Control of High-altitude Power Grid Inspection UAV Using Hierarchical PID Based on Reinforcement Learning

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Abstract. Unmanned aerial vehicles (UAVs) are now being utilized in a wide range of work scenarios to replace humans in performing dangerous tasks and jobs. In the context of high-altitude power grid inspections, UAV inspections have significant advantages. However, the complex environment often poses challenges for controlling UAVs. Building upon traditional PID control, this paper uses MATLAB software to construct the dynamic model and controller of a quadcopter UAV. A cascaded loop is established by selecting the control objects for the inner and outer loops. The stabilization of the UAV is achieved by setting the PID parameters for the inner and outer loops. Additionally, the deep reinforcement learning algorithm is employed to fine-tune the PID parameters based on the Zigler-Nicholes method. The adjustment is performed by considering the reward function values for the UAV under different disturbances. Finally, response curves and dynamic response parameter indicators are obtained. Compared to traditional cascaded PID control, the quadcopter UAV system tuned using this method exhibits significant improvements in both dynamic response parameters and steady-state responses.

Keywords: PID, Cascaded control, DQN, Reward function.

1. Introduction

In the work of grid inspection, the use of drones can greatly reduce the workload of inspection workers [1], increase safety factors, and reduce the operating and maintenance costs of high-voltage transmission lines.

Although unmanned aerial vehicles (UAVs) do not require the presence of flight crew for control and are often utilized to perform specific tasks in dangerous, harsh, or unsuitable environments [2], ensuring their stability and resistance to interference proves challenging for reliable inspections of power lines in high-altitude complex environments. First, there is a severe change in wind speed in high altitudes, which constitutes strong external interference for drones performing inspection work. This may result in unclear images captured during the inspection process, making it difficult to accurately identify and troubleshoot faults on power lines. Second, there is the issue of heat dissipation in the drive system electronic devices. Due to the low air pressure and low air density in high-altitude environments, the airflow for cooling is reduced, thereby lowering the efficiency of convective cooling. Additionally, the high solar radiation in high-altitude environments can have adverse effects on the temperature of electronic devices, making it difficult to ensure the stable operation of the electronic devices on the drone [3].

To address this problem, current research directions both domestically and internationally mainly focus on firstly, improving the mechanical structure of drones by optimizing the frame structure to enhance the structural stress and load capacity [4, 5]; secondly, using advanced integrated sensors for digital signal processing. Wang Yong, Zhang Ying, and others have achieved improved fault detection rates by using a fusion of visible light, thermal infrared, and laser radar sensors for image fusion [6]; thirdly, control methods mainly involve fuzzy control and PID control methods for stable control and regulation of drones [7]. However, facing the highly unstable weather changes in high-altitude environments, traditional control methods applied to drones make takeoff, landing, and

maneuvering in complex terrains difficult, and significantly reduce the fault detection rate during the inspection of power lines.

To better control drones in high-altitude environments using the above methods, this paper first uses MATLAB software to build the physical model of drone motion control, including the construction of the PWM speed control system model, noise simulation, the rotation dynamics equation of the drone itself, and the coordinate transformation motion equation of the drone. Then, the interference introduced by high-altitude environments mainly includes the interference of severe wind speed changes, large temperature differences, and low humidity on the operation of brushless DC motors. Since the inspection drone should maintain a relatively stable posture during the inspection task, the performance requirements for countering strong interference are high. Therefore, based on the currently mature PID control, cascaded PID control is used, with the secondary-loop PID control object being the output current of the brushless motor, and the primary-loop PID control object being the attitude of the drone. This improves the response speed and operating frequency of the system, greatly enhancing the stability of the inspection drone when identifying faults through photography. Meanwhile, during the entire motion process of inspecting the entire line, reinforcement learning algorithms are used to establish a model of maximum reward value in the environment, enabling the entire inspection task to be carried out along the optimal path.

Finally, it is found through comparison that using deep learning methods [8] combined with cascaded PID control and reinforcement learning can make the inspection drone for power line inspection in high-altitude and complex environments highly responsive to strong interference and achieve a stable and effective performance.

2. Method

2.1. Dynamics Modeling based on Quadcopter UAV

Describing the state of a static UAV at a certain moment in time usually requires six physical quantities, which are the x-axis coordinates, y-axis coordinates, and z-axis coordinates describing the location of the UAV in the Earth's coordinate system, as well as three physical quantities used to describe the UAV's attitude at a certain position, which are the roll angle roll, the pitch angle pitch, and the yaw angle yaw.

