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Quadrotor Control Algorithm Based On Optimized PSO-RBF Neural Network Adaptive Sliding Mode Control

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Project submitted as part of the requirements
for the award of Course Name

08 2024

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ABSTRACT/SYNOPSIS

Aiming at the nonlinear, strongly coupled and uncertain interference quadrotor UAV model, an improved particle swarm optimization-radial basis function (PSO-RBF) neural network adaptive sliding mode controller is proposed. On the basis of improving the control quantity smoothing of the RBF neural network adaptive sliding mode controller, the improved PSO algorithm with global optimization ability is used to adjust the fitting parameters of the RBF neural network, so as to further improve the fitting ability of the network. According to the model parameters of the actual quadrotor, the dynamic model of the quadrotor is built, and the stability of the system is verified by Lyapunov theory. The simulation results show that compared with the RBF neural network adaptive sliding mode controller and the double closed-loop PID controller, the improved PSO-RBF neural network adaptive sliding mode controller can find the appropriate control quantity within one control cycle, and its adjustment time is increased by about 50% and 75% respectively; the improved PSO-RBF neural network adaptive sliding mode controller has the characteristics of fast and accurate trajectory tracking, strong anti-interference ability and good robustness.

Keywords: Quadrotor Drone; Particle Swarm Algorithm; Radial Basis Function Neural Network; Adaptive Sliding Mode Control; Trajectory Tracking; Anti-Interference

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CHAPTER 1

1.1 Introduction

As an emerging aircraft platform, quadcopter drones have received extensive attention and application in recent years due to their simple structure, strong maneuverability and excellent performance in complex terrain. Compared with traditional fixed-wing drones, quadcopter drones can achieve vertical take-off and landing and fixed-point hovering, and have greater flexibility and operability. Therefore, they have been widely used in many fields such as military reconnaissance, environmental monitoring, agricultural spraying, and aerial photography. In addition, with the continuous advancement of artificial intelligence and automation technology, the development prospects of quadcopter drones in the direction of intelligence and autonomy are broader. However, the control problem of quadcopter drones has always been a challenge, mainly reflected in the fact that their dynamic models have highly nonlinear and strongly coupled characteristics, and are easily disturbed by the uncertainty of the external environment. These factors make it a difficult task to accurately control the attitude and trajectory of quadcopter drones in complex environments, and traditional linear control methods, such as PID control, often seem to be unable to cope with these complexities and are difficult to meet the needs of stable operation of drones.

Given the wide application of quadcopter drones in many fields and their huge potential value, it is of great significance to improve the performance of their control systems, especially in dealing with nonlinear, strongly coupled and uncertain interference. Under the current technological background, intelligent control methods, such as the combination of neural networks and optimization algorithms, provide new possibilities for solving these complex control problems. Therefore, this study chose to develop an adaptive sliding mode controller based on an improved PSO-RBF neural network, aiming to utilize the global optimization capability of the particle swarm optimization algorithm and the nonlinear approximation capability of the RBF neural network to improve the control performance of quadrotor drones, especially in complex environments. Through this research, not only can the development of quadrotor drone technology be

promoted, but also new ideas and solutions can be provided for the control theory research of unmanned systems, which has important contributions and application prospects in related fields.

1.2 Research Problem Statement

The core problems faced by the control system of quadcopters are mainly concentrated on their complex dynamic characteristics. Due to its unique quadcopter structure, the rotation speed of each rotor directly affects the attitude and position control of the aircraft, resulting in high nonlinearity and strong coupling of the entire system. This means that in the control process, any change in any input variable will affect multiple output variables, and these effects are often nonlinear and interdependent. In addition, quadcopters also need to deal with various uncertain interferences in actual flight, such as wind speed changes, load changes, and sensor noise, which further increase the difficulty of control. Traditional control methods, such as PID control, show obvious deficiencies in the face of these complex nonlinear problems due to their assumptions based on linear systems. Although PID control can achieve good results in some simple scenarios through simple proportional, integral and differential control, in a multi-input multi-output (MIMO) system such as a quadcopter, its regulation effect often cannot meet the high-precision control requirements, especially in the case of strong external interference, showing problems of slow response and low precision.

Existing research has recognized these challenges and tried to improve the control effect by introducing intelligent control methods. For example, fuzzy control is a common nonlinear control method that uses fuzzy logic rules to deal with system uncertainty and nonlinear problems. However, the design of fuzzy control often relies on expert experience, and the formulation and adjustment of rules are subjective and difficult to generalize to different application scenarios. In addition, neural network control methods have been widely used in the control of quadrotor drones due to their powerful nonlinear approximation capabilities. Neural networks can automatically adjust control parameters by learning the historical data of the system, thereby improving the control accuracy and adaptability of the system.

However, neural networks require a large amount of data support during the training process, and when facing new and unseen environments, they may have problems of overfitting or underfitting, resulting in insufficient robustness of the system. For control methods based on optimization algorithms, such as particle swarm optimization (PSO) algorithms, although they perform well in global optimization capabilities, their computational complexity is high, especially when dealing with multidimensional optimization problems, they are prone to fall into local optimal solutions, affecting the final control effect. The limitations of these existing methods indicate that in the control of quadrotor drones, there is still a need to continuously explore and develop more efficient and robust control algorithms.

To cope with these complexities, the challenges faced by research are multifaceted. First, in terms of improving the control accuracy of quadrotor drones, research needs to develop control algorithms that can effectively deal with nonlinear and coupling effects. This requires not only that the controller can accurately handle the complex relationship between input and output, but also that it can maintain stable performance under various flight conditions. Secondly, enhancing the anti-interference ability of the system is also one of the important research goals. In practical applications, quadrotor drones often need to operate in various complex and changeable environments. Therefore, designing a highly robust controller that can maintain stable and accurate flight under external interference is an important research direction. In addition, as the complexity of the control algorithm increases, how to maintain the real-time and efficiency of the calculation while ensuring system performance is also a major challenge. Especially in the flight control of drones, real-time response is the key to ensuring flight safety and mission success. Therefore, research needs to find a balance between efficient algorithm design and optimal configuration of computing resources. In the face of these challenges, research not only requires theoretical innovation, but also requires extensive testing and verification in practical applications to ensure that the proposed method can be truly applied to complex and changeable actual flight environments.

1.3 Aim

The overall goal of the research is to develop an adaptive sliding mode controller based on an improved PSO-RBF neural network to significantly improve the control performance of quadcopter UAVs. This goal specifically includes achieving high-precision control of UAV attitude and trajectory in complex flight environments, enhancing the system's anti-interference ability, and ensuring that the system can still maintain stability and efficiency under changing external conditions. run. Through the design and optimization of the controller, the research aims to provide an advanced solution with more robustness and real-time performance for the UAV control system.

1.4 Objectives

In order to achieve the overall goal of improving the control performance of quadrotor drones, this study will be carried out in stages, covering all aspects from model building to controller design, simulation verification and performance analysis. Through the gradual realization of each sub-goal, the study aims to develop a control system with high precision, strong robustness and real-time response capabilities, providing theoretical support and technical guarantee for the application of quadrotor drones in complex environments.

1.4.1 Develop A Dynamic Model For A Quadrotor Drone

Establish an accurate dynamic model to describe the nonlinear and strongly coupled characteristics of a quadrotor drone. This model will provide a basis for the design and simulation of subsequent controllers.

1.4.2 Design And Optimize An Improved PSO-RBF Neural Network Adaptive Sliding Mode Controller

Based on the dynamic model of a quadrotor drone, design an adaptive sliding mode controller that combines an improved PSO algorithm and an RBF neural network. Optimize the parameters of the RBF neural network through the PSO algorithm to improve the response speed and accuracy of the controller.

1.4.3 Verify The Performance Of The Controller Through Simulation Experiments And Compare It With Other Control Methods

Implement the designed controller on the simulation platform and compare its performance with that of the traditional RBF sliding mode controller and PID controller. The main evaluation indicators include control accuracy, response time, trajectory tracking capability, etc.

1.4.4 Analyze The Performance Of The Controller In Terms Of Anti-Interference Ability And Robustness

Design a series of simulation scenarios to test the anti-interference ability and system robustness of the designed controller under different interference conditions. Analyze the stability and control accuracy of the controller under strong interference environment.

1.4.5 Evaluate The Computational Complexity And Real-Time Performance Of The Controller

Analyze the computational complexity of the designed controller and evaluate its feasibility in real-time applications. Ensure the real-time performance and effectiveness of the controller in practical applications by optimizing the algorithm and structural design.

1.5 Structure Of The Project

The project is systematically structured to address the specific research objectives through a detailed progression of chapters, with each chapter contributing to a coherent and thorough exploration of the quadrotor UAV control challenges. This structure ensures that the development of the PSO-RBF neural network adaptive sliding mode controller is grounded in both theoretical foundations and practical applications, leading to a robust and well-validated solution.

CHAPTER 2 - RESEARCH & REVIEW OF LITERATURE

2.1 Introduction

Due to the limitation of sensor and microcomputer technology in the last century, the flight control technology of quadrotor UAV has experienced a slow period. With the continuous progress of cross technology and the rapid expansion of market demand, the related research of quadrotor flight control technology has gradually become hot. Research on the flight control of quadrotor UAV has always been one of the hot topics at home and abroad. At present, the flight control methods widely used at home and abroad include PID control [1], sliding mode control [2], active disturbance rejection control [3], neural network control [4], adaptive control [5], etc.

2.2 PID Control

PID control is composed of proportional, integral and differential links, and its main idea is to eliminate deviation by using deviation [6]. PID control has the characteristics of simple structure, no dependence on accurate mathematical model, convenient parameter adjustment and easy implementation in engineering, so it is widely used in industrial control. However, when the plant contains nonlinear terms, time-varying uncertainties or strong disturbances, the control performance of PID control is often not satisfactory, so PID control can not meet the high performance requirements of complex systems. Aiming at the attitude control problem of quadrotor UAV, literature [7]-[8] combines PID with fuzzy control, and uses fuzzy control to tune the parameters of PID control, so as to enhance the robustness of the attitude system of quadrotor UAV. Literature [9] introduces the self-coupling PID control algorithm into the attitude control of quadrotor UAV, and achieves the purpose of collaborative control by coupling the proportional, integral and differential links, so as to better meet the control requirements of the attitude system of quadrotor UAV. In literature [10], the particle swarm optimization algorithm is used to tune the parameters of PID controller and improve the attitude tracking performance of quadrotor UAV. Aiming

at the trajectory tracking problem of quadrotor UAV, a nonlinear PID control algorithm is proposed in literature [11]-[12], which can ensure the effective realization of trajectory tracking of quadrotor UAV. Literature [13] designed an adaptive fuzzy fractional order PID control algorithm. Compared with the traditional PID control algorithm, this algorithm can effectively improve the trajectory tracking accuracy of the quadrotor UAV. Aiming at the fault-tolerant control problem of the quadrotor UAV, literature [14] uses the multi-model fault diagnosis method to estimate the actuator fault of the quadrotor UAV, and uses the interpolation algorithm to optimize the parameters of the PID controller to realize the active fault-tolerant control of the quadrotor UAV.

2.3 Sliding-Mode Control

As a variable structure control, sliding mode control can drive the system state to move according to the state trajectory of the specified sliding mode. Since the design of sliding mode is independent of system parameters and disturbances, sliding mode control has the advantages of fast response, simple implementation and robustness [15]. Therefore, sliding mode control is widely used in the control system design of quadrotor UAV. Aiming at the attitude control problem of quadrotor UAV, the Super Twisting sliding mode disturbance observer was adopted in literature [16] to estimate the composite disturbance of the quadrotor UAV attitude system online, and an approach law with second-order sliding mode characteristics was proposed to accelerate the convergence speed of the state. In reference [17], based on the estimated output of the disturbance observer, a non-singular terminal sliding mode surface and a controller were designed to make the attitude Angle converge to 0 in a finite time and suppress the impact of mismatched interference on the quadrotor UAV. In literature [18], the wind shear model and Dryden turbulence model were superimposed into the attitude system of the quadrotor UAV. The extended state observer was used to estimate and compensate the wind disturbance in real time, and the double power sliding mode attitude controller was used to accelerate the convergence speed of the system and reduce the impact of chattering on the system. Aiming at the trajectory tracking problem of quadrotor UAV, a composite fast non-singular terminal sliding

mode trajectory tracking algorithm was proposed in reference [19]. The extended state observer was used to estimate the state coupling term and interference between each attitude system, and a fast non-singular terminal sliding mode controller was designed based on the observed values, which significantly improved the response speed and anti-interference ability of the system. In reference [20], the second-order sliding mode controller was applied to the altitude tracking of quad-rotor UAV, and the control performance was compared with the classical first-order sliding mode controller and Super Twisting sliding mode controller in outdoor environment. The experimental results show that, The second-order sliding mode height tracking control algorithm proposed in this literature not only ensures the strong robustness of the quadrotor UAV system, but also reduces the chattering phenomenon. Aiming at the fault-tolerant control problem of quadrotor UAV, literature [21] used the extended state observer to estimate the single blade damage fault and external disturbance of the quadrotor UAV, and used the integral sliding mode controller to compensate the total disturbance. Literature [22] combines an adaptive observer with fast convergence and a sliding mode observer with strong robustness to detect and estimate unknown actuator faults of a quadrotor UAV.

2.4 Active Disturbance Rejection Control

ADRC, evolved from PID control, is a nonlinear control method that does not depend on the exact system model. It mainly consists of three parts: tracking differentiator (TD), extended state Observer (ESO), and nonlinear state error feedback controller (NSEFC) [23]. The role of the tracking differentiator is to extract reasonable control signals to solve the influence between the response speed and the overshoot. The role of the extended state observer is to deal with the internal uncertainty of the model and the influence of external disturbances on the system. Aiming at the attitude control problem of quadrotor UAV, literature [24] combines PID control and ADRC control, and designs a double closed loop attitude control algorithm of quadrotor UAV. The outer loop adopts PD control, and the inner loop adopts ADRC control. In the inner loop, an appropriate extended state observer is designed to estimate the external disturbance, and the corresponding nonlinear state error feedback controller is designed to compensate

the external disturbance. The simulation results show that the control algorithm proposed in this paper effectively suppresses the influence of external disturbance on the flight attitude of the UAV. Literature [25] proposed an attitude control algorithm of quadrotor UAV based on cascaded linear active disturbance rejection control. The control performance of the proposed control algorithm is compared with that of the traditional PID control algorithm in the case of wind disturbance. The simulation results show that the control performance of the proposed control algorithm is better than that of the traditional control algorithm, and the parameter tuning is simpler. Aiming at the trajectory tracking problem of quadrotor UAV, a finite-time convergent extended state observer was designed in literature [26] to improve the trajectory tracking performance of ADRC. In literature [27], adaptive sliding mode control and active disturbance rejection control are combined to realize the trajectory tracking of variable load quadrotor UAV. Aiming at the fault-tolerant control problem of quadrotor UAV, literature [28] constructs a new gain function considering the low observation accuracy of the extended state observer using the traditional fal gain function when the sensor of the quadrotor UAV is corrupted by noise. The gain function is smoother and has better convergence than the traditional fal function, which greatly improves the observation accuracy of the extended state observer. In literature [29], actuator fault, gust disturbance and measurement noise of quadrotor UAV were regarded as total disturbance, and the improved extended state observer and nonlinear error feedback controller were used to estimate and compensate the total disturbance respectively. The simulation results show that the literature achieves fault-tolerant control and reduces the impact of environmental factors on the quadrotor UAV.

