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A Review of Research on Combining Algorithms to Enhance Flight Robustness and Stability in Quadrotor UAVs

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Abstract:
Quadrotor UAVs are widely used in precision agriculture, disaster emergency response, logistics and transport due to their simple structure and flexible handling. However, its flight performance is often limited by external environmental perturbations, uncertainties, and system nonlinearities, and advanced algorithms are urgently needed to improve its robustness and stability. This study reviews the research progress of traditional control algorithms, intelligent control algorithms, and hybrid control algorithms in UAV flight performance optimisation, systematically analyses their advantages and disadvantages as well as their applicable scenarios, and proposes the challenges faced by the current technology and the future development direction.

Keywords: Unmanned Aerial Vehicles Robustness, Stability, Conventional Control Algorithms, Intelligent Control Algorithms, Hybrid Control Algorithms

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1.Introduction

Due to its unique vertical take-off and landing capability and flexible flight control characteristics, quadrotor UAVs are widely used in various fields such as precision agriculture, environmental monitoring, disaster rescue, and logistics and transport. However, in complex real-world environments, the flight performance of quadcopter UAVs is often affected by many factors, especially external perturbations (e.g., wind speed changes, temperature fluctuations, etc.) and internal system uncertainties (e.g., motor deviations, sensor noise, etc.). These factors directly affect the flight stability and robustness of UAVs, making the control accuracy and safety of the flight process a great challenge when performing some highly dynamic tasks. Therefore, how to effectively improve the robustness and stability of quadrotor UAVs under various environmental conditions has become a key problem to be solved in the current UAV field.

The aim of this study is to review the latest research results in enhancing flight robustness and stability of quadrotor UAVs, analyse the advantages and disadvantages of the existing methods, and explore their potentials and development directions in future applications. By comparing and analysing the traditional control methods and intelligent control methods, this paper will provide valuable references for further research in this field and propose new ideas and possible solutions to the existing problems.

2.Classification of algorithms to improve robustness and stability

Algorithmic research on quadcopter UAVs to improve flight robustness and stability can be summarised into three main categories: traditional control algorithms, intelligent control algorithms and hybrid control algorithms. Traditional control algorithms include PID controllers, LQR (Linear Quadratic Regulator) and MPC (Model Predictive Control), which are mainly based on classical control theory, and realise the attitude and trajectory control of UAVs through accurate mathematical models. Intelligent control algorithms, on the other hand, take deep learning, reinforcement learning and imitation learning as their core, and use artificial intelligence technology to optimise perception, decision-making and control, demonstrating strong dynamic adaptive capability and nonlinear modelling advantages. Hybrid control algorithms achieve a comprehensive application of the advantages of both traditional control algorithms and intelligent control algorithms by combining them, including the optimisation of PID parameters using deep learning, the construction of end-to-end models by combining deep and reinforcement learning, and the enhancement of adaptability to complex environments by fusing model prediction and policy learning. These three broad categories of algorithms provide diverse technical paths for UAV performance optimisation in complex missions.

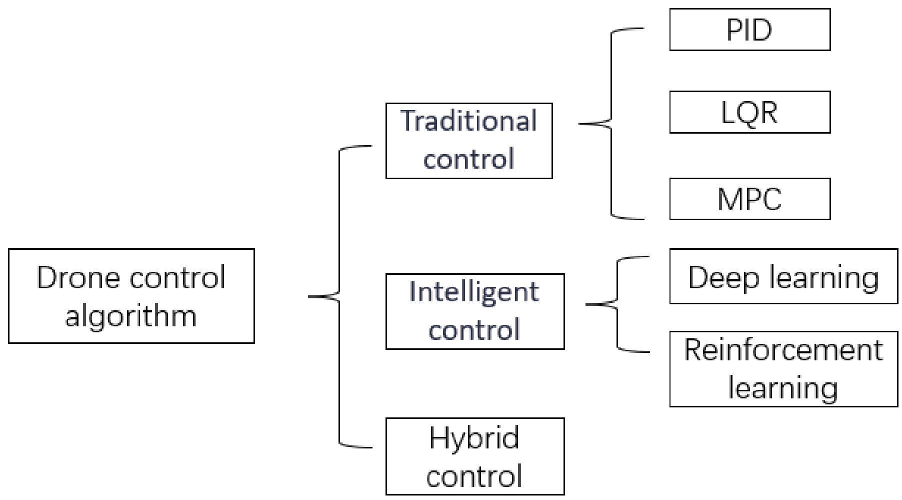

Figure 1 Classification of algorithms to enhance the robustness and stability of UAVs