Based on the relationship between displacement and velocity and Newton's second law, the following formula can be derived.

$$\dot{x} = v_x \tag{1}$$

$$\dot{y} = v_y \tag{2}$$

$$\dot{z} = v_z \tag{3}$$

$$m\dot{x}=F_t(\cos(\phi)\cos(\psi)\sin(\theta)+\sin(\phi)\sin(\psi)) \tag{4}$$

$$m\dot{y}=F_t(\cos(\phi)\sin(\psi)\sin(\theta)-\sin(\phi)\cos(\psi)) \tag{5}$$

$$m\dot{z}=F_t\cos(\phi)\cos(\theta)-mg \tag{6}$$

Using the angle and angular velocity relationship and the moment force arm relationship one can obtain the relevant angular dynamics equations of the quadrotor UAV as follows:

$$\dot{\phi} = p + (r\cos(\phi) + q\sin(\phi))\tan(\theta) \tag{7}$$

$$\dot{\theta} = q\cos(\phi) - r\sin(\phi) \tag{8}$$

$$\dot{\psi} = \frac{r\cos(\phi) + q\sin(\phi)}{\cos(\theta)} \tag{9}$$

$$I_x\dot{p} = (I_y - I_z)qr + {}_p \tag{10}$$

$$I_y\dot{q} = (I_z - I_x)pr + {}_q \tag{11}$$

$$I_z\dot{r} = (I_x - I_y)pq + {}_r \tag{12}$$

Based on the above 12 equations, we can use MATLAB functions to construct a dynamic model of the drone's angles, angular velocities, accelerations, and displacements in Simulink. The modeling process is carried out in MATLAB, and the resulting model is shown in the Figure 1.

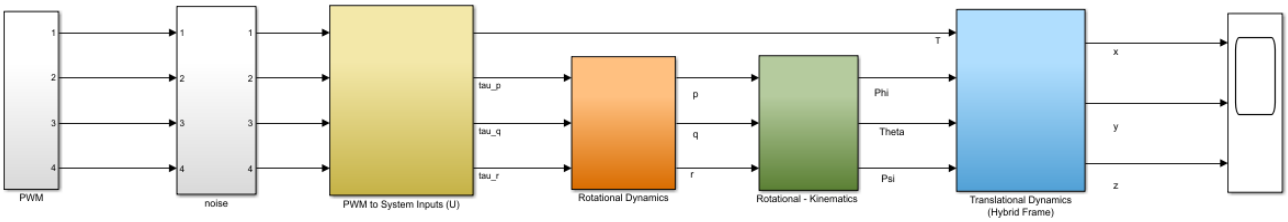


Figure 1. A MATLAB-based drone dynamics model

The parameters used in this paper refer to the data in the article of Liu Haohao and Zhang Suxia of Tianjin University. The data in the research article on tandem PID control of quadcopter UAVs are given as follows UAV's mass m, gravity acceleration g, and other physical quantities reference data as follows table 1, the following data are substituted into the model built in the previous step, and the model is further improvement.

Table 1. Physical parameters required to build the model

parameter name	notation	parameter value
drone quality	m	$1.6(kg)$
gravitational acceleration	g	$9.8(m/s^2)$
arm length	$l0$	$0.25(m)$
three axes moment of inertia	I_x, I_y, I_z	$1.524\times10^{-2}, 1.524\times10^{-2}, 2.793\times10^{-2}\left(kg\square m^2\right)$
propeller moment of inertia	J_r	$2.01\times10^{-4}(kg\square m^2)$
motor lift coefficient	C_t	$1.67\times10^{-5}\left(N/\left(rad/s\right)^2\right)$
motor reverse torque coefficien	C_m	$2.304\times10^{-7}(N\square m/(rad/s)^2)$

2.2. Design of a String-level PID Controller

In a quadcopter unmanned aerial vehicle (UAV) system, there are often multiple disturbances present. In the application scenario considered in this paper, due to factors such as the operating environment and cost constraints, it is often impossible to measure all the disturbances. Therefore, if feedforward control is used, it cannot eliminate the influence of all disturbances on the controlled process. Cascaded control can effectively solve the aforementioned problem.

Meanwhile, looking at the commercially available consumer drones, PID control has already become a mature and widely used control method. Therefore, in this paper, a cascaded PID control method is used to address the stability control function of a high-altitude power grid inspection UAV.