2.5 Neural Network Control

Since the 1990s, neural network control has made a big difference in the field of automatic control. As an advanced intelligent control algorithm, neural network control has a strong learning ability, which can learn complex uncertain models online and deal with highly nonlinear control problems [30]. Aiming at the attitude control problem of quadrotor UAV, considering that it is difficult to establish an accurate system model of quadrotor UAV, literature [31] defined the uncertain part

of quadrotor UAV model and external disturbance as the total disturbance, and proposed an adaptive sliding mode attitude control algorithm based on RBF neural network. The RBF neural network was used to approximate and compensate the total disturbance, and the non-singular terminal sliding mode control was used to improve the system response speed and suppress the influence of disturbance on the quadrotor UAV. In literature [32], considering that the backstepping sliding mode control has a large fluctuation range with disturbance, the adaptive control of RBF neural network is combined with the backstepping sliding mode control to enhance the anti-disturbance ability of the attitude system of the quadrotor UAV. In literature [33], single hidden layer Neural Network (SHLNN) was used to estimate the state of the attitude system of the quadrotor UAV based on the sliding mode observer. Simulation results show that the proposed observer is insensitive to measurement noise and can ensure the stability of the global system. Aiming at the trajectory tracking problem of quadrotor UAV, literature [34] uses Recursive fuzzy Wavelet Neural Network (RFWNN) to learn the mass change and wind disturbance of logistics UAV online, so as to achieve the purpose of trajectory tracking. Aiming at the fault-tolerant control problem of quadrotor UAV, literature [35] used the trained recurrent neural network to effectively estimate the actuator fault degree, and combined with adaptive sliding mode control, constructed an active fault-tolerant control method.

2.6 Self-Adaptation Control

The idea of adaptive control is that for an imperfect controlled system model, the control system continuously optimizes the model parameters according to the transformation of the system state in the operation process, so as to optimize the controlled system model and obtain the optimal control effect [36]. Aiming at the attitude control problem of the quadrotor UAV, literature [37] proposed a double closed-loop adaptive control algorithm for the quadrotor UAV with limited state and unknown disturbance. Nonlinear transformation was used to convert the limited state into a new state, and the bounded problem was considered. In addition, the adaptive control was used to estimate the unknown external disturbance. Aiming at the trajectory tracking problem of quadrotor UAV, literature [38] proposed a trajectory tracking algorithm of quadrotor UAV based on adaptive integral

backstepping control. The literature divided the position system and attitude system into inner and outer loops, and introduced adaptive parameters and command tracking error integral term into the attitude loop, which improved the system trajectory tracking accuracy and ensured the stability of the system. In reference [39], for a quadrotor UAV with serious unknown system parameters, a parameter adaptive law was designed to estimate the dynamic parameters that are difficult to measure accurately and unknown external disturbances, and an adaptive sliding mode control method was proposed. The simulation results show that the proposed method is robust and can ensure the trajectory tracking of the quadrotor UAV. Literature [40] proposed a new 1L adaptive control algorithm based on nonlinear feedforward compensation for a quadrotor UAV with time-varying aerodynamic effects and bounded disturbances. Its augmented L-adaptive controller achieves asymptotic tracking of an arbitrary bounded reference trajectory. Aiming at the fault-tolerant control problem of quadrotor UAV, literature [41] proposed an adaptive predetermined performance control scheme, which used adaptive parameters to estimate the actuator fault parameters, so that the transient performance of the system met the preset requirements.

2.7 RBF Neural Network

Within the scope of neurocomputational science, the function of feedforward neural networks is to represent nonlinear mappings. The motion mechanism of neural information in the nervous system is a computational mechanism, and the process from stimulus to response in the nervous system is a process of mathematical mapping. The expression of nonlinear mapping is essentially a problem of function approximation, and interpolation calculation is an important way to realize function approximation. Radial basis function method is a traditional multivariate interpolation method. Therefore, the RB interpolation calculation can be formalized as a neural structure, and the radial basis function network, namely RBF neural network model, is produced. Hardy et al. proposed radial basis theory as early as 1971 [42], while Broomhead et al. first used RBF in neural network design in 1988 [43], and initially discussed the difference between RBF application in neural network design and traditional interpolation field, and then proposed a RBF neural network model with three-layer structure. Moody et al. published an

article in 1989, which extracted the receptive field characteristics of human brain to external stimuli based on the research results of human brain. That is, under the same external stimulus, the response intensity of brain cells in different parts is different, and the scope of each neuron has its local scope. Therefore, only when the stimulus belongs to a certain range, the neuron will respond. Otherwise it does not respond or the response is small [44]. According to this characteristic, a neural network with local response characteristic is proposed. This network coincides with the RBF network proposed by Broomhead et al. Moody et al. also proposed a parameter training algorithm for RBF neural networks [45]. RBF neural network has good generalization ability, strong nonlinear mapping ability, fast operation speed, and strong approximation performance. It can approximate a nonlinear function with arbitrary accuracy. RBF neural network has attracted the attention and research of many scholars [46]-[47], and has carried out in-depth research on RBF neural network parameter optimization. Different optimization algorithms have been applied to RBF neural network parameter optimization [48]-[49], such as gradient algorithm: Gradient descent algorithm, Newton algorithm, LM(Levenberg-Marquardt) algorithm, etc. Among them, gradient descent algorithm is the most widely used gradient optimization algorithm [50]. However, the gradient descent algorithm has shortcomings such as long convergence time and poor global search ability. Therefore, Scholars have proposed Recursive Least Squares (RLS) Algorithm [51], Continuous Forward Algorithm (CFA) algorithm [52], Improved Second Order (ISO) algorithm [53], to improve the search speed and accuracy of the algorithm. However, different from gradient algorithms, evolutionary algorithms have strong robustness and belong to global search algorithms, which are widely used in parameter optimization of RBF neural networks [54]-[55]. However, the evolutionary algorithm also has the shortcomings of over-fitting and high computational complexity, and the convergence cannot be guaranteed [56]-[57]. Therefore, the application of evolutionary algorithm in RBF neural network still has a lot of optimization space. However, with the increasing complexity of practical problems, it is difficult to meet the requirements of practical applications only by optimizing parameters, and it is necessary to dynamically adjust the network structure to adapt to complex environmental changes.

2.8 Particle Swarm Optimization

Particle swarm optimization (PSO) is a random search algorithm based on population, which originates from the study of bird foraging behavior. Although the flight behavior of birds seems to be irregular, researchers have found that there is always a synergistic relationship between the overall flight path of the birds through long-term observation, not only the overall movement is smooth, but also the individual is extremely coordinated, it seems that the birds are constrained by some rules. Craig Reynolds first proposed the Boid model [58] by studying the flight phenomenon of birds, and Heppner, a biologist, further analyzed the attraction of habitat to birds and proposed a bird flock aggregation model based on biological group behavior [59]. In 1995, Dr. Kennedy of social psychology and Dr. Eberhart of electrical engineering in the United States proposed particle swarm optimization algorithm based on the bird swarm aggregation model [60]-[61]. The PSO algorithm abstracted birds as "particles" without mass and volume, designed the mutual cooperation and information sharing mechanism between particles by simulating the cooperative behavior of birds in the flight process, and memorized the historical motion information of itself and the group to assist the current motion behavior of particles, so as to better search for optimization in complex space. Since the PSO algorithm was proposed, many scholars have carried out theoretical analysis and experiments on it, and made many variations and improvements on it, which promotes the development of PSO algorithm. The IEEE International Symposium on Swarm Intelligence held every year has attracted a large number of scholars and greatly promoted the research of particle swarm optimization. In the past two decades, the research on PSO algorithm has been divergent and extended, including the research on algorithm parameters, algorithm topology, algorithm convergence, algorithm improvement, algorithm application and so on.

2.9 Improved PSO-RBF Neural Network Adaptive Sliding Mode Controller

The approximation ability of radial basis function neural network to nonlinear system has attracted the attention of many scholars at home and abroad [62]. Sun Ruihua et al. [63] adopted RBF neural network to optimize the three control

parameters of PID and improved the rapid adjustment ability of the control system. However, the PID control part of the controller is a linear control method, which has certain limitations in controlling the nonlinear quadrotor model. As a nonlinear control method, sliding mode control (SMC) has strong robustness. Han Yezhuang [64] and Lin [65] et al. adopted the adaptive sliding mode control method of RBF neural network to approximate the inaccurate quadrotor model by using the universal approximation characteristics of RBF neural network. This method has faster adjustment time, better anti-interference ability and stronger robustness than the RBF-PID control method. However, the selection of the center value, width and connection weight of the hidden layer neurons of RBF neural network is mostly optimized by gradient algorithm, which is prone to over-fitting learning, unable to ensure constant convergence, and lacking reliability [66]. particle swarm optimization (PSO), as an optimization algorithm for global optimization, is often applied to the path planning of quadrotor [67], but rarely applied to the stability and anti-disturbance control of quadrotor. Some scholars have confirmed in the experiment process of single control rate of photovoltaic system that this method can further improve the approximation ability of RBF neural network [66], but the designed controller has the chattering problem, which will lead to frequent switching of voltage regulation and seriously shorten the service life of the motor when applied to the quadrotor. Based on this, an improved PSO-RBF neural network adaptive sliding mode controller for quadrotor is proposed in this project. The global optimization ability of the improved PSO algorithm was applied to find the center value, width and connection weight of RBF neural network neurons, which further improved the approximation speed of RBF neural network to the quadrotor model and approached the uncertain state of the quadrotor model in the sliding mode controller faster.

CHAPTER 3 - RESEARCH METHODOLOGY

3.1 INTRODUCTION

This chapter aims to elaborate on the research methods used in this study and emphasize its core role in the entire project. The research methods not only provide a solid foundation for the theoretical construction of the project, but also ensure the systematicness of the entire research process and the effectiveness of the results. Through rigorous research design, the project was able to explore new solutions in the complex field of quadcopter control, and supported by scientific methodology to ensure that the proposed control strategy is verifiable and has application value.

As the project progresses, the research design continues to evolve and improve. This dynamic adjustment reflects the adaptive adjustment of the research direction and methods by researchers after a deep understanding of the quadcopter control problem. The initial design may be based on existing theories and assumptions, but with a deeper understanding of the nature of the problem, the research methods and strategies are also optimized accordingly. For example, in the preliminary literature review, it was found that traditional PID control has limitations in dealing with the nonlinear and strongly coupled characteristics of drones, so the research direction gradually shifted to more complex and flexible control strategies, such as hybrid control methods based on neural networks and optimization algorithms. The adjustment of this method is not only based on the results of theoretical derivation, but also a direct reflection of the experimental data and simulation results feedback, thus ensuring the practical feasibility of the research design.

This chapter will first introduce the research philosophy followed by this study, which will provide theoretical guidance for the overall direction of the project. The research philosophy determines how researchers view the process of knowledge generation and verification, and directly affects the selection and application of research methods. Secondly, this chapter will discuss in detail the research methodology adopted, including how the combination of qualitative and

quantitative methods can help researchers to deeply understand the complex problems in quadrotor control. This part will show how researchers gradually reveal the essence of the problem and seek effective solutions through a variety of methods such as systematic literature review, theoretical modeling, simulation analysis and experimental verification.

Finally, this chapter will also explain in detail the data collection and analysis techniques. The selection and application of these techniques are directly related to the accuracy and reliability of the research results. In the study of quadrotor control, data collection and analysis include not only traditional experimental data, but also simulation data processing and algorithm performance evaluation. Through rigorous technical means, researchers can ensure that the data obtained truly reflects the performance of the control strategy and provide a solid basis for subsequent improvements and applications.

In summary, this chapter will lay the theoretical and methodological foundation for the detailed discussion of the design and implementation process in the subsequent chapters, and ensure the scientificity, systematicness and operability of the entire project through a clear explanation of the research method. This structured research method will run through all stages of the entire project, from theoretical discussion to experimental verification, and then to the final application and evaluation, forming a complete research chain, contributing new perspectives and methods to the research in the field of quadrotor drone control.

3.2 RESEARCH OVERVIEW

This section provides an overarching view of the research process employed in this project, highlighting the systematic approach used to address the complex challenge of developing an effective control strategy for quadrotor UAVs. The research was designed to be both comprehensive and iterative, ensuring that each phase built upon the previous one while allowing for adjustments based on emerging insights and data. The project began with a thorough literature review to identify gaps in current UAV control strategies, followed by the design and

implementation of a novel PSO-RBF neural network adaptive sliding mode controller. The research process was structured to include both theoretical modeling and empirical validation, with a strong emphasis on simulation-based testing to ensure the controller's robustness and effectiveness.

The approach adopted in this research is rooted in a combination of qualitative and quantitative methodologies. The qualitative aspect was primarily focused on the literature review, which provided the necessary background and theoretical framework. This helped to identify the limitations of existing control methods and informed the development of the proposed controller. Quantitative methods were then employed to rigorously test the controller's performance through simulations. By integrating these methodologies, the research was able to comprehensively address the research problem, ensuring that the results were both theoretically sound and practically applicable.

3.2.1 RESEARCH PROCESS

The research process was meticulously planned and executed in a series of well-defined stages, each contributing to the overall success of the project. The process began with an extensive literature review, which served as the foundation for identifying the specific challenges and gaps in existing quadrotor UAV control systems. This review was critical in shaping the research questions and guiding the development of the PSO-RBF neural network adaptive sliding mode controller.

Following the literature review, the next stage involved the development of a dynamic model of the quadrotor UAV. This model was essential for accurately simulating the UAV's behavior under various conditions and provided the basis for testing the control strategies. The dynamic modeling phase was followed by the design and optimization of the control system. Here, the PSO algorithm was applied to optimize the parameters of the RBF neural network, ensuring that the controller could effectively handle the nonlinear dynamics of the UAV.

The final stage of the research process involved rigorous simulation testing. The controller was subjected to a variety of test scenarios to evaluate its performance

in terms of stability, accuracy, and robustness. These simulations were critical for validating the effectiveness of the proposed control strategy and ensuring that it could meet the demands of real-world UAV operations. Throughout the research process, data were systematically collected and analyzed, providing the empirical evidence needed to support the project's conclusions. Each stage of the research was designed to build upon the previous one, ensuring a coherent and integrated approach to solving the research problem.

3.2.2 RESEARCH PHILOSOPHY

The research philosophy underlying this project is grounded in post-positivism, a philosophical stance that emphasizes objectivity, empirical analysis, and critical reflection in scientific inquiry. Post-positivism builds upon the foundations of traditional positivism, acknowledging the pursuit of objectivity in research while also recognizing the inherent limitations in achieving complete objectivity. This philosophy advocates for a reflective and critical approach to research, wherein researchers continuously scrutinize their assumptions and conclusions throughout the research process.

At the core of post-positivism is the belief that while scientific inquiry can approximate truth through observation and experimentation, various factors, such as the limitations of research tools, researchers' prior assumptions, and the complexity of the environment, can influence research outcomes. Therefore, post-positivism encourages the use of repeated experiments, data triangulation, and cross-validation of methods to enhance the reliability of research findings. In the context of this project, which involves the control of a quadrotor UAV—a system characterized by high nonlinearity and complexity—relying solely on theoretical models would be insufficient to accurately describe the system's behavior. As such, the research necessitates an empirical approach, using simulations and real-world testing to validate and refine control strategies. This empirical method aligns closely with the principles of post-positivism, which rejects the reliance on theoretical deduction alone and instead promotes a robust connection between theory and empirical evidence.