3 Conventional control algorithms

3.1 PID controller

PID (Proportional-Integral-Derivative) control is a classical feedback control algorithm, which achieves precise regulation of the system output through the synergy of the three control actions, namely proportional (P), integral (I) and differential (D). In the field of quadrotor UAVs, PID control is widely used for attitude stabilisation and trajectory control. Proportional control is used to reduce errors in flight attitude or position, integral control eliminates steady-state errors, and differential control optimises the dynamic response by predicting error trends. PID control is one of the core algorithms in UAV flight control due to its simplicity in design, real-time performance, and excellent performance in low-speed and smooth flight tasks

In the field of quadcopter UAVs, PID control is widely used in attitude stabilisation and trajectory control due to its simple design and real-time characteristics. Hovering control is one of the most important flight modes of quadrotor UAVs, and using this unique flight ability we can apply the quadrotor UAV with surveillance video equipment in fixed-point surveillance, such as electric power monitoring, traffic monitoring, etc., and the application of which can be regarded as a broader prospect. Li Yibo et al. in the literature [1] using fuzzy self-tuning control algorithm, the quadrotor unmanned helicopter can quickly and stably change from flight cruise state to fixed-point hovering state, and the robustness of the system is relatively good.

However, conventional PID control exhibits certain limitations when dealing with complex nonlinear systems and strongly perturbed environments. These limitations mainly include high dependence on parameter tuning, difficulty in dealing with multivariate coupling problems in dynamic environments, and insufficient adaptability in highly dynamic tasks.

To solve the above problems, researchers have proposed various improvement methods in recent years. In the literature [2], Hongtao Zhen et al. proposed a robust adaptive backstepping controller design method. The method treats

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external disturbances, unmodelled dynamics of the system and system parameter ingress as generalized uncertainties for treatment, which reduces the complexity of system modelling and improves the robustness of the controller.

In addition, these improvements provide the theoretical basis and technical support for further optimisation of PID controllers for complex flight missions

3.2 LQR (Linear Quadratic Regulator)

The Linear Quadratic Regulator (LQR, Linear Quadratic Regulator), proposed by Rudolf E. Kalman in 1960, is a classical algorithm based on the theory of optimal control. The core objective of the LQR is to achieve a weighted quadratic performance index of the system's state variables and the control inputs by minimising the optimal control of linear systems (Kalman, 1960). By virtue of its theoretical completeness and ability to optimise energy consumption, LQR is widely used in UAV flight control tasks, and excels in attitude stabilisation and trajectory optimisation.

In the field of quadrotor UAVs, LQR has attracted much attention due to its efficient control capability for multi-variable coupled systems. It is shown that the optimisation of different control objectives can be achieved by adjusting the weight matrix in the LQR controller, thus effectively improving the attitude stability and dynamic performance of the UAV.

The LQR control is more robust and can handle the difference between linear and nonlinear system models very well, and produces very low steady state error, but has a relatively large transition delay. Gao Qing et al. in the literature [3] used backstepping control to ensure the convergence of the internal state of the quadcopter UAV, through comparison, the LQR control was chosen and improved to achieve the attitude control of the quadcopter UAV, and the simulation results show that the transient response performance of the improved controller has been significantly improved, and the steady state error is almost zero.

LQR has significant superiority in theory and application, but its dependence on linearised models limits its applicability to strongly nonlinear tasks. In complex flight environments, system uncertainties and external disturbances may lead to difficulties in maintaining high control accuracy with traditional LQR control methods. Therefore, how to improve the LQR algorithm to better adapt to nonlinear systems and complex environments is a direction worthy of in-depth research.

3.3 MPC (Modelled Predictive Control)

Model Predictive Control (MPC, Model Predictive Control) has become an important method to improve the flight stability and robustness of quadrotor UAVs by virtue of its real-time optimisation capability and flexibility in constraint handling. By predicting the future state of the system, MPC is able to optimise the control inputs to ensure that the UAV meets the mission requirements while satisfying the physical constraints, which is particularly suitable for dynamic, multivariable coupled flight control scenarios.