By utilizing the characteristics and advantages of the cascaded control system, the main disturbance, namely the external noise signal, is placed in the inner loop. The inner loop controller suppresses this disturbance, while the components with smaller time constants are placed within the inner loop. This results in faster and smaller suppression of the disturbance. Considering that the main objective of the model is to observe the displacement of the UAV in the three spatial coordinate axes, the controlled object in the outer loop is set as three independent displacement deviations, and both the inner and outer loops are subjected to PID control.

When using the cascaded control method to control the power grid inspection UAV, the structure is as shown in the diagram below. Firstly, under all open-loop conditions, the inner loop is designed. The input deviation of the PWM signal is chosen as the input of the inner loop, and the torque of the rotor serves as the output of the inner loop. This is because external noise exists in the process of PWM input [8]. In the simulation, random signals following the Gaussian distribution have been used to simulate this, as shown in the signal diagram below. Through PID control in this stage, this paper effectively reduces the interference of the noise signal on the output torque. Additionally, the internal PID control can respond promptly to disturbances, reducing the time required for response adjustments due to errors throughout the control process. The effect after performing PI control on the inner loop is shown in the graph below (see Figure 2). It can be observed that the noise in the input signal, after being subjected to PID control in the inner loop, is significantly reduced.

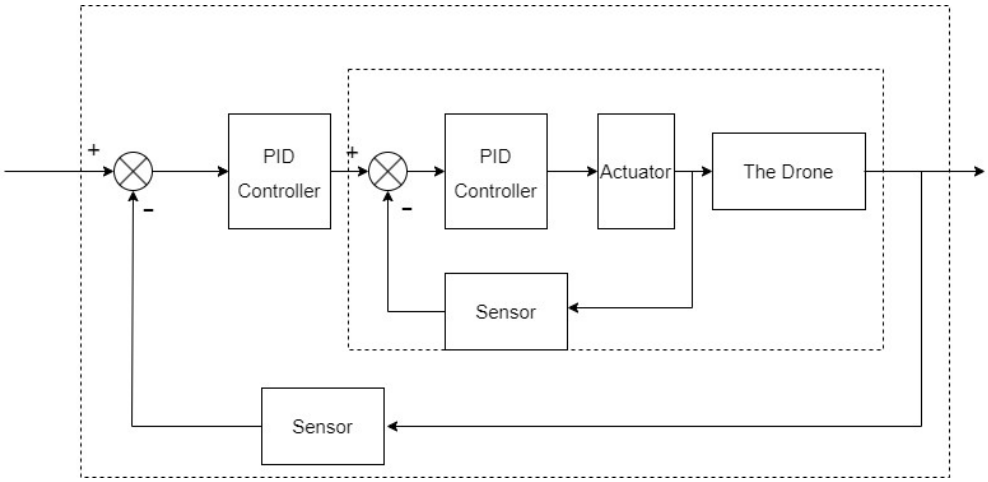


Figure 2. Cascade PID control structure diagram

The utilization of the inner loop for regulating the PWM input is mainly because the severe temperature changes in high-altitude environments can affect the power of electronic devices in the motor speed control system. Therefore, stabilizing the PWM output is crucial. By intervening in this disturbance within the inner loop, the response speed can be greatly improved.

In the outer loop, PID control is applied to the displacement to ensure that the UAV's position in the world coordinate system is conducive to the inspection of faults on power lines by the onboard camera.

When simulating the noise signal, the random number module function in Simulink is used. The variance of the noise signal is set to 1, and the simulated signal obtained is as shown in the Figure 3.