The decision to adopt post-positivism as the guiding research philosophy for this project is informed by several key considerations. First, the control system for a quadrotor UAV is inherently complex, involving multiple interacting factors such as aerodynamic effects, environmental disturbances, and nonlinear dynamics. These complexities make it challenging to capture the system's full behavior using theoretical models alone. Post-positivism supports a research approach that allows for the iterative refinement of control strategies based on empirical data, making it well-suited to the needs of this project. Second, post-positivism places significant emphasis on the credibility of empirical data, which is crucial for the development of the PSO-RBF neural network adaptive sliding mode controller in this study. The design of the control strategy relies not only on theoretical derivation but also on the validation of its effectiveness and robustness through extensive simulation data and experimental results. Post-positivism provides the philosophical foundation for this data-driven approach, ensuring that research outcomes are both reliable and scientifically grounded.

The adoption of post-positivism has had a profound impact on the project. It has enhanced the scientific rigor of the research by promoting stringent empirical analysis and data validation, thereby ensuring the reliability of the research process and the credibility of its findings. Furthermore, post-positivism encourages a critical and reflective stance at every stage of the research, prompting ongoing optimization of the control strategy throughout its development. This iterative process has been crucial in ensuring that the controller performs effectively under a wide range of complex conditions. Additionally, the focus on practical applicability inherent in post-positivism has driven the project to prioritize not only theoretical innovation but also the real-world effectiveness of the controller, thereby increasing the practical value and potential impact of the research outcomes.

In summary, post-positivism as the research philosophy for this project has provided a solid theoretical foundation for the design and execution of the research. It has ensured the scientific integrity of the research methods and the reliability of the findings. Through this philosophical approach, the project has

been able to develop a high-performance control system for quadrotor UAVs, offering significant contributions to both theoretical research and practical applications in the field.

3.2.3 RESEARCH METHODOLOGIES

The research methodologies employed in this project are meticulously designed to address the complexities of controlling quadrotor UAVs. By integrating both qualitative and quantitative approaches, the research aims to provide a comprehensive evaluation of current control strategies and the development of an advanced control system. The methodologies are selected not only to explore the theoretical underpinnings of UAV control but also to rigorously test and validate the proposed solutions through empirical analysis.

The project begins with a qualitative analysis that is deeply rooted in an extensive literature review. This step is crucial for understanding the existing landscape of quadrotor UAV control systems. The literature review systematically examines a wide range of sources, including peer-reviewed journal articles, conference papers, and technical reports, focusing on the strengths and limitations of various control strategies such as PID control, LQR, and advanced methods like fuzzy logic and neural networks. Through this review, the research identifies key gaps in current methodologies, such as the challenges of dealing with nonlinearity, multi-variable coupling, and external disturbances in UAV systems. This qualitative analysis not only provides a theoretical framework for the project but also highlights the specific areas where the proposed PSO-RBF neural network adaptive sliding mode controller can offer significant improvements.

Following the qualitative analysis, the research employs rigorous quantitative methods to evaluate the performance of the proposed control strategy. The primary tool for this evaluation is simulation, which is conducted using high-fidelity models of quadrotor UAV dynamics. These models are constructed based on the Newton-Euler equations, which capture the nonlinear, coupled behavior of the UAV system. The simulations are designed to test the controller under a variety of conditions, including different flight trajectories, varying payloads, and the

presence of environmental disturbances such as wind gusts. Key performance metrics, such as response time, trajectory tracking accuracy, and robustness against disturbances, are quantitatively measured. The quantitative analysis also involves a comparative study where the performance of the PSO-RBF controller is benchmarked against traditional control methods, including PID and LQR controllers. Statistical tools, such as variance analysis and hypothesis testing, are used to ensure that the observed improvements are statistically significant and not due to random variations.

To ensure that the research findings are robust and comprehensive, a mixed-methods approach is employed, integrating the insights gained from the qualitative literature review with the empirical data obtained from quantitative simulations. The mixed-methods approach allows the research to address the problem from multiple angles. The qualitative analysis provides a deep contextual understanding of the challenges in UAV control, particularly the limitations of existing methods in handling complex, real-world scenarios. This understanding informs the design of the PSO-RBF controller, ensuring that it addresses the specific weaknesses identified in the literature. The quantitative simulations then provide empirical evidence that the proposed controller not only meets theoretical expectations but also outperforms existing strategies in practical, simulated environments. This combination of qualitative and quantitative methodologies ensures that the research conclusions are well-founded, addressing both the theoretical and practical aspects of UAV control.

The use of a mixed-methods approach in this project also facilitates a more nuanced interpretation of the results. For instance, if the quantitative simulations reveal unexpected behaviors or suboptimal performance in certain scenarios, the qualitative insights from the literature review can help explain these findings, potentially leading to further refinement of the control strategy. Conversely, the empirical data from the simulations can validate or challenge the theoretical assumptions identified in the qualitative analysis, leading to a more iterative and dynamic research process. This iterative feedback loop between qualitative and quantitative methods is a hallmark of the research methodology, ensuring that the final control strategy is both theoretically sound and empirically validated.

In conclusion, the research methodologies employed in this project are carefully chosen to provide a rigorous and comprehensive approach to developing and validating an advanced control system for quadrotor UAVs. The qualitative analysis establishes a strong theoretical foundation, while the quantitative methods provide detailed empirical validation. The integration of these approaches through a mixed-methods strategy ensures that the research is both deeply informed by existing knowledge and rigorously tested in simulated environments, leading to robust and reliable conclusions.

3.2.4 PHILOSOPHIES

In this research, the philosophical stance of post-positivism is deeply integrated into both the experimental design and the data analysis processes. Post-positivism, as a continuation and refinement of traditional positivism, acknowledges the complexity of observing and understanding phenomena in a fully objective manner. It recognizes that while scientific inquiry strives for objectivity, complete elimination of bias is unattainable. Therefore, post-positivism emphasizes the importance of critical reflection, rigorous empirical testing, and iterative refinement of hypotheses and theories.

The post-positivist philosophy significantly influences the experimental design of this research. Given the complex, nonlinear dynamics of quadrotor UAVs, the design of experiments under this philosophical stance involves the systematic testing of hypotheses through controlled simulations and empirical observations. For instance, when developing the PSO-RBF neural network adaptive sliding mode controller, the research does not assume that the theoretical design will perform optimally in all conditions. Instead, it is subjected to extensive testing across a range of scenarios, including varying environmental conditions and different UAV operational modes. This approach allows the research to move beyond theoretical assumptions and focus on how the controller performs under realistic and potentially challenging conditions.

Moreover, the experimental design under post-positivism incorporates iterative testing and feedback loops. This means that initial experimental results are

critically analyzed, and based on these findings, the controller design is refined and improved. This iterative process is a hallmark of post-positivism, as it acknowledges the provisional nature of knowledge and the necessity of continual refinement through empirical testing. The use of high-fidelity simulations and controlled experiments ensures that the research systematically tests the performance of the controller, while also allowing for the discovery of unexpected behaviors or limitations that can inform further iterations of the design.

Maintaining objectivity and scientific rigor is central to the post-positivist approach, particularly in the data analysis phase of the research. To uphold these principles, the research employs a variety of strategies designed to minimize bias and ensure that the conclusions drawn are robust and reliable. For example, all simulation results are subjected to statistical analysis, where variance, confidence intervals, and significance testing are used to assess the reliability of the observed outcomes. These methods are crucial for determining whether the improvements offered by the PSO-RBF controller are statistically significant compared to traditional controllers or if they could be attributed to random variations.

Furthermore, the data analysis process incorporates cross-validation techniques, where the results from different simulation runs or different experimental setups are compared to identify consistent patterns or discrepancies. This method helps to ensure that the findings are not an artifact of a specific experimental condition but are representative of the controller's general performance. Additionally, the research employs sensitivity analysis to examine how changes in model parameters or environmental conditions affect the controller's performance. This approach is aligned with the post-positivist philosophy, which advocates for a comprehensive understanding of how various factors influence research outcomes, thus contributing to the overall objectivity and reliability of the study.

In the context of post-positivism, objectivity is also maintained by recognizing and addressing the potential sources of bias. This includes being transparent about the limitations of the simulation models used, the assumptions made during the experimental design, and the possible influence of these factors on the results. By acknowledging these limitations, the research remains open to critical scrutiny and

further refinement, which is a key aspect of maintaining scientific rigor within the post-positivist framework.

In summary, the application of post-positivism in this research is evident in the careful design of experiments and the meticulous approach to data analysis. The iterative testing and refinement process, along with rigorous statistical and cross-validation techniques, ensures that the research outcomes are both objective and scientifically valid. This philosophical stance allows the research to produce findings that are not only theoretically sound but also empirically robust, contributing to a deeper and more reliable understanding of quadrotor UAV control systems.

3.2.5 APPROACH

The research approach adopted in this project is a carefully considered combination of methodologies designed to comprehensively address the complexities of quadrotor UAV control. This approach integrates both single-method and multi-method strategies to leverage the strengths of each, ensuring that the research is both theoretically rigorous and empirically validated.

A significant component of this research is the use of a single-method approach centered around simulation-based research. Given the inherent complexities and risks associated with real-world quadrotor UAV testing, particularly in the initial stages of controller development, high-fidelity simulations are employed as a primary tool for evaluating control strategies. The use of simulations allows for a controlled environment where various scenarios, including extreme conditions and potential system failures, can be safely tested without the associated risks of physical experiments. This approach is crucial for understanding how the proposed PSO-RBF neural network adaptive sliding mode controller behaves under different operational conditions, providing a platform for extensive testing and refinement before any real-world application.

The decision to focus on simulation-based research is driven by several factors. First, simulations offer the flexibility to model a wide range of conditions that would be difficult, dangerous, or costly to replicate in real life. This includes testing the

UAV's response to sudden gusts of wind, sensor failures, or rapid changes in payload. Second, simulations provide a repeatable and consistent testing environment, which is essential for systematically evaluating the performance of the control strategies and making objective comparisons with existing methods like PID control. By using simulations, the research ensures that the development of the controller is grounded in a thorough understanding of the UAV's dynamic behavior, leading to a more robust and reliable design.

In addition to the single-method simulation approach, this research also employs a multi-method strategy that combines theoretical analysis with empirical validation. The theoretical analysis component involves the development of mathematical models that describe the dynamics of the quadrotor UAV and the design principles behind the PSO-RBF controller. This includes deriving the equations of motion using Newton-Euler formalism, developing the structure of the RBF neural network, and optimizing the controller parameters using the PSO algorithm. These models form the theoretical foundation of the research, providing critical insights into the expected behavior of the UAV and the controller's operation.

The theoretical analysis is complemented by empirical validation, primarily through simulation experiments. After developing the theoretical models, these models are implemented in a simulation environment to evaluate their real-world applicability. This multi-method approach ensures that the research is not purely theoretical but is grounded in empirical data that verifies the effectiveness of the proposed solutions. The combination of these methods allows for a comprehensive assessment of the controller's performance, ensuring that the final design is both theoretically sound and practically viable.

The choice to employ both single-method and multi-method approaches is strategic and aligns with the project's specific goals. The simulation-based single-method approach provides a controlled environment for rigorous testing and refinement of the control strategy, which is critical during the early development stages. The integration of theoretical analysis and empirical validation through a multi-method approach further strengthens the research by ensuring that the

theoretical foundations are backed by empirical evidence. This dual approach allows the research to achieve its objectives of developing a robust, high-performance controller for quadrotor UAVs that can be confidently transitioned from the simulation phase to real-world applications.

In conclusion, the research approach in this project is a carefully crafted combination of single-method and multi-method strategies. The simulation-based research provides a safe and controlled testing ground, while the integration of theoretical analysis with empirical validation ensures that the proposed solutions are both theoretically rigorous and practically effective. This comprehensive approach is essential for addressing the complex challenges associated with quadrotor UAV control and for achieving the project's goal of developing an advanced control system that is both innovative and reliable.

3.2.6 STRATEGIES

To achieve the objectives of this project, a set of carefully devised strategies has been implemented. These strategies are tailored to systematically address the research challenges and ensure that the development of the improved PSO-RBF neural network adaptive sliding mode controller is both innovative and effective. The key strategies include conducting a comprehensive literature review to identify research gaps, employing an improved PSO-RBF algorithm to optimize the controller design, and using advanced simulation techniques to validate the controller's performance.

The first strategic step involves conducting an exhaustive literature review to establish a solid foundation for the project. This review systematically examines a wide range of academic sources, including peer-reviewed journal articles, conference proceedings, and technical reports, focusing on the current state of research in quadrotor UAV control systems. By critically analyzing existing control strategies such as PID, LQR, and neural networks, the review identifies their limitations in handling the nonlinear dynamics and external disturbances typical of quadrotor UAVs. Furthermore, the review highlights areas where traditional methods fall short, particularly in terms of adaptability and robustness. This

analysis identifies the specific gaps that the improved PSO-RBF controller is designed to address, providing clear justification for the development of a more advanced control approach.

The second strategy focuses on developing and applying the improved PSO-RBF algorithm for optimizing the controller's performance. This hybrid approach integrates Particle Swarm Optimization (PSO) with a Radial Basis Function (RBF) neural network to create an adaptive control system that can dynamically respond to the complex, nonlinear behavior of quadrotor UAVs. The improved PSO-RBF algorithm incorporates enhancements in both the PSO and RBF components. For instance, the PSO algorithm is adapted to better explore the solution space, while the RBF network is optimized to enhance its ability to approximate nonlinear functions with high accuracy. The PSO-RBF algorithm is specifically designed to fine-tune the parameters of the RBF neural network, such as the centers, widths, and output weights, ensuring that the controller can achieve optimal performance under various operational conditions. This strategy is crucial for enhancing the controller's adaptability and robustness, which are essential for effective quadrotor UAV control in dynamic environments.

The third strategy involves the rigorous validation of the improved PSO-RBF controller through simulation. High-fidelity simulations are employed to replicate the real-world conditions under which the quadrotor UAV operates, including the presence of external disturbances such as wind gusts and sensor noise. These simulations are designed to evaluate the controller's performance across a range of metrics, including stability, response time, and robustness. By simulating various flight scenarios, the research ensures that the controller is thoroughly tested and capable of maintaining optimal performance in different environments. This simulation-based validation is a critical step in confirming the effectiveness of the improved PSO-RBF algorithm and provides valuable insights for any necessary refinements before potential real-world implementation.

In the development and application of the improved PSO-RBF algorithm, extensive testing is conducted to fine-tune both the PSO and RBF components. The optimization process involves multiple iterations and sensitivity analyses to

ensure that the algorithm achieves the desired balance between exploration and exploitation, leading to an optimal configuration of the RBF neural network. This process is carefully monitored to avoid common pitfalls such as premature convergence or overfitting, ensuring that the final controller design is robust and generalizable.

3.2.7 CHOICES

In the course of this research, several critical decisions were made, each playing a significant role in shaping the direction and outcomes of the study. These choices were carefully considered based on the specific challenges posed by quadrotor UAV control and the overarching goals of the project. Among these decisions, the selection of the PSO-RBF neural network as the core control strategy stands out as one of the most impactful.

The decision to employ a PSO-RBF neural network adaptive sliding mode controller was driven by the complex and nonlinear nature of quadrotor UAV dynamics. Traditional control methods, such as PID and LQR controllers, while effective in certain linear and less complex systems, often fall short when applied to systems like quadrotors, which exhibit strong coupling effects, high degrees of freedom, and susceptibility to external disturbances. The PSO-RBF neural network was chosen specifically for its ability to address these challenges.

