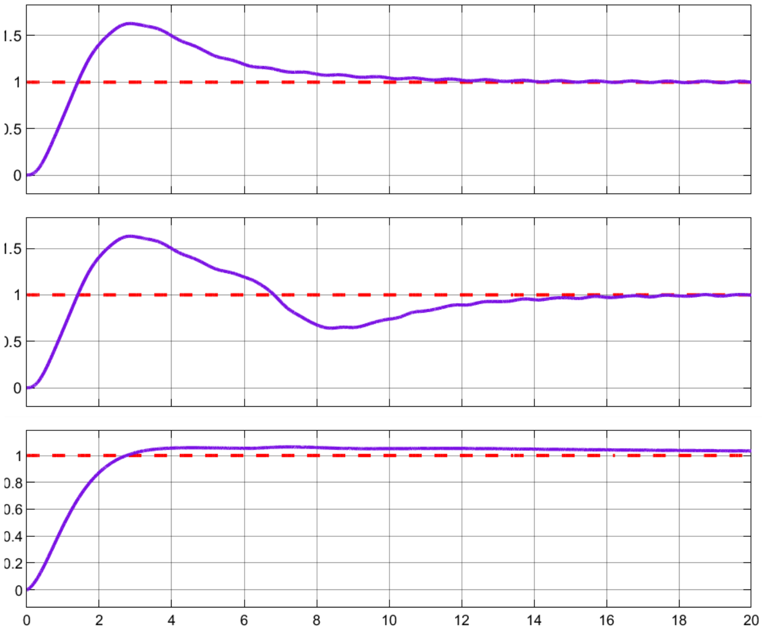

Figure 12. Position of UAV with Traditional PID in Strong Wind Condition.

6.2. GA-Optimized PID

With Strong Wind:

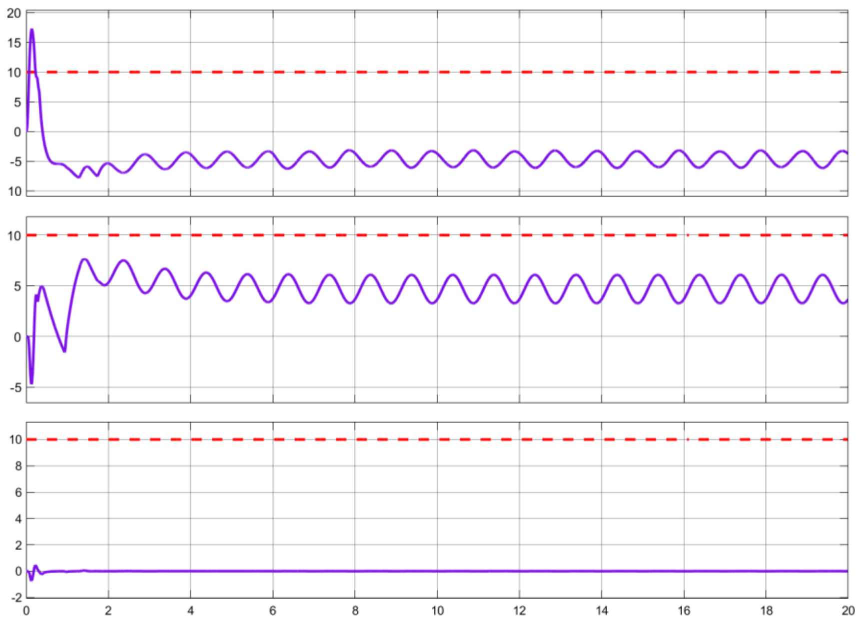

Figure 13. Attitude of UAV with GA-Optimized PID in Strong Wind Condition.