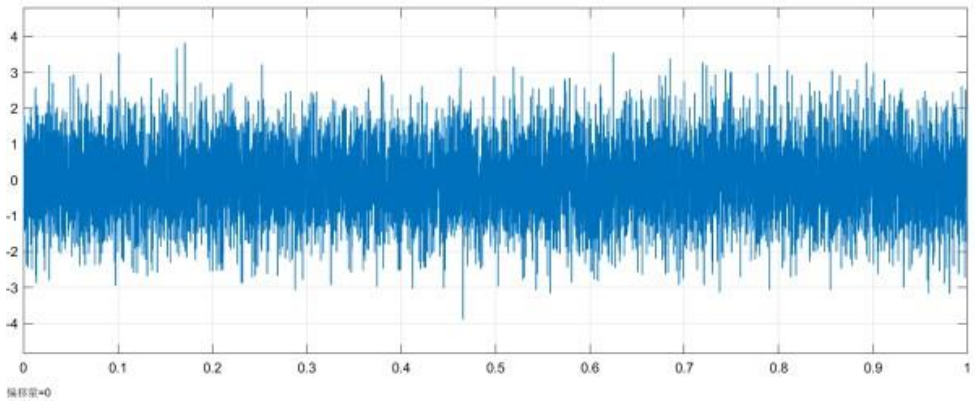


Figure 3. Simulating noise with random signals following a Gaussian distribution

When processing the PWM input signal, PI control is used to adjust the output of the actuator [9]. The superposition of the step signal and the noise signal is shown in the upper graph of Figure 3. After PID processing, the noise signal is greatly reduced, and the signal fluctuates around the original step input. Since the motor signals of the four rotors adopt the same control method with the same

parameters, this work will use one of them as an example to construct a PI controller as shown in the Figure 4.

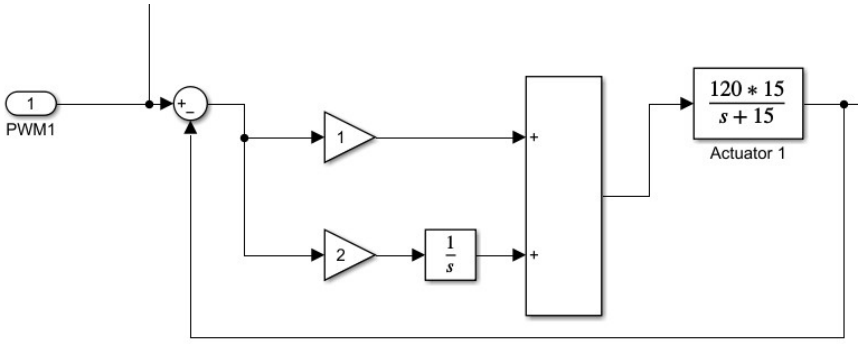


Figure 4. Inner loop PID parameter tuning

When processing the PWM input signal, PI control is used to adjust the output of the actuator. The superposition of the step signal and the noise signal is shown in the upper graph of Figure 4. After PID processing, the noise signal is greatly reduced, and the actual signal fluctuates around the original step input. The specific effect is shown in the Figure 5.

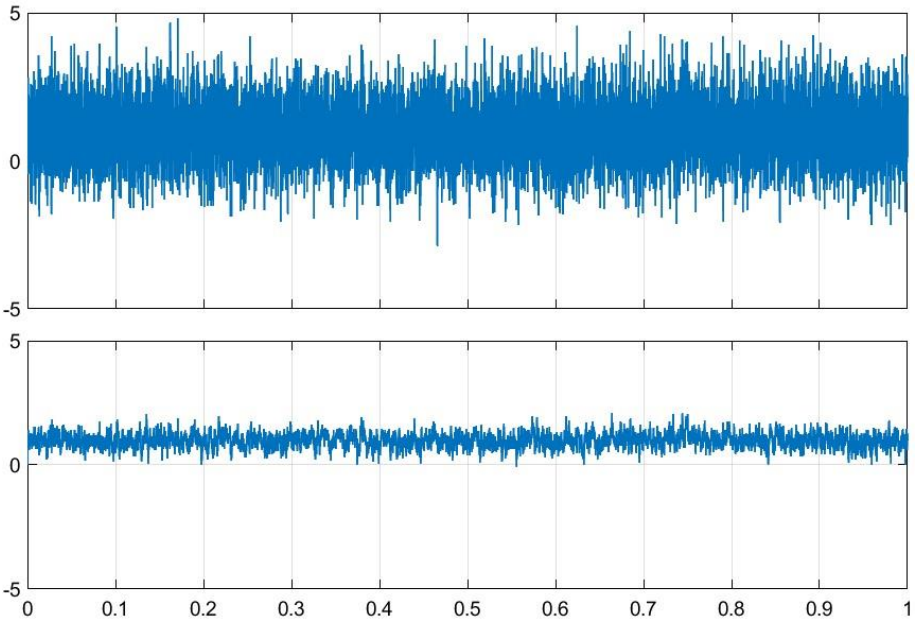


Figure 5. Comparison of input and output after inner loop PID control

After designing the inner loop, the outer loop design is carried out based on it. In this case, since the final output is the displacement on the x-axis, y-axis, and z-axis in a three-dimensional coordinate system, the input for the outer loop is chosen as the displacement error, and the output is the displacement. For the outer loop, PD control is selected as shown in the Figure 6.