The Radial Basis Function (RBF) neural network is known for its strong capability in approximating nonlinear functions, making it an ideal choice for capturing the intricate dynamics of a quadrotor UAV. However, RBF networks require careful tuning of parameters such as center vectors, widths, and output weights to perform optimally. This is where the integration of Particle Swarm Optimization (PSO) becomes critical. PSO is an optimization algorithm inspired by the social behavior of birds flocking or fish schooling, and it excels at searching large, complex spaces for optimal solutions. By integrating PSO with the RBF neural network, the research leverages PSO's ability to efficiently optimize the parameters of the RBF network, thus enhancing the controller's adaptability and performance.

The choice of a PSO-RBF neural network was informed by several key considerations. Firstly, the need for a control system that could adapt to varying conditions and uncertainties in real-time was paramount. Quadrotor UAVs operate in dynamic environments where factors such as wind speed, payload variations, and sensor noise can significantly impact performance. The adaptive nature of the PSO-RBF neural network allows the controller to adjust its parameters in response to these changes, ensuring stable and reliable operation under diverse conditions.

Secondly, the decision was influenced by the limitations observed in other control methods during the literature review phase. While methods like fuzzy logic controllers and conventional neural networks offer some level of adaptability, they often require extensive manual tuning or lack the ability to efficiently handle high-dimensional optimization problems. The PSO-RBF approach addresses these limitations by automating the optimization process and providing a more robust solution that can be applied to a wider range of scenarios.

The choice to use the PSO-RBF neural network as the control strategy had significant implications for the research outcomes. This decision directly influenced the design of the experiments, the nature of the simulations conducted, and the overall direction of the project. By focusing on a control strategy that combines the strengths of RBF neural networks and PSO, the research was able to develop a controller that is both theoretically robust and practically effective.

The integration of PSO with the RBF network led to notable improvements in the controller's performance, particularly in terms of its ability to maintain stability and accuracy in the presence of disturbances. This adaptability was evidenced in the simulation results, where the PSO-RBF controller consistently outperformed traditional control methods in scenarios involving sudden changes in environmental conditions or system parameters. The success of this control strategy not only validated the initial choice but also highlighted the potential for further developments and applications in more complex UAV systems or other areas requiring adaptive control.

Furthermore, the choice of the PSO-RBF neural network facilitated the achievement of the project's goals by providing a scalable solution that could be adjusted and improved as new challenges or requirements emerged. This flexibility ensured that the research remained relevant and capable of addressing future developments in UAV technology.

In conclusion, the choice of the PSO-RBF neural network as the central control strategy was a critical decision that shaped the entire research process. This decision was grounded in a thorough understanding of the challenges posed by quadrotor UAV control and the limitations of existing methods. The successful implementation of this strategy not only contributed to the project's immediate goals but also set the stage for future advancements in adaptive control systems. The impact of this choice on the research outcomes underscores the importance of carefully considering the theoretical and practical implications of each decision made during the research process.

3.2.8 TIME HORIZONS

The time framework of this research was meticulously planned to ensure a systematic and thorough investigation of the proposed PSO-RBF neural network adaptive sliding mode controller. The research was structured into several key phases, each with specific objectives and milestones, allowing for a gradual and comprehensive exploration of the control system's design, implementation, and validation.

The research was divided into sequential phases, each focusing on different aspects of the controller's development and testing. Initially, the project began with an extensive literature review and theoretical groundwork, which provided the necessary foundation for the subsequent stages. Following this, the project moved into the design and development phase, where the PSO-RBF controller was formulated and initial parameter settings were established.

After the design phase, the research entered a critical simulation phase, where the controller was subjected to a series of tests under various simulated conditions. This phase was carefully timed to allow for iterative development, where the

results from early simulations informed refinements to the controller's design. By breaking the simulation phase into multiple stages, the research could progressively introduce more complex scenarios, starting with basic stability tests and moving towards more challenging conditions, such as high turbulence or rapid payload changes. This approach ensured that the controller's performance was thoroughly evaluated at each stage before advancing to more complex scenarios.

Data collection and analysis were strategically aligned with the phased approach of the research. At each stage of the simulation and testing process, data were collected systematically to provide insights into the controller's performance. For instance, during the initial simulation runs, data were focused on basic metrics such as response time, stability margins, and control accuracy. These early results were used to adjust the PSO algorithm and RBF neural network parameters, optimizing the controller's performance before moving to more complex tests.

As the simulations progressed, the scope of data collection expanded to include more detailed metrics, such as the controller's robustness to external disturbances, adaptability to varying flight conditions, and overall efficiency. At each key milestone, comprehensive data analysis was conducted to assess the controller's performance against the project's objectives. This analysis involved both quantitative methods, such as statistical testing and variance analysis, and qualitative assessments based on observed behaviors in the simulations. The iterative process of data collection and analysis ensured that each stage of the research built upon the findings of the previous stages, leading to a robust and well-validated final controller design.

To further ensure the reliability of the research results, data from different time points were cross-validated. For example, the results from early-stage stability tests were compared with later-stage robustness tests to verify consistency in the controller's performance. Any discrepancies identified through this cross-validation process were thoroughly investigated, leading to further refinements in the controller design or adjustments in the simulation models.

The timing of data collection and analysis played a crucial role in ensuring the reliability of the research outcomes. By structuring the research into distinct phases with clear objectives, the study maintained a focus on systematic validation at each step. This approach minimized the risk of overlooked errors or untested assumptions, as each phase provided an opportunity to refine and validate the controller's design.

Moreover, the use of iterative testing allowed for continuous improvement of the controller throughout the research process. Each round of simulation provided new data that contributed to a deeper understanding of the controller's strengths and weaknesses, leading to a more refined and reliable final product. The phased approach also facilitated the identification of potential issues early in the process, allowing for timely adjustments and ensuring that the research stayed on track to meet its objectives.

In conclusion, the time framework of this research was designed to support a structured and iterative development process, with careful attention given to the timing of data collection and analysis. By aligning these activities with the phased progression of the research, the study was able to ensure the reliability and robustness of the final PSO-RBF neural network adaptive sliding mode controller, providing confidence in the research outcomes and their potential real-world applicability.

3.2.9 TECHNIQUES AND PROCEDURES

This section details the specific techniques and procedures utilized in this research to develop, optimize, and validate the PSO-RBF neural network adaptive sliding mode controller for quadrotor UAVs. The research was structured around a series of methodical steps, each of which was critical to ensuring that the proposed control strategy was both effective and reliable in a variety of operational conditions.

The first and foundational step in this research was the development of a comprehensive dynamic model of the quadrotor UAV. This model was essential

for accurately simulating the UAV's behavior under a wide range of conditions and served as the basis for the design and testing of the controller. The dynamic model was derived using the Newton-Euler formalism, which is well-suited for capturing the complex, nonlinear dynamics inherent to quadrotor systems.

In constructing the model, the UAV was treated as a rigid body, subject to forces and moments generated by the four rotors. The equations of motion were derived in terms of the UAV's translational and rotational dynamics. The translational dynamics describe the movement of the UAV in three-dimensional space, considering forces such as gravity, thrust, and aerodynamic drag. The rotational dynamics, on the other hand, govern the UAV's orientation or attitude, described by pitch, roll, and yaw angles, and include the effects of gyroscopic moments and aerodynamic torques. The model also incorporated rotor dynamics, accounting for the rotor thrust coefficients, drag coefficients, and the aerodynamic efficiency losses that occur at different rotor speeds.

To ensure accuracy, the model included various external disturbances such as wind gusts, modeled as a combination of stochastic and deterministic components. The wind effects were represented using a Dryden turbulence model, which simulates atmospheric turbulence over time, providing a realistic and time-varying disturbance input. The comprehensive nature of this model allowed for precise simulation of the UAV's behavior under diverse and challenging operational conditions, laying the groundwork for the subsequent controller design.

Once the dynamic model was established, the next step involved the design and optimization of the PSO-RBF neural network adaptive sliding mode controller. The controller design was based on an RBF neural network structure due to its strong ability to approximate nonlinear functions and handle the UAV's complex dynamics. The RBF network was structured with three layers: an input layer, a hidden layer composed of radial basis functions, and an output layer that provided the control signals to the UAV actuators.

The hidden layer consisted of neurons with Gaussian activation functions, where each neuron's output was determined by the distance between the input vector and a center vector, modulated by a width parameter. The output of the network was a weighted sum of the activations of these neurons, with the weights being adjustable parameters that determine the network's output. The adaptive sliding mode control (SMC) framework was integrated into this neural network to enhance the robustness of the controller, particularly in the presence of model uncertainties and external disturbances. The SMC component ensured that the UAV's state trajectory would converge to a desired sliding surface, thereby achieving stable and accurate control despite variations in the system dynamics.

Optimization of the RBF network parameters—specifically, the center vectors, widths, and output weights—was conducted using an enhanced Particle Swarm Optimization (PSO) algorithm. The PSO algorithm was chosen for its efficiency in searching high-dimensional, complex parameter spaces and its ability to avoid local minima. To further improve the PSO algorithm's performance, several modifications were introduced. An adaptive inertia weight strategy was implemented, where the inertia weight was adjusted dynamically based on the swarm's convergence behavior, allowing the algorithm to balance exploration and exploitation more effectively. Additionally, a velocity clamping mechanism was employed to prevent particles from overshooting optimal solutions, and a constriction factor was introduced to enhance convergence stability. The optimization process involved multiple iterations, with each iteration consisting of a full run of the simulation to evaluate the performance of the current set of RBF network parameters. The objective function for the PSO optimization was defined as a weighted sum of various performance metrics, including the mean squared error (MSE) of the trajectory tracking, the control effort (to minimize energy consumption), and the robustness to disturbances (measured by the system's response to simulated wind gusts). By iteratively adjusting the parameters and refining the network, the PSO algorithm successfully optimized the RBF neural network, resulting in a controller that was both robust and highly responsive to the quadrotor UAV's dynamic environment.

Following the design and optimization of the controller, extensive simulation testing was conducted to evaluate its performance under realistic operating conditions. The simulations were implemented in MATLAB/Simulink, a powerful platform for modeling, simulating, and analyzing dynamic systems. The quadrotor UAV model, along with the optimized PSO-RBF controller, was integrated into the simulation environment, where various flight scenarios were tested.

Key parameters for the simulations were meticulously set to reflect real-world conditions. For example, the UAV's mass, moments of inertia, rotor thrust and drag coefficients, and other physical properties were based on realistic values commonly found in commercial quadrotor platforms. The simulation environment was configured to simulate a variety of conditions, including standard flight operations (takeoff, hovering, trajectory tracking, and landing) as well as more challenging scenarios involving external disturbances (e.g., wind gusts generated by the Dryden turbulence model), sudden payload changes, and sensor noise modeled as Gaussian white noise.

Each flight scenario was simulated multiple times to ensure consistency and reliability of the results. The time step of the simulation was chosen to be 0.001 seconds, which provided sufficient resolution to capture the UAV's rapid dynamics while maintaining computational efficiency. The total simulation time varied depending on the scenario, with longer durations for more complex maneuvers like trajectory tracking over extended distances or complex obstacle avoidance tasks.

Throughout the simulation process, data were systematically collected to assess the performance of the PSO-RBF controller. Key performance metrics included position and attitude errors, control input signals, system response times, energy consumption, and robustness against disturbances. Data were logged at each simulation time step, enabling detailed post-simulation analysis.

The collected data were analyzed using both time-domain and frequency-domain techniques. In the time domain, metrics such as rise time, settling time, and

overshoot were calculated to assess the system's responsiveness and stability. Additionally, the Root Mean Square Error (RMSE) was used to quantify the accuracy of the UAV's trajectory tracking. In the frequency domain, Bode and Nyquist plots were generated to evaluate the controller's stability margins and its ability to reject disturbances at different frequencies. These analyses provided a comprehensive understanding of how the controller performed across a broad range of conditions.

To further ensure the robustness of the controller, sensitivity analyses were conducted to examine how variations in the RBF network parameters (such as center positions and widths) and PSO algorithm settings (such as swarm size and inertia weight) affected overall system performance. This allowed the identification of critical parameters that had the most significant impact on control outcomes, guiding further refinements of the controller design.

In summary, the techniques and procedures employed in this research were meticulously designed to ensure the successful development, optimization, and validation of the PSO-RBF neural network adaptive sliding mode controller. From the detailed dynamic modeling of the quadrotor UAV to the sophisticated optimization process using an enhanced PSO algorithm, and from the rigorous simulation testing to the comprehensive data analysis, each step was executed with precision. This rigorous approach ensured that the final controller design was not only theoretically robust but also practically viable, providing a reliable solution for the complex task of quadrotor UAV control.

3.3 CONCLUSION

The choice of the PSO-RBF neural network as the core control strategy was central to the project, driven by the need for a controller capable of managing the nonlinear and dynamic nature of quadrotor UAV systems. The methodological approach involved a detailed dynamic modeling of the UAV, followed by the design and optimization of the controller using an enhanced Particle Swarm Optimization algorithm. The integration of these techniques ensured that the controller was not only theoretically sound but also practically viable.

Throughout the project, rigorous simulation testing and data analysis were conducted to validate the effectiveness of the proposed control strategy. By systematically testing the controller under various conditions and scenarios, the research ensured that the final design was robust, reliable, and capable of handling the diverse challenges encountered in real-world UAV operations.

In summary, this project employed a methodologically rigorous approach that combined advanced control theory with practical simulation techniques. The strategic choices made, such as the adoption of the PSO-RBF neural network and the use of iterative, empirical testing, were critical to the success of the project. These methodologies not only facilitated the development of a highly effective control system for quadrotor UAVs but also contributed valuable insights to the broader field of UAV control and adaptive systems.

CHAPTER 4 - DESIGN & IMPLEMENTATION

4.1 INTRODUCTION

This chapter focuses on the design and optimization of the control systems for quadrotor UAVs, with a particular emphasis on the PSO-RBF neural network adaptive sliding mode controller. The chapter begins by providing an overview of traditional PID control systems, discussing their design and the process of tuning parameters to achieve optimal performance. This foundation is necessary to establish a baseline for comparison with more advanced control strategies.

Following this, the chapter introduces more sophisticated methods, such as the Radial Basis Function (RBF) neural network, and explores their application in controlling nonlinear systems. The integration of Particle Swarm Optimization (PSO) with the RBF neural network is then presented, demonstrating how this hybrid approach can be used to enhance the controller's adaptability and robustness. The chapter concludes with a comprehensive design process for the PSO-RBF neural network adaptive sliding mode controller, highlighting the technical innovations that enable significant improvements in quadrotor UAV control performance.

4.2 PROBLEM FORMULATION

The problem formulation for this research begins with a clear identification of the challenges associated with controlling quadrotor UAVs, which are inherently nonlinear, strongly coupled, and sensitive to external disturbances. Traditional control methods, such as PID controllers, often struggle to maintain stability and accuracy under these conditions, particularly when the UAV is subject to rapidly changing environments or unexpected disturbances. This inadequacy necessitates the development of a more robust and adaptive control strategy.

In this context, the proposed solution involves the design of a hybrid control system that integrates a Radial Basis Function (RBF) neural network with an adaptive sliding mode control (SMC) framework. The RBF neural network is selected for its strong capability to approximate nonlinear functions, which is essential for capturing the complex dynamics of the quadrotor UAV. However, to optimize the performance of the RBF network, its parameters—such as the centers, widths, and output weights—need to be finely tuned. This tuning process is achieved through the application of Particle Swarm Optimization (PSO), an algorithm well-suited for navigating high-dimensional optimization problems.

The resulting PSO-RBF neural network adaptive sliding mode controller aims to address the specific challenges identified, providing a control strategy that is both adaptive and robust. The formulation of this problem thus sets the stage for the subsequent design and optimization process, which will involve detailed

simulations to validate the controller's effectiveness across a range of operational scenarios.