MPC demonstrates great flexibility in attitude and trajectory control. By constructing linear or nonlinear system models, MPC is able to achieve accurate flight control in dynamic tasks, especially in the face of wind perturbations, load variations or uncertainties, and its robustness is significantly better than that of traditional methods. In addition, the advantages of MPC in path planning are also fully demonstrated. By transforming the path optimisation problem into a rolling optimisation problem solved online, MPC is able to achieve autonomous navigation of UAVs in dynamic environments, thus performing well in complex tasks. For example, Zhang et al [4] proposed a decision model for UAV trajectory tracking by training a neural network based on the demonstration data obtained from sampling the Model Predictive Control (MPC) controller, which does not need the a priori information of the UAV's complete state and obstacle positions, and only needs to take the laser point cloud data and the raw IMU data as the inputs of the strategy network directly to obtain a robust control strategy. Since deep convolutional networks have strong image information extraction capability, the model can be applied to the UAV.

In addition, MPC relies heavily on the accuracy of the system model, and modelling errors may lead to degradation of control performance. Come to that, by combining data-driven modelling techniques and distributed optimisation frameworks, MPC is expected to achieve higher accuracy and robustness in complex nonlinear tasks, providing a more reliable solution for UAV flight control in dynamic and uncertain environments.

4. Intelligent control algorithms

4.1 Deep learning

Deep learning, with its superior nonlinear modelling capability and autonomous feature extraction advantages, provides a brand new solution for flight control, environment sensing and path planning of quadrotor UAVs. As an important branch of artificial intelligence, deep learning simulates the human learning process through multi-layer neural networks, and excels in dealing with complex data and multi-variable coupling problems, which significantly improves the UAV's autonomous flight capability in dynamic environments.

In terms of environment perception, deep learning, with convolutional neural network (CNN) as the core technology, is able to extract high-dimensional features from visual data collected by cameras or sensors to achieve accurate perception of obstacles, target objects, and flight environment. Especially in complex unstructured environments, deep learning significantly improves the UAV's ability to detect and avoid dynamic obstacles, laying a solid foundation for autonomous navigation tasks. For example, Xu Yiming [5] and others quadrotor UAV can complete the autonomous flight, proposed in the deep learning how to design the control quadrotor UAV system based on the design of the UAV's obstacle avoidance function, carried out the flight test of the speed control method, test and verify the feasibility and control performance of the speed control method. The flight tests were conducted to test and verify the feasibility and control performance of the speed control method. The immunity and robustness of the proposed method were verified by comparing the traditional control methods and the experiments conducted to verify the theory.

In terms of path planning and control optimisation, deep reinforcement learning is combined with trial-and-error learning strategies to continuously optimise the flight path and attitude control strategies through reward signals. Unlike traditional optimisation methods, the deep learning algorithm is able to adapt to dynamic environments with high uncertainty, especially during mission execution, and dynamically adjusts the control strategy without pre-modelling, thus achieving highly robust and accurate flight control.

Nevertheless, the application of deep learning in UAVs still faces certain challenges. Its high computational complexity and reliance on large-scale data are major bottlenecks, limiting its real-time application in embedded systems. In addition, the “black-box” nature of deep learning models increases the risk of mission failure.

4.2 Enhanced learning

Reinforcement learning, as a machine learning method that learns optimal strategies through interaction, has been widely used in the flight control and mission planning of quadrotor UAVs in recent years. Reinforcement learning optimises control strategies in dynamic environments through trial-and-error exploration and reward feedback mechanisms, and is particularly suitable for autonomous decision-making tasks of UAVs in complex and uncertain environments.

In the field of path planning, reinforcement learning demonstrates superior dynamic adaptation. By defining state, action and reward functions, UAVs can learn the optimal flight path from any starting point to the target location. In the area of attitude control and flight stability, reinforcement learning significantly improves the dynamic responsiveness of the UAV by introducing a policy optimisation method in continuous action space.

Reinforcement learning has made significant progress in the field of unmanned aerial vehicles (UAVs), Liu Xuguang et al. in the literature [6] combined reinforcement learning with iterative learning control algorithms, and proposed the Reinforcement Learning-Iterative Learning Control (RL-ILC) algorithm. Under different environments and tasks, the powerful learning search ability of reinforcement learning can ensure that the iterative learning algorithm converges quickly and achieves the optimal control effect, while reducing the dependence of the system on the environment, thus greatly improving the interference resistance, stability and practicality of the algorithm. Despite the significant progress in the application of reinforcement learning in UAV control, there are still some challenges. High sample complexity and training cost are the main issues limiting its large-scale application, while the algorithms are highly dependent on the accuracy of environment modelling. In the future, through the introduction of distributed training frameworks and self-supervised learning methods, the application potential of reinforcement learning in the UAV field will be further released, providing more reliable technical support for the efficient execution of complex tasks.