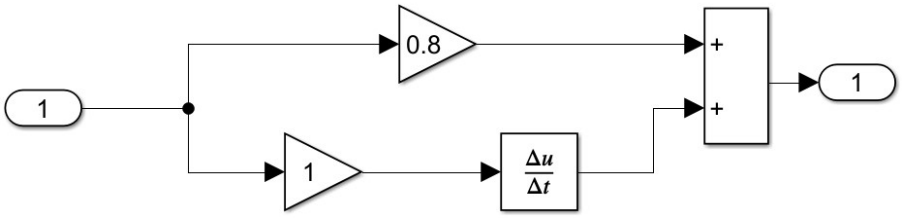


Figure 6. Outer Loop PID Parameter Tuning

After setting up the cascaded control with the inner and outer loops, and determining the PID parameters of the inner and outer loops using the Ziegler-Nichols method, the final output obtained when given specified displacement inputs along the three coordinate axes is shown in the Figure 7.

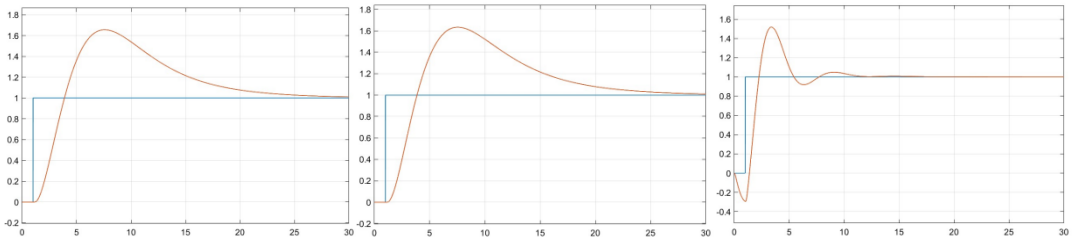


Figure 7. From left to right, the response curves of x, y, and z-axis displacements under serial PID control are shown

From the three input-output diagrams above, it can be seen that cascaded PID control can achieve steady-state response for grid inspection drones in high-altitude and complex environments. However, due to the setting of PID parameters and the complexity of the environment, the dynamic response of the final displacement is poor. Offline settings like these still cannot meet the real-time changes and responses required for inspection drones in complex and unpredictable environments. To achieve this goal, this study utilizes reinforcement learning to modify and adjust the PID parameters.

2.3. Tuning PID parameters using reinforcement learning

The ultimate task of the drone is to complete grid inspection tasks in a nonlinear and highly disturbed environment. To further control the drone by obtaining maximum rewards from the environment, reinforcement learning is employed [10]. Moreover, due to limited sensors on the inspection drone and limited external information available, the deep reinforcement learning algorithm DQN is adopted for implementation. By using multi-layer neural network connection layers, the lack of perception information from the external environment can be compensated, thereby improving the control strategy for the drone. In the figure below, the input to the neural network is the data detected by the position sensor in the environment as State, which is calculated by the feedback control loop to derive the desired input i.e., the difference between the Agent State and the three actual positions s in the x, y, and z axes are denoted as Δx, Δy, and Δz, respectively. The environmental reward value w under this PID parameter is calculated by Q learning [11], after which another parameter modification to get a new reward until the maximum reward value is obtained. Figure 8 showed the deep reinforcement learning network architecture diagram.

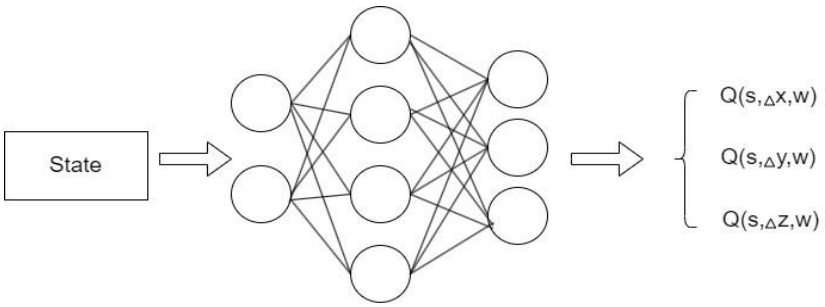


Figure 8. Deep reinforcement learning network architecture diagram

First, let's define the architecture of the neural network, which is mainly divided into the input layer, intermediate network layer, and output layer. The input layer primarily consists of a one-dimensional state vector space, composed of sensor information and the relative distance between the drone and the next target position. Since inspection drones are typically equipped with cameras, the relative position between the drone and the inspection target can be calculated through image processing and binocular recognition technologies. The drone's attitude can be determined using an inertial measurement unit sensor.