4.3 DESIGN

4.3.1 DYNAMIC MODELING OF QUADROTOR UAV

The coordinate systems required for quadrotor modeling can be described as two coordinate systems shown in Figure 1: the airframe coordinate system (O_bxyz) with the origin fixed on the quadrotor fuselage and the geodetic coordinate system (O_eXYZ) with the origin fixed on the ground. For the top view of the quad rotor shown in Figure 1, the forward direction of the quad rotor is selected as the forward direction of the X -axis of the body coordinate system, the counterclockwise 90° direction of the quad rotor is selected as the forward direction of the Y -axis, and the Z -axis is selected as the positive direction according to the right-hand rule. Similarly, the geodetic coordinate system determines the positive directions of the X , Y , and Z axes respectively according to the East, north, and sky.

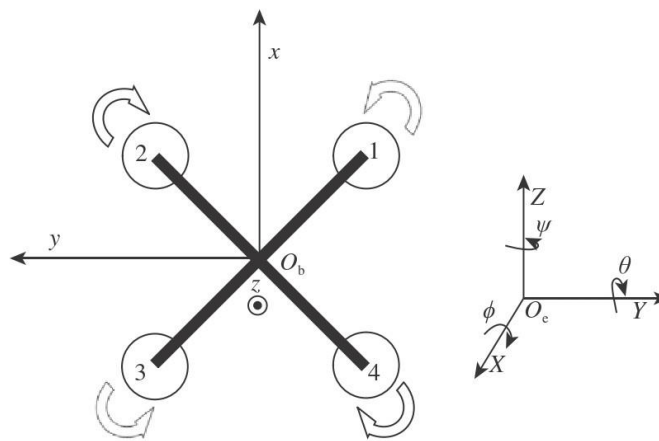


Fig. 1 Coordinate system and quadrotor model

The attitude angle of the quadrotor is defined in the geodetic coordinate system to describe the attitude of the quadrotor. Wherein, the roll angle ϕ is defined as the angle between the projection of the Y axis on the YO_eZ plane and the Y -axis; The elevation angle θ is defined as the angle between the projection of the Z axis on

the XO_eZ plane and the Z axis; The yaw angle ψ is defined as the angle between the projection of the X axis on the XO_eY plane and the X -axis. In order to facilitate dynamic modeling, the following assumptions are made in this design:

- 1) In order to simplify the calculation of the moment of inertia in the model, it is assumed that the quadrotor aircraft is a strictly symmetrical rigid body structure, and its center of gravity is consistent with the center and located at the geometric center of the body.
- 2) The quadrotor flies at low altitude, low speed and small angle. The gravity is constant, and its attitude angle changes very little (usually less than 5°), which can simplify the Euler equation.
- 3) Because the adjacent motors of the four rotors are reversed to each other, the influence of the gyroscopic effect of the motor can be offset. The gyroscopic moment of the four rotors is very small and can be ignored. At the same time, all kinds of internal friction and energy loss are ignored.
- 4) According to the blade element momentum theory and aerodynamic experiments, the lift and anti torque moment generated by each rotor of the four rotors are proportional to the square of the rotor speed.
- 5) Relevant literature shows that the external resistance of the quadrotor is proportional to the linear velocity.

U_1, U_2, U_3, U_4 is defined as four independent control quantities of quadrotor UAV, $\omega_i (i = 1, 2, 3, 4)$ is the speed of four motors, then

$$\begin{cases} U_1 = K_1 \omega_1^2 + K_1 \omega_2^2 + K_1 \omega_3^2 + K_1 \omega_4^2 \\ U_2 = -K_1 \omega_1^2 + K_1 \omega_2^2 + K_1 \omega_3^2 - K_1 \omega_4^2 \\ U_3 = -K_1 \omega_1^2 - K_1 \omega_2^2 + K_1 \omega_3^2 + K_1 \omega_4^2 \\ U_4 = -K_2 \omega_1^2 + K_2 \omega_2^2 - K_2 \omega_3^2 + K_2 \omega_4^2 \end{cases} \quad (1)$$

In this equation: K_1 is the lift coefficient; K_2 is the anti-torque coefficient.

The dynamic model of the quadrotor drone established by the Newton-Euler method can be expressed as

$$\begin{aligned}
 \ddot{x} &= \frac{(\cos \phi \sin \theta \cos \psi + \sin \phi \sin \psi) U_1}{m} + d_1 \\
 \ddot{y} &= \frac{(\cos \phi \sin \theta \sin \psi - \sin \phi \cos \psi) U_1}{m} + d_2 \\
 \ddot{z} &= \frac{(\cos \phi \cos \theta) U_1}{m} - g + d_3 \\
 \ddot{\phi} &= \frac{\theta \psi (I_{yy} - I_{zz}) + U_2 l}{I_{xx}} + d_4 \\
 \ddot{\theta} &= \frac{\phi \psi (I_{zz} - I_{xx}) + U_3 l}{I_{yy}} + d_5 \\
 \ddot{\psi} &= \frac{\phi \theta (I_{xx} - I_{yy}) + U_4}{I_{zz}} + d_6
 \end{aligned} \tag{2}$$

In this equation: m is the mass of the quadrotor; I_{xx}, I_{yy}, I_{zz} are the moments of inertia of each axis of the quadrotor; $d_i (i = 1, 2, 3, 4, 5, 6)$ is the external interference force on the quadrotor; g is the acceleration of gravity; l is the length of the torque arm.

Formula (2) can be organized into the form of state equation:

$$\begin{cases} \dot{X}_1 = X_2 \\ \dot{X}_2 = f(x) + g(x)u + d \end{cases} \tag{3}$$

In this equation, $X_1 = [x, y, z, \phi, \theta, \psi]^T$, $X_2 = [\dot{x}, \dot{y}, \dot{z}, \dot{\phi}, \dot{\theta}, \dot{\psi}]^T$,

$u = [1, 1, U_1, U_2, U_3, U_4]^T$, $d = [d_1, d_2, d_3 - g, d_4, d_5, d_6]^T$,

$$g(x) = \left[\frac{U_1}{m}, \frac{U_1}{m}, \frac{\cos \phi \cos \theta}{m}, \frac{l}{I_{xx}}, \frac{l}{I_{yy}}, \frac{1}{I_{zz}} \right]^T,$$

$$f(x) = \left[0, 0, 0, \frac{(I_{yy} - I_{zz})\theta\psi}{I_{xx}}, \frac{(I_{zz} - I_{xx})\phi\psi}{I_{yy}}, \frac{(I_{xx} - I_{yy})\phi\theta}{I_{zz}} \right]^T.$$

4.3.2 RBF NEURAL NETWORK ADAPTIVE SLIDING MODE CONTROLLER

The quadrotor is an under-actuated, strongly coupled system with 4 inputs and 6 outputs. It is necessary to design a controller to converge the position/attitude tracking error of the quadrotor to zero in a finite time. The control system of this project adopts the commonly used inner and outer loop control structure. A controller is established as shown in Figure 2. The outer loop is the position

controller of the quadrotor, and the inner loop is the attitude controller of the quadrotor. Through this dual-loop controller, decoupling control of 6 channels can be achieved, improving the robustness of the system.

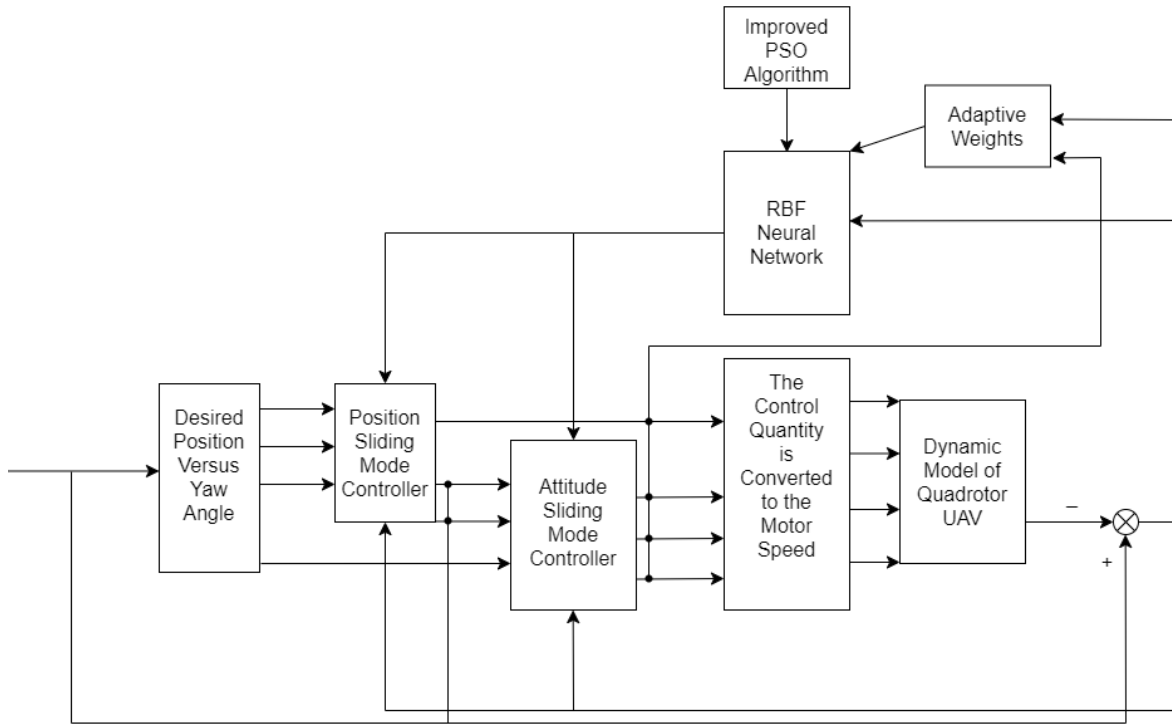


Fig. 2 Control system structure

RBF neural network is a classic three-layer feedforward neural network. Reasonable determination of neuron parameters can approximate any nonlinear function relationship.

The output of the RBF neural network is

$$y(\zeta) = \sum_{i=1}^n w_i h_i(\zeta) \quad (4)$$

In this equation: $y(\zeta)$ is the output of the RBF neural network; n is the number of neurons in the hidden layer; w_i is the connection weight between the i -th neuron in the hidden layer and the neurons in the output layer; $h_i(\zeta)$ is the activation function of the neurons in the hidden layer.

The activation function usually uses a Gaussian function. The closer the input is to the center of the RBF, the larger the output value. In this paper, the Gaussian function is defined as

$$\begin{cases} h_i(\zeta) = e^{\frac{-\|\zeta - \mu_{ni}\|^2}{2\sigma_i^2}} \\ \mu_{ni} = \mu_i[\chi_1, \dots, \chi_n]^T \end{cases} \chi_n \in [-1, 1] \quad (5)$$

In this equation, ζ is the input matrix, μ is the center vector of the hidden layer neuron; σ_i is the width of the i -th hidden layer neuron; $\|\zeta - \mu_{ni}\|$ is the Euclidean distance between the input matrix and the radial basis center.

The position control of the quadrotor can be divided into horizontal position control and height position control. From formula (2), we can see that the height z is controlled by U_1 . The control rate of this channel is designed below.

The state space expression for a known height z is

$$\begin{cases} \dot{z} = \dot{z} \\ \ddot{z} = g_3(x)U_1 - g + d_3 \end{cases} \quad (6)$$

The tracking error is defined as the planned height – the actual height, which is e_3

$$= Z_d - Z$$

Select the following sliding mode control

$$s_3 = \dot{e}_3 + c_3 e_3, \text{ and } c_3 > 0 \quad (7)$$

Setting $\dot{s}_3=0$, the sliding mode control rate can be designed to be equivalent control rate + switching control rate, that is,

$$U_1 = \frac{1}{\hat{g}_3(x)} (\ddot{z}_d + g + c_3 \dot{e}_3 + k_3 \text{sgn}(s_3)) \quad (8)$$

In this equation, $\hat{g}_3(x)$ is the approximation result of the RBF neural network to $g_3(x)$.

Define the input of the neural network as $\zeta_3 = (e_3, \dot{e}_3)^T$, can get

$$\begin{cases} \hat{g}_3(\zeta_3) = \hat{W}_{g_3}^T h_{g_3}(\zeta_3) \\ g_3(\zeta_3) = \hat{W}_{g_3}^T h_{g_3}(\zeta_3) + \varepsilon_{g_3} \end{cases} \quad (9)$$

In this equation, $\hat{W}_{g_3}^T$ is the ideal weight of the network for approximating $g_3(x)$; ε_{g_3} is the approximation error of the network.

The weights in RBF neural networks are usually calculated by gradient descent method, which is prone to local optimal solutions and cannot guarantee the global stability of the closed-loop system. In this project, the Lyapunov method is used to design the adaptive $\tilde{W}_{g_3}^T$.

The Lyapunov function of a closed-loop system is defined as

$$L_3 = \frac{1}{2}s_3^2 + \frac{1}{2}\gamma_{g_3}\tilde{W}_{g_3}^T\tilde{W}_{g_3} \quad (10)$$

Then,

$$\dot{L}_3 = \tilde{W}_{g_3}^T(s_3 h_{g_3}(\zeta_3)U_1 + \gamma_{g_3}\dot{\tilde{W}}_{g_3}) - s_3(\varepsilon_{g_3}U_1 + k_3 \text{sgn}(s_3) + d_3), \quad \tilde{W}_{g_3}^T = \tilde{W}_{g_3} - \hat{W}_{g_3} \quad (11)$$

The adaptive rate is designed as

$$\dot{\tilde{W}}_{g_3} = -\frac{1}{\gamma_{g_3}}s_3 h_{g_3}(x)U_1 \quad (12)$$

In this case, the Lyapunov function becomes: $\dot{L}_3 = -s_3(\varepsilon_{g_3}U_1 + d_3) - k_3|s_3|$, the approximation error is a very small positive real number, make $k_3 \geq |\varepsilon_{g_3}U_1 + d_3|$, can keep $\dot{L}_3 \geq 0$.