4.3 Imitation learning

Imitation learning, a machine learning method for fast control optimisation by learning expert demonstration strategies, demonstrates unique advantages in improving the stability and robustness of quadrotor UAVs. The method is able to learn control strategies directly from expert data, avoiding the complexity of explicitly modelling environmental dynamics and enabling the UAV to exhibit higher adaptability when dealing with dynamic environments and complex tasks.

In terms of flight stability, imitation learning effectively optimises the attitude control and trajectory tracking strategies of UAVs by directly mimicking the best control behaviour of experts. This approach can accurately capture the expert's operating habits in complex environments, thus providing highly stable control strategies for UAVs, which is especially suitable for flight missions under high load or bad weather conditions. In addition, the introduction of the data expansion algorithm significantly improves the robustness of the imitation learning strategy.

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By continuously optimising and adjusting the execution strategy, the UAV can reduce the performance degradation caused by deviation from the expert data distribution, and thus maintain high-precision control during long-duration flights.

To further enhance robustness, recent research has focused on the application of generative imitation learning techniques. Generative adversarial imitation learning uses generative adversarial networks to generate diverse virtual training data, enabling UAVs to cover a wider distribution of scenarios during training and enhance their adaptability to unknown environments. At the same time, combined with online learning technology, imitation learning enables UAVs to dynamically optimise their strategies during real-time flight, ensuring that they maintain stable flight in the face of complex perturbations.

5. Hybrid algorithms

By combining traditional control algorithms with intelligent control algorithms, hybrid control algorithms synthesize the stability of traditional control and the nonlinear modelling capability of intelligent algorithms, providing a more efficient and flexible solution for the flight control of quadrotor UAVs. In recent years, hybrid control algorithms have made significant progress in optimising PID parameters, constructing end-to-end perception-decision-control models, and enhancing the adaptability to complex environments.

Firstly, optimising traditional PID control parameters using deep learning is one of the important applications of hybrid control algorithms. Using deep learning to optimise the PID parameters, the PID parameters are adjusted in real time, so that the UAV can better adapt to changes in the dynamic environment. This method significantly improves the control accuracy and stability of the UAV under strong disturbance conditions. Such methods make up for the shortcomings of traditional PID control in strong nonlinear scenarios, and provide strong support for the performance of UAVs in complex flight missions.

Secondly, the combination of deep learning and reinforcement learning constructs an end-to-end perception-decision-control model, which becomes another important research direction in hybrid control algorithms. Deep Q-Network (DQN, Deep Q-Network) is a typical algorithm that combines deep learning with reinforcement learning. This method provides strong support for autonomous navigation of UAVs in high-dimensional state space by estimating the action-value function using deep neural networks.DQN significantly improves the path planning and obstacle avoidance capabilities of UAVs in complex dynamic environments. In addition, some studies have shown that the dynamic control performance of UAVs can be further improved by introducing reinforcement learning algorithms such as Deep Deterministic Policy Gradient (DDPG, Deep Deterministic Policy Gradient) in the continuous action space, especially in nonlinear control tasks. Liang Ji proposed an end-to-end UAV autonomy control algorithm based on reinforcement learning in the literature [7]. Compared with expert controllers, network controllers do not require complex parameter tuning as well as model construction, and directly map the state of the UAV to the output of the servo, which reduces the intermediate complex computational process. The controller constructed by the ESAC algorithm can achieve the same or even better control effect as the PID controller, and at the same time, it is better than the controller constructed by SAC and DDPG in terms of stability and accuracy.

In addition, the combination of model-based reinforcement learning and traditional model predictive control (MPC) provides new ideas for UAV flight optimisation in complex environments. In literature [8], Zhendong Wang designed PID controller and model predictive controller for different channels, and combined the advantages of the two controllers by using time and error as switching conditions to design a predictive-PID composite controller for flight control of the system. Through the study of predictive control and combined with the classical PID control to design the prediction-PID composite control, the prediction-PID controller is designed for four channels, and the closed-loop simulation of the system is carried out on MATLAB/Simulink, and comparative simulation is carried out, and the simulation results verify that the prediction-PID composite controller has the characteristics of high steady state accuracy and good robustness.