The construction of the intermediate network layer mainly relies on the Rectified Linear Unit (ReLU) function, which is chosen as the activation function for the hidden layer. This enables maximum value operations. Unlike the limitations of the Sigmoid and Tanh activation functions, the ReLU function does not suffer from gradient saturation problems. The output layer includes the

displacement deviations in the x, y, and z axes as part of the input, with a linear activation function chosen for the output layer. The reward function is computed to obtain the corresponding reward value, and ultimately, the input parameters are adjusted to achieve maximum rewards. The neural network adopts gradient descent to converge the weight values.

The reward function, also known as the incentive function, evaluates the actions taken by the mobile robot to guide it in choosing the most advantageous action at the moment. To enable the mobile robot to understand the effectiveness of each action in various environments and timely receive feedback from the environment, it is necessary to assign a certain reward value to each action when designing the reward function. This value reflects the quality of the mobile robot's action in that environment. Based on this, a nonlinear piecewise function reward is used in this study, consisting of target reward, fault penalty, and continuous reward.

The process steps are as follows:

1) Obtain the current coordinates (x, y, z) of the drone by acquiring its pose information.

2) Calculate the differences between the desired displacement and the actual output displacement for each axis (x, y, z).

Therefore, the overall reward function (reward) is as follows:

$$R(t) = \sum_{s=0}^{t} e_s^2 \tag{13}$$

This method first utilizes the traditional Zigler-Nicholes method to set a baseline for the PID parameters. The corresponding PID parameters are denoted as K_p, K_i, and K_d. The PID controller established based on this baseline is capable of better tolerating disturbances and uncertainties inherent in the original model, as well as strong disturbances that may occasionally occur.

Based on this, reinforcement learning is applied to the originally established cascaded PID drone control model. The operation steps and process can be seen in the Figure 9.

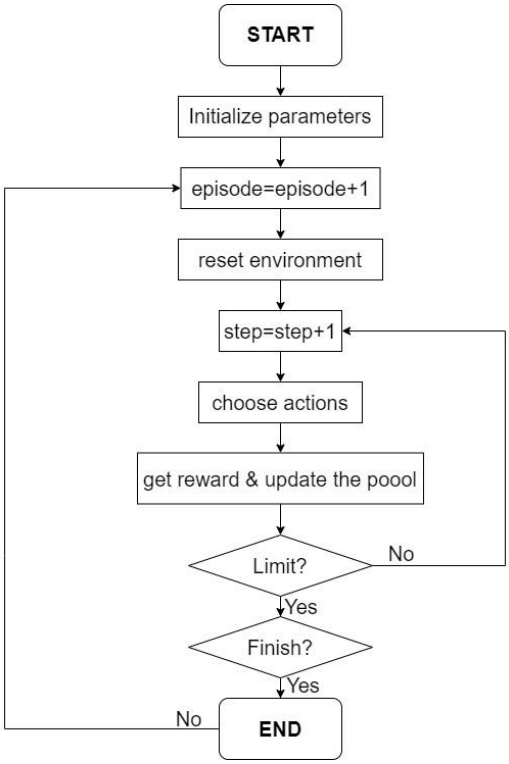


Figure 9. Deep reinforcement learning algorithm workflow

3. Results

While maintaining consistent external disturbance conditions, new outer loop PID parameters are obtained through reinforcement learning, as shown in the following table:

Table 2. Outer loop PID parameters corrected by reinforcement learning

	P	I	D
x	8	0.1	1
y	8	0.1	1
z	4	1	1

The final input-output response curve is shown in the Figure 10.