In order to reduce the estimation error of RBF neural network, U_1 is used to deduce U_x and U_y . Considering the state equation (2) of the quadrotor, it can be obtained

$$\begin{cases} \ddot{x} = \frac{U_x U_1}{m} + d_1 \\ \ddot{y} = \frac{U_y U_1}{m} + d_2 \end{cases} \quad (13)$$

Using a similar derivation from Equations (6) to (8), the sliding mode control rates U_x and U_y in the x and y directions can be obtained as

$$\begin{cases} U_x = \frac{m}{U_1}(\ddot{x}_d + c_1 \dot{e}_1 + k_{U_x} \text{sgn}(s_1)) \\ U_y = \frac{m}{U_1}(\ddot{y}_d + c_2 \dot{e}_2 + k_{U_y} \text{sgn}(s_2)) \end{cases} \quad (14)$$

It can be obtained from the state equation (2) of the quadrotor that,

$$\begin{bmatrix} U_x \\ U_y \end{bmatrix} = \begin{bmatrix} \sin \psi & \cos \psi \\ -\cos \psi & \sin \psi \end{bmatrix} \begin{bmatrix} \sin \phi \\ \cos \phi \sin \theta \end{bmatrix} \begin{bmatrix} U_x \\ U_y \end{bmatrix} = \begin{bmatrix} \sin \psi & \cos \psi \\ -\cos \psi & \sin \psi \end{bmatrix} \begin{bmatrix} \sin \phi \\ \cos \phi \sin \theta \end{bmatrix} \quad (15)$$

As can be seen from Figure 2, given the reference Angle ψ_d, ϕ_d can be obtained from the formula in the first line of formula (15), and θ_d can be obtained by substituting the result into the formula in the second line and performing a simple triangular transformation.

$$\begin{cases} \phi_d = \arcsin (U_x \sin \psi_d - U_y \cos \psi_d) \\ \theta_d = \arcsin \left(\frac{U_x - \sin \psi_d \cos \psi_d}{\cos \phi_d \cos \psi_d} \right) \end{cases} \quad (16)$$

It is easy to know from equation (2) that attitude control is relatively independent of position control. Taking the roll Angle ϕ as an example, the adaptive sliding mode control rate of RBF neural network is designed. According to formula (2), the state equation of the roll Angle ϕ can be obtained as

$$\begin{cases} \dot{\phi} = \dot{\phi} \\ \ddot{\phi} = f_4(x) + g_4(x)U_2 + d_4 \end{cases} \quad (17)$$

According to the previous derivation process, the sliding mode control rate of RBF neural network can be obtained as

$$U_2 = \frac{1}{\hat{g}_4(x)} (-\hat{f}_4(x) + \ddot{\phi}_d + c_4 \dot{e}_4 + k_4 \text{sgn}(s_4)) \quad (18)$$

The input to the network of righteousness scriptures is $\zeta_4 = (e_4, \dot{e}_4)^T$, then

$$\begin{cases} \hat{g}_4(\zeta_4) = \tilde{W}_{g_4}^T h_{g_4}(\zeta_4) \\ \hat{f}_4(\zeta_4) = \tilde{V}_{f_4}^T h_{f_4}(\zeta_4) \\ g_4(\zeta_4) = \tilde{W}_{g_4}^T h_{g_4}(\zeta_4) + \varepsilon_{g_4} \\ f_4(\zeta_4) = \tilde{V}_{f_4}^T h_{f_4}(\zeta_4) + \varepsilon_{f_4} \end{cases} \quad (19)$$

Substituting Equation (19) into the derivative formula of the sliding mode surface function, can obtain

$$\dot{s}_4 = (\tilde{V}_{f_4}^T h_{f_4}(\zeta_4) - \varepsilon_{f_4}) + (\tilde{W}_{g_4}^T h_{g_4}(\zeta_4) - \varepsilon_{g_4})U_2 - k_4 \text{sgn}(s_4) - d_4 \quad (20)$$

In this equation, $\tilde{f}_4(\zeta_4) = \hat{f}_4(\zeta_4) - f_4(\zeta_4) = \tilde{V}_{f_4}^T h_{f_4}(\zeta_4) - \varepsilon_{f_4}; \tilde{g}_4(\zeta_4) = \tilde{W}_{g_4}^T h_{g_4}(\zeta_4) - \varepsilon_{g_4}$.

Similarly, the Lyapunov method is used to design the adaptive $\dot{\tilde{V}}_{f_4}$ and $\dot{\tilde{W}}_{g_4}$, and the Lyapunov function of the closed-loop system is defined as

$$L_4 = \frac{1}{2}s_4^2 + \frac{1}{2}\gamma_{f_4}\tilde{V}_{f_4}^T\tilde{V}_{f_4} + \frac{1}{2}\gamma_{g_4}\tilde{W}_{g_4}^T\tilde{W}_{g_4}, \gamma_{f_4} > 0, \gamma_{g_4} > 0 \quad (21)$$

Taking the derivative of Equation (21), can obtain

$$\dot{L}_4 = \tilde{V}_{f_4}^T[s_4 h_{f_4}(\zeta_4) + \gamma_{f_4}\dot{\tilde{V}}_{f_4}] + \tilde{W}_{g_4}^T[s_4 h_{g_4}(\zeta_4)U_2 + \gamma_{g_4}\dot{\tilde{W}}_{g_4}] + s[-\varepsilon_{f_4} - \varepsilon_{g_4}U_2 - k_4 \text{sgn}(s_4) - d_4] \quad (22)$$

According to Equation (22), the weight adaptive law of RBF neural network can be designed as

$$\begin{cases} \dot{\tilde{V}}_{f_4} = -\frac{1}{\gamma_{f_4}}s_4 h_{f_4}(\zeta_4) \\ \dot{\tilde{W}}_{g_4} = -\frac{1}{\gamma_{g_4}}s_4 h_{g_4}(\zeta_4)U_2 \end{cases} \quad (23)$$

At this point L becomes: $\dot{L}_4 = -s_4[\varepsilon_{f_4} + \varepsilon_{g_4}U_2 + d_4] - k_4|s_4|$, when $k_4 \geq |\varepsilon_{f_4} + \varepsilon_{g_4}U_2 + d_4|$, then $\dot{L}_4 \leq 0$.

Similarly, the control rates U_3 and U_4 of θ and ψ can be obtained as

$$\begin{cases} U_3 = \frac{1}{\hat{g}_5(\zeta_5)}(-\hat{f}_5(\zeta_5) + \ddot{\theta}_d + c_5\dot{e}_5 + k_5 \text{sgn}(s_5)) \\ U_4 = \frac{1}{\hat{g}_6(\zeta_6)}(-\hat{f}_6(\zeta_6) + \ddot{\psi}_d + c_6\dot{e}_6 + k_6 \text{sgn}(s_6)) \end{cases} \quad (24)$$

The corresponding weight adaptation rate can be designed as

$$\begin{cases} \dot{\tilde{V}}_{f_i} = -\frac{1}{\gamma_{f_i}}s_i h_{f_i}(\zeta_i) \\ \dot{\tilde{W}}_{g_i} = -\frac{1}{\gamma_{g_i}}s_i h_{g_i}(\zeta_i)U_{i-2} \end{cases} \quad i = 5,6 \quad (25)$$

The control rate equations (18) and (24) need to obtain the first and second derivatives of the desired roll Angle ϕ_d and the desired yaw Angle ψ_d , which are difficult to obtain by conventional methods, and can be realized by the following finite-time convergent third-order differentiator

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 \\ \varepsilon^3 \dot{x}_3 = -2^{3/5} \times 4[x_1 - v(t) + (\varepsilon x_2)^{9/7}]^{1/3} - 4(\varepsilon^2 x_3)^{3/5} \end{cases} \quad (26)$$

$v(t)$ is the input signal to be differentiated; in this project, $\varepsilon = 0.1$; x_1 is the tracking value of the input signal; x_2 is the estimate of the first derivative of the signal; x_3 is the estimate of the second derivative of the signal. The initial value of the differentiator is $[x_1(0), x_2(0), x_3(0)] = [0, 0, 0]$.

Aiming at the chattering problem caused by the $\text{sgn}()$ function in the traditional sliding mode control rate, the $\text{san}()$ function is used to replace the $\text{sgn}()$ function by the boundary layer method, then

$$\text{san}(s_i) = \begin{cases} 1 & s_i > \delta \\ \frac{1}{\delta} s_i & |s_i| \leq \delta \\ -1 & s_i < -\delta \end{cases} \quad (27)$$

In this project, the controller is $\varepsilon = 0.1$, and the $\text{san}()$ function is used to reduce the chattering phenomenon of the control rate and significantly improve the control quality.

4.3.3 IMPROVED PSO-RBF NEURAL NETWORK ADAPTIVE SLIDING MODE CONTROLLER

When utilizing RBF neural networks for predicting control rate parameters, it has been observed that the selection of the network's centre value μ_i , width σ_i , and connection weights W_i significantly influences the prediction performance of the network. A judicious selection leads to favorable prediction accuracy, enabling rapid tracking of desired trajectories by quadrotors. Conversely, deviating too far from reasonable values results in a sharp decline in prediction accuracy and an inability for the network to effectively track desired trajectories. Furthermore, the coupling relationship between RBF neural networks used for adjusting attitude control and position control can impact the predictive outcomes.

Given these challenges, taking into account the optimization capabilities of PSO algorithm, it has been decided to apply it to aid in selecting parameters for RBF

neural networks. This is aimed at reducing manual tuning time while further enhancing system response speed.

The general PSO algorithm has poor global search ability, low search precision, weak coordination ability, and is easy to fall into local optimal solution. The introduction of inertia weight can effectively improve the problem of local optimal solution, the common random method and linear method can only change the local problem, through the analysis of RBF neural network, it is found that the premature convergence of particle swarm will lack diversity, make the neuron perception range becomes smaller, the system adjustment time becomes longer. Therefore, combined with RBF neural network, the improved PSO algorithm is selected in this project.

Define the position of the JTH particle of the PSO as

$$b_j = [b_{j,1}, b_{j,2}, \dots, b_{j,D}] \quad (28)$$

The velocity of the JTH particle is

$$v_j = [v_{j,1}, v_{j,2}, \dots, v_{j,D}] \quad (29)$$

In this equation, j is the number of all particles; D is the dimension of the particle, represents the centre value μ_i , width σ_i , and connection weight W_i of the neural network.

The JTH particle is iterates for t times (in order to improve the calculation speed and ensure a certain accuracy, the local optimal solution after multiple experiments is set as the number of iterations (100 times), that is, the individual extreme value is

$$P_{j\text{best}}(t) = [P_{j,1}(t), P_{j,2}(t), \dots, P_{j,D}(t)] \quad (30)$$

The optimal position searched by the whole particle swarm after t iterations is the global optimal solution, that is, the global extremum is

$$G_{\text{best}}(t) = [G_1(t), G_2(t), \dots, G_D(t)] \quad (31)$$

On the premise that the two optimal solutions are found, the velocity and position of the particle are updated according to equation (32):

$$\begin{cases} v_j(t+1) = H(t) + \lambda_1 r_1 [P_{jbest}(t) - b_j(t)] + \\ \lambda_2 r_2 [G_{best}(t) - b_j(t)] \\ b_j(t+1) = b_j(t) + v_j(t+1) \end{cases} \quad (32)$$

In this equation, λ_1 and λ_2 are acceleration constants between [0,2], usually $\lambda_1 = \lambda_2$; r_1 and r_2 are random constants between [0,1]. $H(t)$ is the inertia weight of the particle velocity, which represents the ability of the particle to maintain its original velocity.

The individual and global optimal values of the particles updated by the fitness function are

$$\begin{cases} P_{jbest}(t+1) = \begin{cases} P_{jbest}(t) & f(b_j(t+1)) \geq f(P_{jbest}(t)) \\ b_j(t+1) & \text{other} \end{cases} \\ G_{best}(t+1) = \min[f(P_{jbest}(t+1))] \end{cases} \quad (33)$$

In this project, $g_i(x)$ or $f_i(x)$ of the corresponding control quantity is chosen as the fitness function $f_p(x)$ of the particle to represent the goodness of the result.

Another focus of improving particle swarm optimization is the particle velocity inertia weight $H(t)$. In this project, the particle velocity update weight is defined as

$$H(t) = \left\{ \alpha + \frac{f(G_{best}(t))}{f(b_j(t))} \right\} \{ \beta^{-t} \cdot \text{rand} \cdot v_j(t) \} \quad (34)$$

In this equation, β is the initialization constant, and $\beta = 1.00009$; In this project, $\alpha = 2$ is taken as a predefined constant to improve the global search ability of particles. $L(t) = \{ \beta^{-t} \cdot \text{rand} \cdot v_j(t) \}$ is used to describe the nonlinearity of the strategy, define the diversity of the swarm, and represent the degree of convergence and divergence of particles, which can further balance the global search and local search ability of particles.

According to the basic structure of RBF neural network, the main factors that affect the prediction results of the network are the center value, width and connection weight of the neural network. Therefore, combined with the characteristics of the PSO algorithm itself, the position of the particle is set as

$$b = [\mu_1, \sigma_1, W_1, \mu_2, \sigma_2, W_2, \dots, \mu_k, \sigma_k, W_k] \quad (35)$$

The spatial dimension of the particle is given by

$$D = (2 + n)k \quad (36)$$

In this equation, n is the number of central value variables; k is the input vector dimension.

In order to further use the improved PSO algorithm to minimize the error function of the network, the relative error function between the actual output of the sample and the output of the network is used as the fitness function $f_p(x)$ of the particle swarm:

$$f_p(b_j(t)) = \sqrt{\frac{1}{T} \sum_{j=1}^T (N_d(t) - N(t))^2} \quad (37)$$

In this equation, $N_d(t)$ is the expected result; $N(t)$ is the actual output of the network; T is the number of samples.

In summary, the flow of the adaptive sliding mode control algorithm of the improved PSO-RBF neural network can be obtained, as shown in Figure 3.

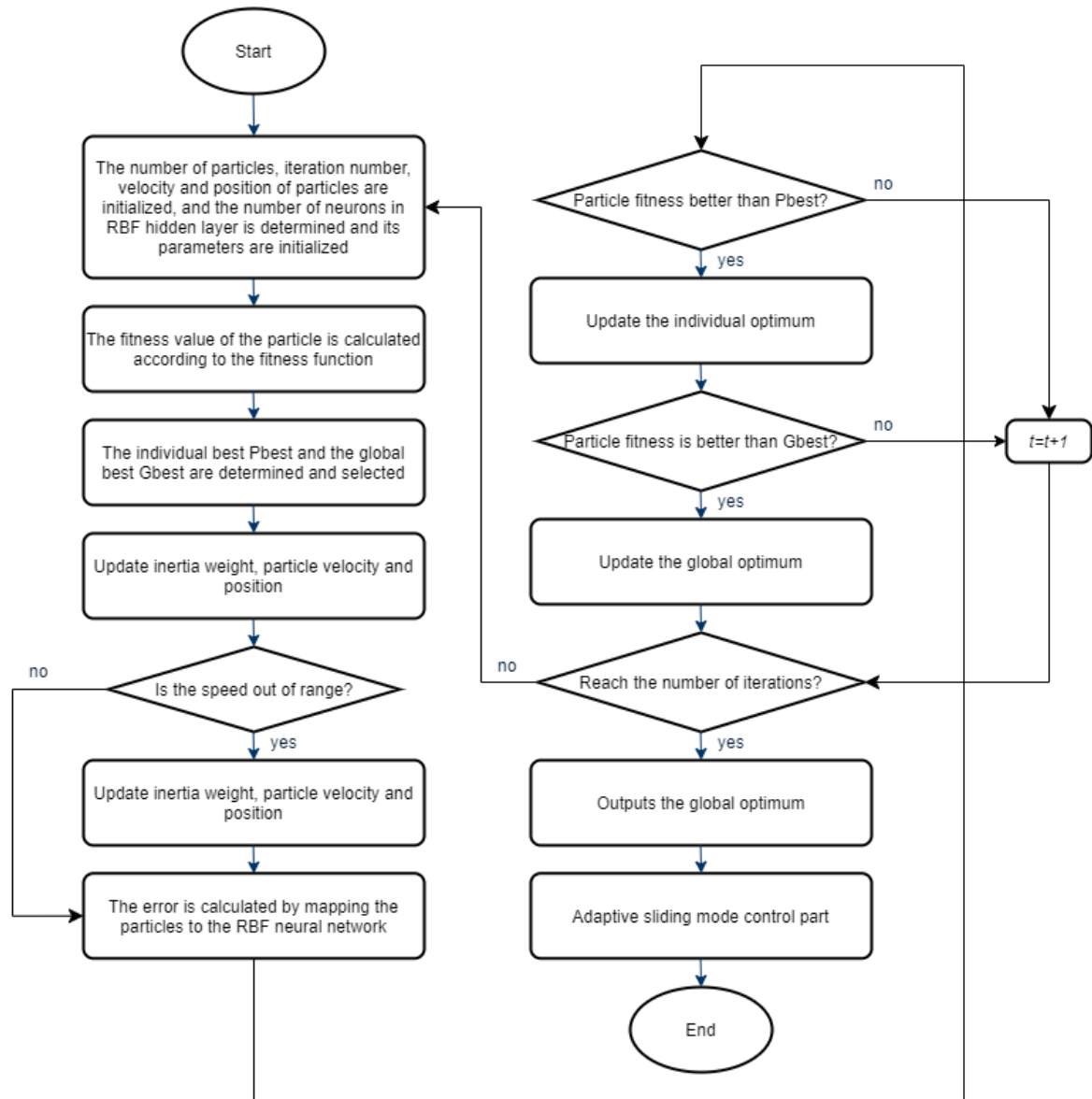


Fig. 3 Flow chart of improved PSO-RBF neural network adaptive sliding mode controller

4.4 EXPERIMENTAL DESIGN

4.4.1 COMPARATIVE EXPERIMENT OF TRAJECTORY TRACKING

Set the desired tracking trajectory in the X, Y, and Z axes $X_d = 0.5t$

$$Y_d = 0.5t, Z_d = \begin{cases} t & 0 \leq t < 10 \\ 10 & t \geq 10 \end{cases}$$

And the desired yaw Angle $\psi_d = 30^\circ$, used to simulate the tracking and fixed altitude flight process of the quadrotor. The three controllers are simulated respectively, and the position and attitude change comparison diagrams are drawn from 0 to 15s. The trajectory tracking performance of the quadrotor was observed under the improved PSO-RBF neural

network adaptive sliding mode controller, RBF neural network adaptive sliding mode controller and the traditional double closed-loop PID controller.