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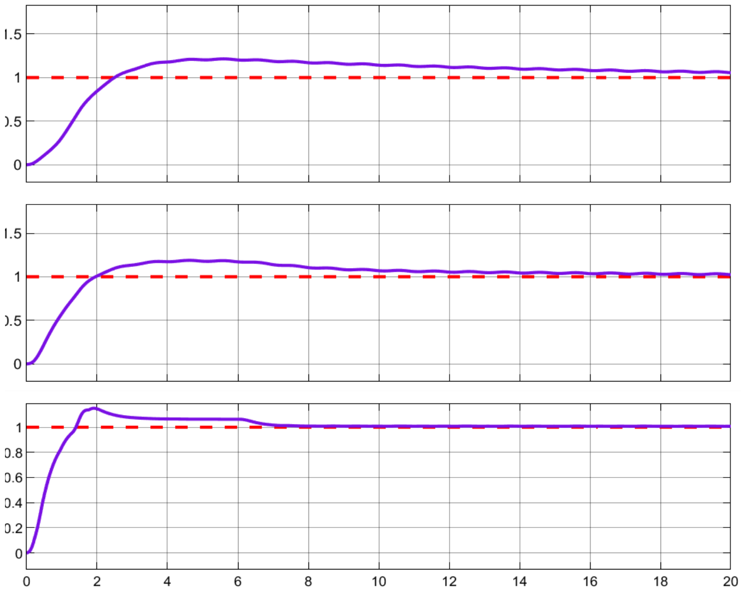

Figure 14. Position of UAV with GA-Optimized PID in Strong Wind Condition.

6.3. SA-Optimized PID

With Strong Wind:

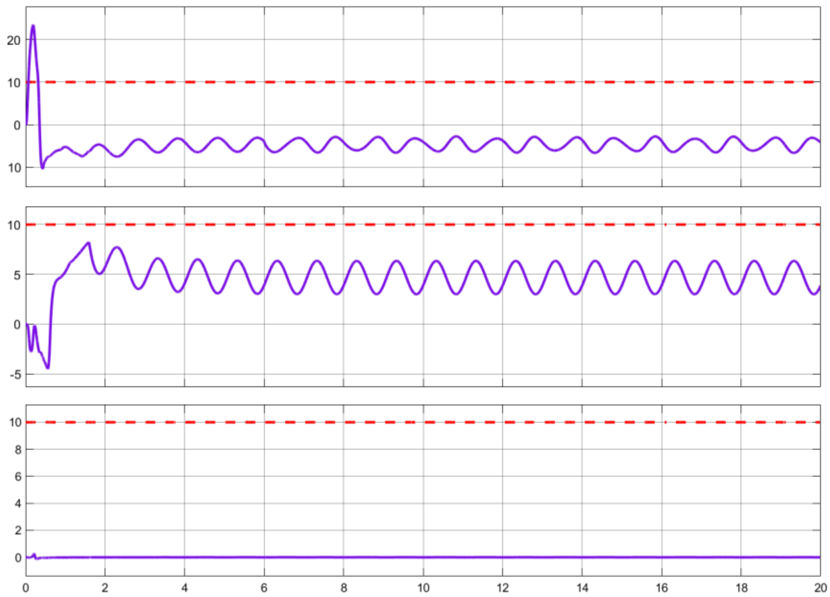

Figure 15. Attitude of UAV with SA-Optimized PID in Strong Wind Condition.