Table 1 Comparative analysis of different algorithms

Algorithm category	vantage	drawbacks	Applicable Scenarios
PID controller	simple and efficient	Not suitable for strong nonlinearities	Smooth flight at low speeds
LQR	Energy optimisation	Difficult to handle complex nonlinearities	Small trajectory control
MPC	For multivariable systems	High computational complexity	High precision flight

deep learning	Strong non-linear modelling skills	High demand for data	dynamic environment
Intensive learning	Dynamic adaptability	Ineffective learning	route planning
hybrid algorithm	Combining multiple strengths	High implementation complexity	Integrated mission scenarios

6. Technical challenges and development proposals

6.1 Technical challenges

Modelling problems for highly nonlinear systems: the flight process of quadcopter UAVs involves complex nonlinear dynamics, and traditional control algorithms (e.g., PID, LQR) are inadequate in dealing with these nonlinear characteristics. Especially in the case of strong wind disturbances or system failures, traditional algorithms may not be able to provide sufficient robustness and stability. Therefore, how to effectively model and control these nonlinear dynamics becomes the primary technical challenge to improve the robustness and stability of quadcopter UAVs.

Computational complexity and real-time problem: Many intelligent control algorithms, such as deep learning and MPC, can provide accurate control in multivariable coupled systems, but their high computational complexity often leads to algorithms that are difficult to meet real-time requirements. In flight control systems, any delay or computational error may lead to flight instability, so how to design control algorithms with low computational burden that can guarantee real-time performance is an urgent problem.

Data Dependency and Training Efficiency Problem: Methods such as deep learning and reinforcement learning rely on a large amount of data for training, and collecting this high-quality data is not only costly but also time-consuming in UAV applications. In addition, the training process of these algorithms usually requires a large amount of interaction data, resulting in high sample complexity and limiting their popularity in practical applications. How to improve the efficiency of data utilisation and reduce the dependence on a large amount of training data has become the key to achieving the widespread application of intelligent control algorithms.

Challenges of environmental adaptability and diverse missions: UAVs are often flying in dynamic and uncertain environments while performing their missions. Control algorithms need to be robust and adaptive, able to adjust dynamically to changing environments in real time. Existing algorithms often rely on static or hypothetical environment models, which makes them prone to failure in complex environments. How to enhance the adaptability of algorithms to unknown and sudden environmental changes is a key issue in improving the robustness and stability of UAV flight.

6.2 Development proposal

Enhancing the nonlinear modelling capability of intelligent algorithms: future research can focus on combining intelligent algorithms such as deep learning and reinforcement learning with traditional control algorithms to form a hybrid control framework. This will make up for the limitations of traditional algorithms in linearising the model, and at the same time use the advantages of intelligent algorithms in dealing with complex nonlinear dynamics to enhance the adaptability of the quadcopter UAV in a variable environment.

Optimising computational efficiency and real-time performance: lightweight deep learning models and efficient control algorithms can be explored in the future for high computational complexity problems. By using quantisation techniques, model compression and other methods, the computational burden of the algorithms can be reduced, while ensuring their real-time performance in embedded systems.

Extension of Self-Supervised Learning and Online Learning: In order to solve the data dependency problem, self-supervised learning and online learning can be promoted in the future. These methods can improve data utilisation and reduce the need for large amounts of labelled data through autonomous learning by UAVs in flight. In addition, the combination of adaptive learning strategies enables the UAV to continuously optimise the control strategy in real tasks, further improving the robustness.

Fusion of multi-modal sensing technology and dynamic decision-making system: multi-sensor fusion technology can provide UAVs with more comprehensive environmental sensing capabilities, helping the system to cope with different flight scenarios. By fusing multiple sensor data such as vision, radar and IMU, combined with deep learning and reinforcement learning algorithms, it enhances the UAV's flight stability and anti-jamming ability. Meanwhile, the development of an end-to-end perception-decision-control system will help improve the efficiency and accuracy of UAV decision-making in dynamic environments.

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Cross-disciplinary co-optimisation and innovation: future research should further promote the integration of interdisciplinary technologies. For example, combining UAV control with edge computing and cloud computing to achieve the co-optimisation of control algorithms and computing resources. Through the combination of distributed computing and collaborative control strategies, the performance and stability of UAVs in complex flight missions can be improved.

7. Concluding remarks

As a highly flexible and adaptable flight platform, quadrotor UAVs have been widely used in many fields. However, in the face of complex and dynamic flight environments, its flight stability and robustness still face many challenges. This paper reviews the research progress of combining various control algorithms to enhance the flight performance of quadcopter UAVs in recent years, covering the application and development of traditional control algorithms, intelligent control algorithms, and hybrid control algorithms. In the future, with the improvement of computing power and further optimisation of algorithms, quadrotor UAVs will be able to play a more important role in more complex flight missions, providing strong technical support for intelligent and automated applications.

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