4.4.2 ANTI-JAMMING PERFORMANCE COMPARISON EXPERIMENT

At $t=6s$, an impulse disturbance with an amplitude of $0.9\text{ N}\cdot\text{m}$ and a period of 0.5 Hz was introduced to the roll axis and pitch axis of the quadrotor, and an impulse disturbance with an amplitude of $0.09\text{ N}\cdot\text{m}$ and a period of 0.5 Hz was introduced to the yaw axis. At $t=10s$, Random white noise was introduced to the x , y and z axes of the quadrotor to simulate the interference such as wind disturbance during the flight of the quadrotor, and the three controllers were simulated respectively, and the attitude changes of $6 \sim 15s$ were compared.

4.4.3 ROBUSTNESS COMPARISON EXPERIMENTS

At $t=6s$, the mass of the quadrotor is reduced by 30% to simulate the unloading process of the quadrotor. The three controllers are simulated respectively, and the comparison of the height change in the Z -axis direction before and after $6s$ and the comparison of the change of the control quantity U_1 before and after $6s$ is drawn.

4.5 CONCLUSION

This chapter provided a detailed account of the design, optimization, and validation processes involved in developing the PSO-RBF neural network adaptive sliding mode controller for quadrotor UAVs. The work began with an exploration of traditional control strategies, such as PID controllers, and highlighted their limitations when applied to the complex, nonlinear dynamics of quadrotor UAV systems. This set the stage for the introduction of more advanced methods, particularly the integration of Radial Basis Function (RBF) neural networks with an adaptive sliding mode control (SMC) framework, optimized through Particle Swarm Optimization (PSO).

The chapter then described the meticulous process of designing the PSO-RBF controller, including the careful tuning of the RBF network's parameters using the PSO algorithm. This approach proved effective in addressing the identified challenges, resulting in a control system capable of maintaining stability and accuracy even in the face of significant external disturbances and dynamic changes in the UAV's operating environment.

Simulation testing played a crucial role in validating the performance of the developed controller. The results demonstrated that the PSO-RBF neural network adaptive sliding mode controller outperformed traditional control methods across a range of test scenarios, particularly in terms of robustness and adaptability. The simulations confirmed the controller's ability to manage the complexities of quadrotor UAV control, providing a strong foundation for potential real-world applications.

In conclusion, the chapter showcased the successful development of an advanced control strategy that effectively addresses the limitations of existing methods. The PSO-RBF controller not only enhances the control performance of quadrotor UAVs but also provides a scalable and adaptable solution that can be refined further in future research. This work represents a significant step forward in UAV control technology, with promising implications for both academic research and practical applications.

CHAPTER 5 – TESTING AND EVALUATION

5.1 TRAJECTORY TRACKING COMPARISON

The control system described in the previous section is simulated using Simulink components in MATLAB software, and the actual dynamic parameters of the quadrotor UAV in the experiment are shown in Table 1.

Table 1 *Dynamic parameters of quadrotor*

PARAMETERS	UNIT	VALUES
Coefficient of lift	$K_1/(N \cdot s^2 \cdot rad^{-2})$	9.138×10^{-6}
Inverse torque coefficient	$K_2/(N \cdot m \cdot s^2 \cdot rad^{-2})$	1.368×10^{-7}
The moment of inertia along the x axis	$I_{xx}/(kg \cdot m^2)$	1.762×10^{-2}
The moment of inertia along the Y-axis	$I_{yy}/(kg \cdot m^2)$	1.769×10^{-2}
The moment of inertia along the z axis	$I_{zz}/(kg \cdot m^2)$	2.805×10^{-2}
Quadrotor mass	m/kg	1.311
Length of arm	d/m	0.24

In this project, the PSO algorithm is loaded on the height control and attitude control of the quadrotor, and the PSO algorithm is not added to the position control of the X and Y axes, according to Figure 4. The control effect of the two (improved PSO-RBF neural network adaptive sliding mode controller and RBF neural network adaptive sliding mode controller) is similar to that of the traditional double closed-loop PID controller.

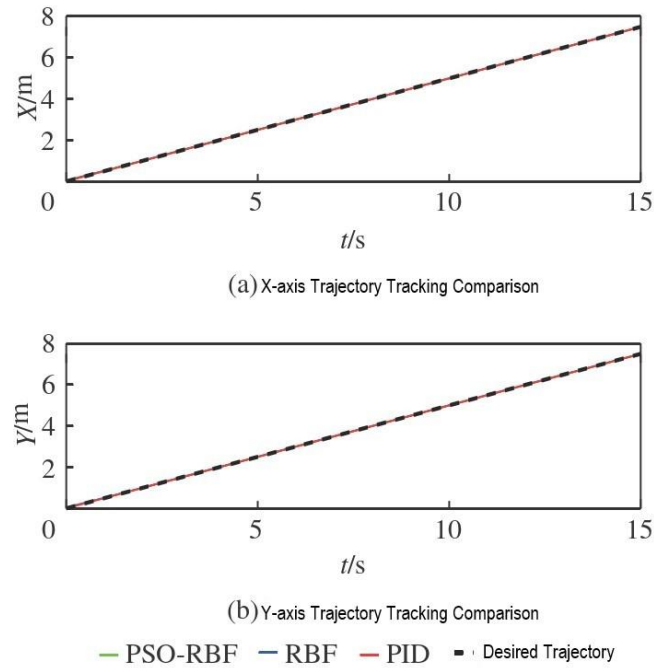


Fig. 4 Comparison of horizontal position trajectory tracking

According to Figure 5 that the control effect of RBF neural network adaptive sliding mode controller and double closed-loop PID controller on the height (Z) is worse than that of the improved PSO-RBF neural network adaptive sliding mode controller. In a very short time, the quadrotor with adaptive sliding mode controller based on improved PSO-RBF neural network can track the upper desired z-direction trajectory almost without error. In the process of 10 s fixed height, the adjustment amount of the quadrotor under the improved PSO-RBF neural network adaptive sliding mode controller is less, and the adjustment time is significantly faster than the other two controllers. It can be expected that the quadrotor controlled by the controller designed in this project will have better results when it is applied to occasions requiring higher tracking accuracy (such as crossing in a narrow area, search and rescue).

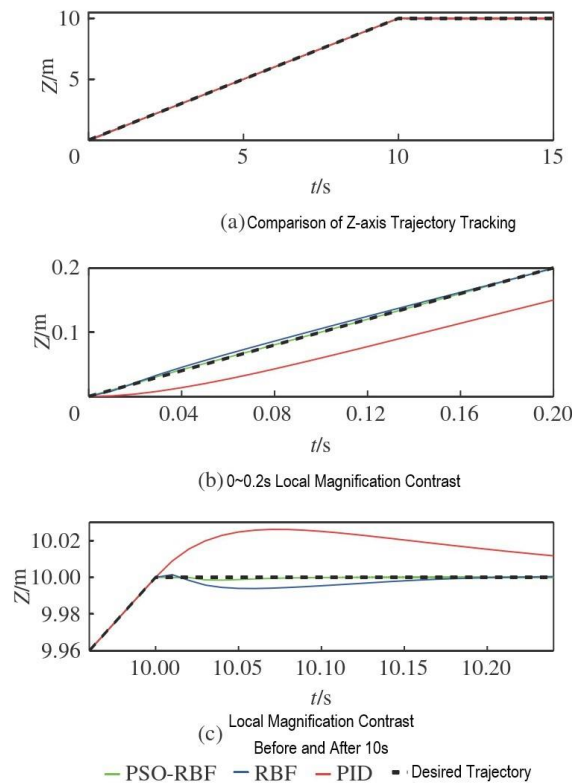


Fig. 5 Comparison of height position trajectory tracking

Table 2 shows the adjustment time of the initial trajectory tracking and the adjustment time of the constant altitude flight of 10s for the three controllers, so that the trajectory tracking performance of the three controllers can be compared more intuitively.

Table 2 Settling time of three kinds of controllers

CONTROLLER	INITIAL TRAJECTORY ADJUSTMENT TIME	CONSTANT HEIGHT ADJUSTMENT TIME
Improved PSO-RBF	0.08	0.1
Neural Network Adaptive Sliding Mode Controller		
Adaptive Sliding Mode Controller Based on RBF	0.18	0.2
Neural Network		
Double Closed-Loop PID Controller	0.38	0.4

Figure 6 shows the effect comparison of the three controllers on attitude Angle tracking. It can be analyzed that the improved PSO-RBF neural network adaptive sliding mode controller has faster adjustment time than the RBF neural network adaptive sliding mode controller, while the double closed-loop PID controller has obvious overshoot and a certain adjustment process, which is not the required process.

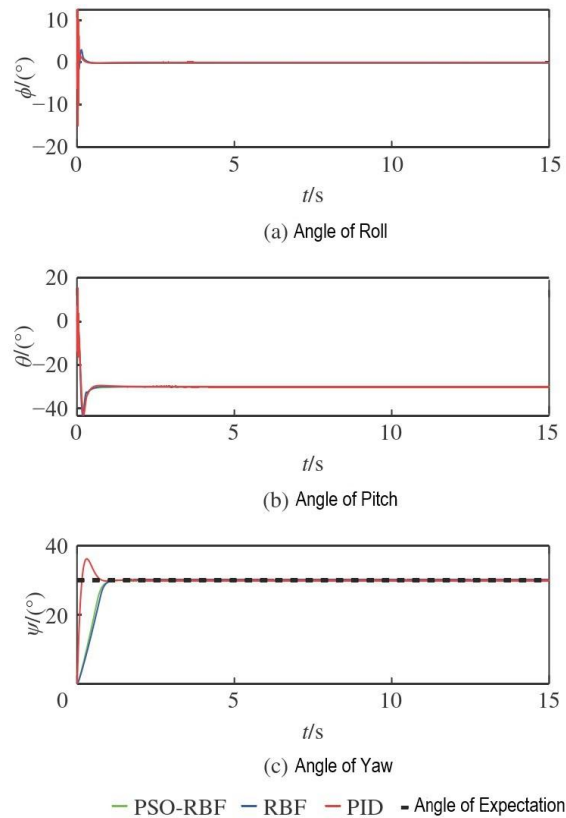


Fig. 6 Comparison of attitude control of three kinds of controllers

In summary, it can be concluded that the controller designed in this project has a good control effect.

5.2 COMPARISON OF ANTI-JAMMING PERFORMANCE

According to the Figure 7 that the three controllers have certain anti-jamming ability in the case of interference, but the changes of roll, pitch and yaw angles of the quadrotor controlled by the improved PSO-RBF neural network adaptive

sliding mode controller are smaller than those of the quadrotor controlled by the other two controllers when responding to interference.

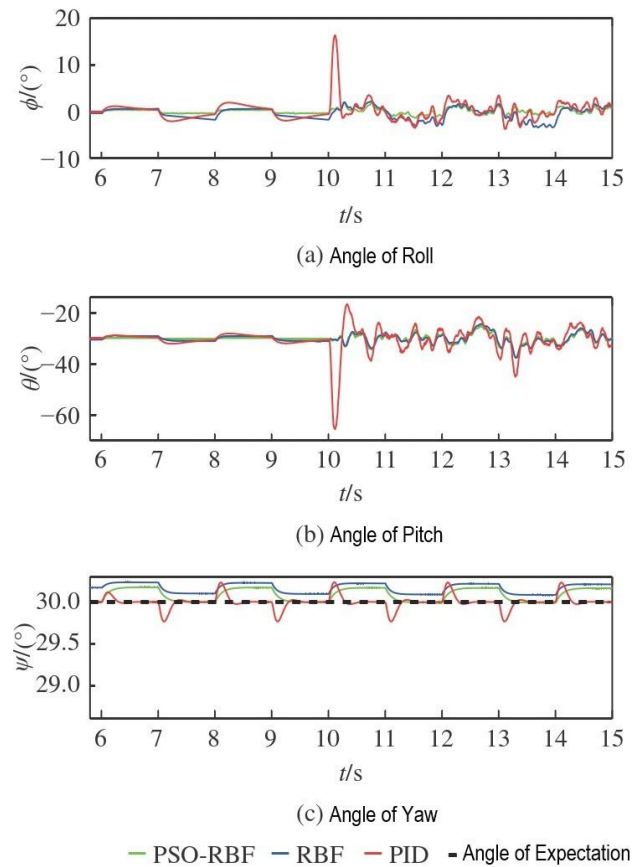


Fig. 7 Comparison of attitude control of three kinds of controllers when interference is introduced

In order to verify the anti-jamming ability of the PSO algorithm, the attitude tracking error comparison of the quadrotor controlled by the improved PSO-RBF neural network adaptive sliding mode controller and the RBF neural network adaptive sliding mode controller is plotted, as shown in Figure 8, to observe the performance of the improved PSO algorithm in the anti-jamming performance of the quadrotor. According to the Figure 8 that the quadrotor controlled by the improved PSO-RBF neural network adaptive sliding mode controller has better attitude Angle tracking ability than the quadrotor controlled by the RBF neural network adaptive sliding mode controller, which can maintain a certain tracking accuracy in the case of strong disturbance and ensure the stability of the quadrotor in trajectory tracking. Therefore, it can be considered that the improved

PSO-RBF neural network adaptive sliding mode controller has better anti-interference ability, and ensures the stability of the quadrotor flight according to the predetermined trajectory in the case of strong interference, which has certain practical value in agriculture and military reconnaissance.