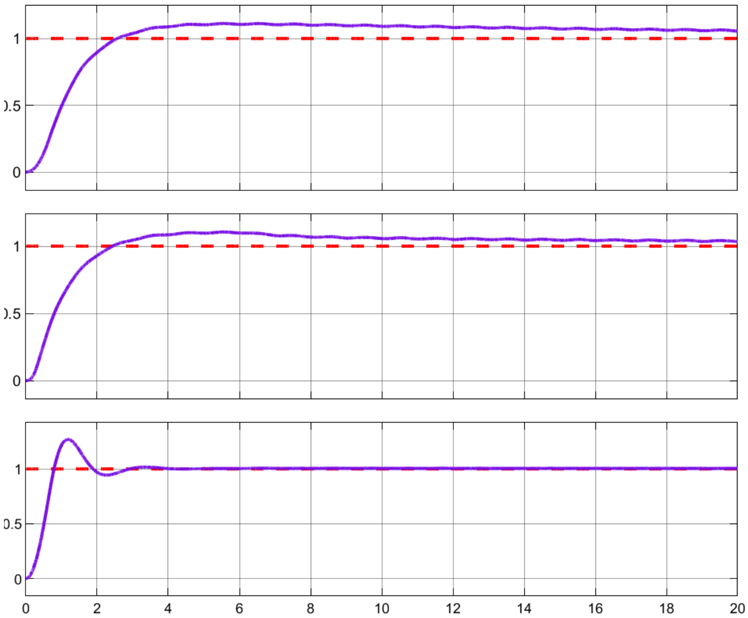

Figure 16. Position of UAV with SA-Optimized PID in Strong Wind Condition.

6.4. Comparison of Results for Three Algorithms

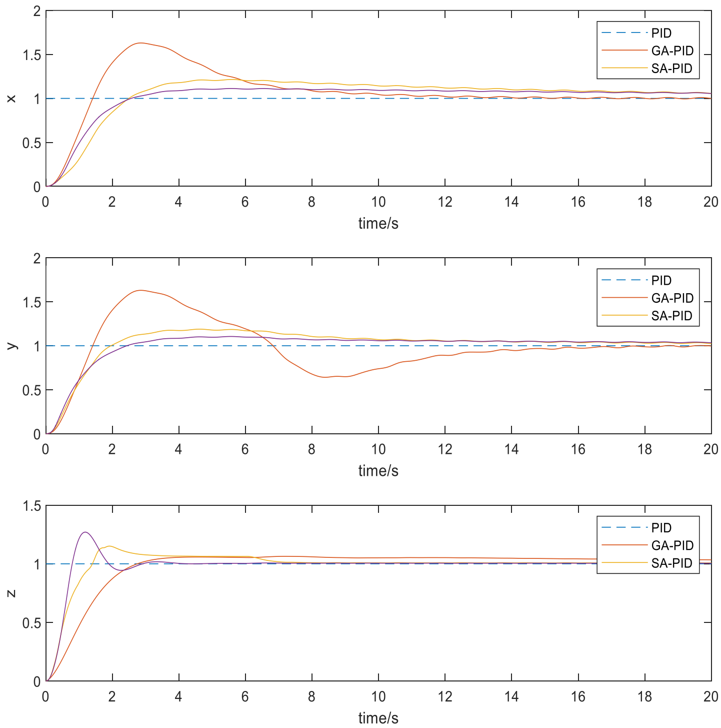

Figure 17. Comparison of Attitude under Three Algorithms.

7. Conclusion

This study addresses the challenge of stable trajectory tracking for quadcopter unmanned aerial vehicles (UAVs) in complex environments by employing an optimized adaptive PID control strategy. The research incorporates genetic algorithms and simulated annealing algorithms for fine-tuning PID controller parameters, resulting in substantial improvements in UAV flight stability and control accuracy.

In the experiments conducted in this study, PID controller parameters were initially optimized using genetic algorithms and simulated annealing algorithms. This optimization process enables us to achieve precise and flexible control, especially in complex environments, including situations with unstable weather conditions like strong winds. The outcomes of this research strongly underscore the potential of the adaptive PID control strategy in enhancing the robustness and adaptability of UAVs during flight.

Meanwhile, recent developments in UAV research indicate a growing focus on the application of deep learning technology. Employing deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) allows UAVs to better perceive their surroundings, make intelligent decisions, and execute control actions. This trend aligns well with our research on adaptive PID control strategies. Future studies may consider combining deep learning techniques with optimization algorithms to further enhance UAV performance in complex environments.

In conclusion, this study highlights the potential of the adaptive PID control strategy to improve UAV flight performance and aligns with recent trends in the UAV field, including deep learning technology and multi-agent collaborative control systems. Future research should continue exploring these areas and validate new technologies and algorithms through real flight tests to ensure safe and efficient UAV mission execution in dynamically changing environments.

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