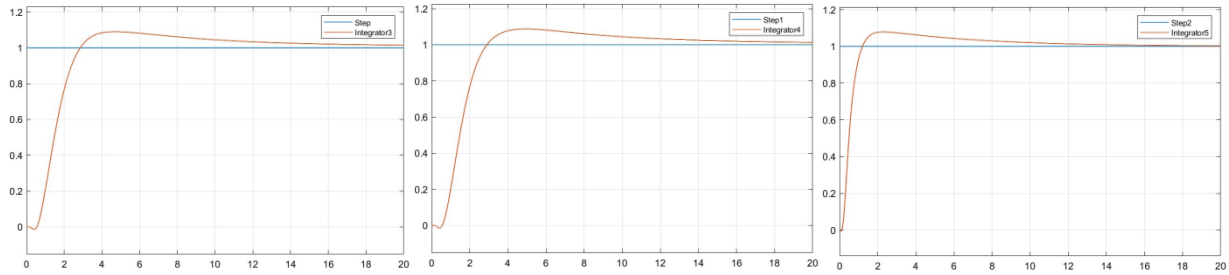


Figure 10. Displacement response curves of x, y and z axes after adjusting the PID parameters by reinforcement learning (from left to right)

It can be observed that the overshoot in the displacement response curves on each coordinate is significantly reduced, and the adjustment time is greatly shortened compared to direct cascaded PID control. This method also addresses the issue of traditional PID controllers being unable to handle disturbances in complex high-altitude environments. By utilizing deep reinforcement learning neural networks, it becomes possible to dynamically adjust and apply the PID controller parameters in real time. This allows inspection drones for power grid inspections to perform their tasks more effectively in environments with multiple disturbances and strong interferences.

4. Conclusion

This study builds a dynamic model of a quadcopter unmanned aerial vehicle (UAV) and utilizes a cascaded PID control method to control the UAV for power grid inspection in high-altitude and complex environments. To achieve stable performance and respond to multiple and strong disturbances, a deep reinforcement learning algorithm is employed to regulate the PID parameters of the outer loop in the cascaded control. It is deep reinforcement learning algorithm that include typing in the transformation of the performance and is responsible to the multiple and strong disturbances. The results show that this summary of the overshoot and adjustment performance indicators are significantly improved in the actual response. This approach can be applied to real-time control of working UAVs and products with high stability requirements. In addition, this study focuses on the main interference caused by the noise in the quadcopter UAV's power control system. As the disturbances in quadcopters are similar, it is necessary to address issues such as reasonable path planning to improve the UAV's performance in power grid inspection tasks. The study came on that, which will be a serious discipline of the system, and it is addressing that a practical definition for example for many of the UAV's performance in the power control system.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

[1] Song Yuxuan (2022). Design and implementation of autonomous flight system for quadcopter in unknown environment. Aeronautics and Astronautics Science and Technology.

[2] Chen Yuhong, Gao Feifei (2022). Multi-objective unmanned aerial vehicle path planning based on deep reinforcement learning [J]. Radio Communications Technology, 2022, 48 (6): 957-970.

[3] Song Wenlei (2021). Research on heat dissipation of electronic devices in aircraft propulsion systems in high-altitude environments (Master's Thesis, Tianjin Business University).

[4] Zhao Junjie & Shu Panfeng (2022). Design of a new type of multi-rotor unmanned aerial vehicle structure and its control system Algorithm. Journal of Jiangsu Polytechnic Institute 06, 57-64.

[5] Wang Zhipeng, Liu Hui & Cao Jian (2022). Topology optimization design of quadcopter frame structure with multiple performance constraints. Mechanical Design and Research 06, 173-176.

[6] Wang Yong, Zhang Ying, Liao Ruchao, Guo Qidi, Yuan Xinxing & Kang Taizhong (2020). Fusion method for unmanned aerial vehicle images based on visible light, Thermal Infrared and LiDAR Sensing. Laser Journal 02, 141-145.

[7] Luo Mingda, Deng Jizhong, Huo Jinglang, Zhang Jianling, Ye Jiahang, Lei Luocheng & Zhang Zichao (2024). Design of variable spray system for crop protection unmanned aerial vehicle based on compound fuzzy PID. Agricultural Mechanization Research 02, 9-15.

[8] Gao Han, Yan Shicheng (2021). Research on flight attitude control technology for quadcopter UAV in high-altitude environment [A]. Electronic Design Engineering,

[9] Ding Wa, Wu Gongping, He Wenshan, Li Mouyuan (2022). Self-switching cascade PID control method for attitude angles of quadcopter aircraft [A]. Mechanical Design and Manufacturing.

[10] Huang Zhidu, Cui Zhimei (2022). Research on UAV flight trajectory and geological survey based on deep learning [A]. Computing Technology and Automation.

[11] Kingds T.G. (2022). Drone technology [J]. ASEE Prism 07.