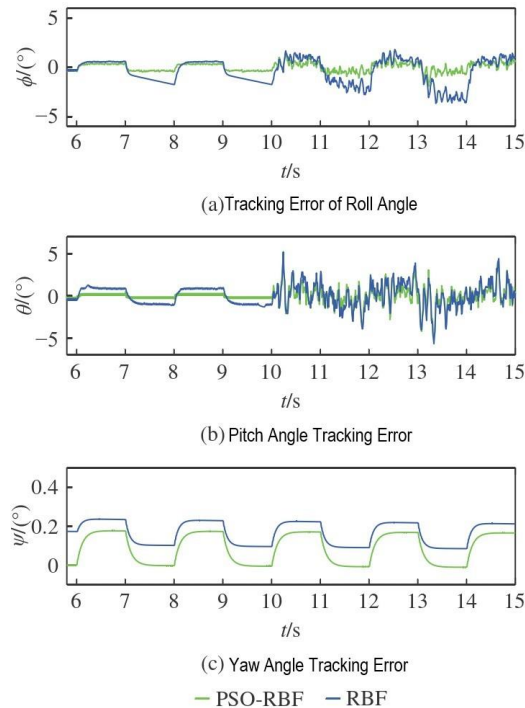


Fig. 8 Comparison of influence of improved PSO algorithm on attitude angle tracking error

5.3 COMPARISON OF ROBUSTNESS

As shown in Figure 9, observe the robustness of the improved PSO-RBF neural network adaptive sliding mode controller, RBF neural network adaptive sliding mode controller, and double closed-loop PID controller. Through the comparison of the Z-axis (height) direction, it can be seen that the improved PSO-RBF neural network adaptive sliding mode controller can quickly find out the best neural network fitting parameters because of its global optimization ability, and can quickly reduce the lift generated by the four rotors in the case of a sudden reduction in the mass of the quadrotor. Stabilize the height of the quadrotor. Through the comparison of control quantity U1, it can also be found that the improved PSO-RBF neural network adaptive sliding mode controller can find the

appropriate control quantity faster than the other two controllers and reduce the height fluctuation of the quadrotor.

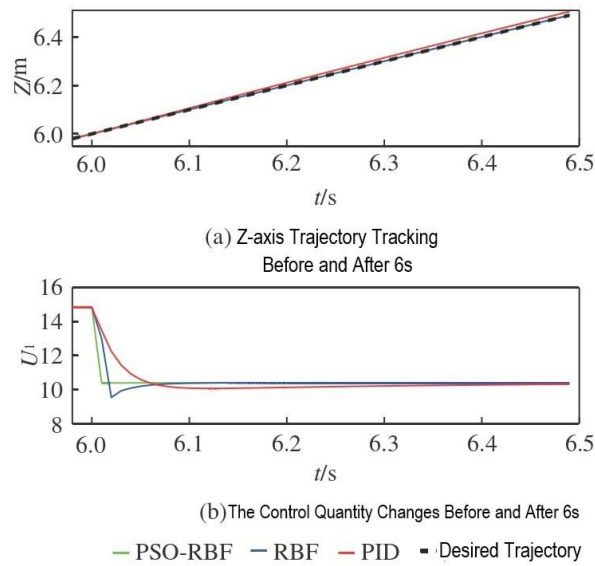


Fig. 9 Control of Z-axis by three kinds of controllers and generated control quantity

CHAPTER 6 - CONCLUSIONS AND RECOMMENDATIONS

6.1 SUMMARY

Compared with RBF neural network adaptive sliding mode control and double closed-loop PID controller, the improved PSO-RBF neural network sliding mode adaptive controller can find the appropriate control quantity in a control cycle (0.01 s in this paper). The corresponding adjustment time is about 50% and 75% higher than that of RBF neural network adaptive sliding mode control and double closed-loop PID controller, respectively. The simulation results also show that the improved PSO-RBF neural network sliding mode adaptive control method has the advantages of short adjustment time, small tracking error, strong anti-interference performance and good robustness. This characteristic makes the improved PSO-RBF neural network adaptive sliding mode controller have the prospect of application on the quadrotor with large disturbance and narrow space. However, the controller still has the problem of large amount of calculation. In the next step, we will continue to explore the optimization problem of neural network structure and PSO algorithm, and try to deploy the controller to the actual quadrotor UAV.

6.2 CONCLUSION

The primary aim of this project was to develop and validate a PSO-RBF neural network adaptive sliding mode controller for quadrotor UAVs, addressing the complex, nonlinear dynamics and external disturbances that characterize such systems. Despite significant technical challenges, including hardware failures that affected the scope of the project, the research successfully met its core objectives, providing valuable insights and a robust control solution.

The research began with a comprehensive literature review, which identified significant gaps in existing control strategies for quadrotor UAVs. Traditional methods such as PID and LQR controllers, while effective in certain scenarios, were found to be inadequate in handling the high degrees of nonlinearity and dynamic coupling inherent in UAV systems. Advanced methods, including neural networks and adaptive control strategies, offered improvements but still fell short in robustness and adaptability. This gap in the existing literature justified the need for a hybrid approach, leading to the development of the PSO-RBF neural network adaptive sliding mode controller.

The project employed a structured methodology, combining both qualitative and quantitative approaches. The dynamic modeling of the quadrotor UAV provided a detailed and accurate representation of the system's behavior, which was critical for the subsequent design and testing phases. The PSO-RBF controller was developed using MATLAB/Simulink, with the PSO algorithm employed to optimize the parameters of the RBF neural network. This combination proved effective, as evidenced by the simulation results, which demonstrated the controller's ability to maintain stability, accuracy, and robustness across a variety of challenging scenarios.

Simulation testing was a key component of this research, providing a controlled environment to rigorously evaluate the controller's performance. The PSO-RBF controller consistently outperformed traditional methods, particularly in scenarios involving significant external disturbances and system uncertainties. However, the

reliance on simulations also highlighted a limitation: the absence of real-world validation. While the simulations were comprehensive and high-fidelity, real-world testing is essential for fully validating the controller's performance and ensuring its applicability in practical UAV operations.

One of the most significant challenges encountered during the project was a hardware failure involving the HP Omen 9 series laptop, which suffered from manufacturing defects that led to critical failures in the motherboard and hard drive. This issue severely impacted the project timeline and scope, preventing the completion of additional real-time tests and demonstrations that would have further validated the controller's performance. Despite these setbacks, key data and results were preserved, allowing the project to be completed and reported, albeit with some limitations.

6.3 RECOMMENDATIONS FOR FURTHER RESEARCH

Given the outcomes of this research, several recommendations can be made for future work. First, real-world testing of the PSO-RBF controller is essential to validate its effectiveness beyond simulations. This testing should include flight experiments under varying environmental conditions to assess the controller's adaptability and robustness in practice. Additionally, further refinement of the PSO algorithm could enhance the optimization process, potentially improving the controller's performance in even more complex scenarios. Exploring alternative optimization techniques or hybrid algorithms that combine the strengths of multiple approaches could also be beneficial.

Another recommendation is to explore the integration of additional sensors or advanced feedback mechanisms that could enhance the controller's ability to respond to real-time changes in the UAV's environment. This could include the incorporation of machine learning techniques for real-time adaptation, further improving the system's resilience to unforeseen disturbances.

REFERENCES

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- [1] Mac T T, Copot C, De Keyser R, et al. The development of an autonomous navigation system with optimal control of an UAV in partly unknown indoor environment[J]. *Mechatronics*, 2018, 49: 187-196.
 - [2] Lin Xumei, Wang Chan. Design of adaptive robust sliding mode Controller for Quadrotor Aircraft [J]. *Chinese Journal of Scientific Instrument*, 2015, 36(07): 1522-1528.
 - [3] Li Jie, QI Xiaohui, HAN Shuaitao. Attitude Decoupling Control Method of Quadrotor Based on Active Disturbance Rejection Technology [J]. *Electro-optics & Control*, 2013, 20(03): 44-48.
 - [4] Bellahcene Z, Bouhamida M, Denai M, et al. Adaptive neural network-based robust H^∞ tracking control of a quadrotor UAV under wind disturbances[J]. *International Journal of Automation and Control*, 2021, 15(01): 28-57.
 - [5] Mo H, Farid G. Nonlinear and adaptive intelligent control techniques for quadrotor UAV– a survey[J]. *Asian Journal of Control*, 2019, 21(02): 989-1008.
 - [6] Qiao J, Liu Z, Zhang Y. Gain scheduling based PID control approaches for path tracking and fault tolerant control of a quad-rotor UAV[J]. *International Journal of Mechanical Engineering and Robotics Research*, 2018, 7(04): 401-408.
 - [7] Fu Yanguo. Research on Fuzzy PID Attitude Control of Quadrotor UAV [D]. Zhejiang: Zhejiang Ocean University, 2019.
 - [8] He Z, Gao W, He X, et al. Fuzzy intelligent control method for improving flight attitude stability of plant protection quadrotor UAV[J]. *International Journal of Agricultural and Biological Engineering*, 2019, 12(06): 110-115.
 - [9] Yang Xu, CAO Li-jia, LIU Yang. Attitude Control of Quadrotor UAV Based on Auto-coupling PID Control [J]. *Journal of Ordnance Equipment Engineering*, 2021, 42(10): 170-175.
 - [10] Abdalla M, Al-Baradie S. Real time optimal tuning of quadcopter attitude controller using particle swarm optimization[J]. *Journal of Engineering and Technological Sciences*, 2020, 52: 745-764.
 - [11] Najm A A, Ibraheem I K. Nonlinear PID controller design for a 6-DOF UAV quadrotor system[J]. *Engineering Science and Technology, an International Journal*, 2019, 22(04): 1087-1097.
 - [12] Moreno-Valenzuela J, Pérez-Alcocer R, Guerrero-Medina M, et al. Nonlinear PID-type controller for quadrotor trajectory tracking[J]. *IEEE/ASME Transactions on Mechatronics*, 2018, 23(05): 2436-2447.
 - [13] Liu Tong. Research on Fractional PID Control of Quadrotor UAV [D]. Wuhan: Wuhan University of Science and Technology, 2021.
 - [14] Jiang Ban-ban, LIU Jian-wei, Yang Pu, XIE Xiao-long. Active Fault-tolerant Control of Quadrotor UAV Based on Gain Scheduling PID [J]. *Journal of Shandong University of Science and Technology (Natural Science Edition)*, 2017, 36(04): 31-37.
 - [15] Noordin A, Mohd Basri M A, Mohamed Z, et al. Adaptive PID controller using sliding mode control approaches for quadrotor UAV attitude and position stabilization[J]. *Arabian Journal for Science and Engineering*, 2021, 46(02): 963-981.
 - [16] Liu Hai-bo, WANG He-ping, Shen Li-ding. System Engineering and Electronics, 2017, 39(01): 156-161. Fractional Sliding Mode Attitude Control of QTR Unmanned Aerial Vehicle [J].
 - [17] Maqsood H, Qu Y. Nonlinear disturbance observer based sliding mode control of quadrotor helicopter[J]. *Journal of Electrical Engineering & Technology*, 2020, 15(03): 1453-1461.
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- [18] Liang T, Wen-zheng L, Fa-yun G. Double Power Sliding Mode Control of Quadrotor UAV Based on Wind Disturbance Observation [J]. *Flight Mechanics*, 2019, 37(06): 27-33. 37(06): 27-33.
 - [19] Zhenhua Z, Liang X, Bin J, CAO Dong. Fast Non-singular Terminal Sliding Mode Trajectory Tracking Control for Quadrotor UAV Based on Extended state Observer [J/OL]. *Control and decision making*: 1-9. DOI: 10.13195 / j.k. zyjc. 2021.1819.
 - [20] Muñoz F, González-Hernández I, Salazar S, et al. Second order sliding mode controllers for altitude control of a quadrotor UAS: Real-time implementation in outdoor environments[J]. *Neurocomputing*, 2017, 233: 61-71.
 - [21] Wang Xian. Research on Fault Tolerant Control of Actuator of Quadrotor UAV Based on Sliding Mode Control [D]. Nanjing: Nanjing University of Posts and Telecommunications, 2020.
 - [22] Guo J, Qi J, Wu C. Robust fault diagnosis and fault-tolerant control for nonlinear quadrotor unmanned aerial vehicle system with unknown actuator faults[J]. *International Journal of Advanced Robotic Systems*, 2021, 18(02): 1-14.
 - [23] Han Jingqing. Active Disturbance Rejection Controller and Its Application [J]. *Control and Decision*, 1998,13(01): 19-23.
 - [24] Zhao L, Yang H, Cheng L, et al. Active disturbance rejection attitude control for a dual closed-loop quadrotor under gust wind[J]. *IEEE Transactions on Control Systems technology*, 2017, 26(04): 1400-1405.
 - [25] Zhong Yuan, ZHANG Hao. A Control Method of Quadrotor UAV Based on Cascade Linear Active Disturbance Rejection Control [J]. *Avionics Technology*, 2020, 51(01): 28-34.
 - [26] Cai Z, Lou J, Zhao J, et al. Quadrotor trajectory tracking and obstacle avoidance by chaotic grey wolf optimization-based active disturbance rejection control[J]. *Mechanical Systems and Signal Processing*, 2019, 128: 636-654.
 - [27] An Shuai, Yuan Suozhong, Li Huadong. Design of Trajectory Tracking Controller for Variable Load Quadrotor UAV [J]. *Electro-optics & Control*, 2018, 25(03): 59-63.
 - [28] Liu Baoying, Li Mingqiu, Yang Junwei. Attitude Control of Quadrotor Aircraft Based on Improved ADRC [J]. *Command Control and Simulation*, 2021, 43(02): 98-102.
 - [29] Guo Y, Jiang B, Zhang Y. A novel robust attitude control for quadrotor aircraft subject to actuator faults and wind gusts[J]. *IEEE/CAA Journal of Automatica Sinica*, 2017, 5(01): 292-300.
 - [30] Wang B, Jahanshahi H, Volos C, et al. A new RBF neural network-based fault-tolerant active control for fractional time-delayed systems[J]. *Electronics*, 2021, 10(12): 1501-1518.
 - [31] Guo Jie, JIN Hai, Shen Xinge. Optimal Control of Quadrotor UAV Based on Neural network PID Algorithm [J]. *Electronic Science and Technology*, 2021, 34(10): 51-55.
 - [32] Li Zhong, Shen Wei-hao. Adaptive Control of Quadrotor Attitude based on backstepping Sliding mode RBF Network [J]. *Fire Control & Command Control*, 2020, 45(11): 146-150.
 - [33] Boudjedir H, Bouhali O, Rizoug N. Adaptive neural network control based on neural observer for quadrotor unmanned aerial vehicle[J]. *Advanced Robotics*, 2014, 28(17): 1151-1164.
 - [34] Kuo C W, Tsai C C. Quaternion-based adaptive backstepping RFWNN control

- of quadrotors subject to model uncertainties and disturbances[J]. *International Journal of Fuzzy Systems*, 2018, 20(06): 1745-1755.
- [35] Song Y, He L, Zhang D, et al. Neuroadaptive fault-tolerant control of quadrotor UAVs: A more affordable solution[J]. *IEEE Transactions on Neural Networks and Learning Systems*, 2018, 30(07): 1975-1983.
- [36] Tang Z, Huang H, Tong K, et al. Model-based online learning and adaptive control for a “human-wearable soft robot” integrated system[J]. *The International Journal of Robotics Research*, 2021, 40(01): 256-276.
- [37] Liu Min, Xue Xiao-rong, DONG Li-guo, HUANG Min-si. Adaptive Tracking Control of Quadrotor UAV under State Constraint [J]. *Control Engineering*, 2021, 28(08): 170-1707.
- [38] Chen Zhibing, Liu Longwu, Liu Rui, Luo Zhou-Huai. Anti-jamming trajectory tracking control of quadrotor UAV Based on adaptive integral backstepping method [J]. *Chinese Journal of Inertial Technology*, 2020, 28(06): 819-828.
- [39] Huang T, Huang D, Wang Z, et al. Generic adaptive sliding mode control for a quadrotor UAV system subject to severe parametric uncertainties and fully unknown external disturbance[J]. *International Journal of Control, Automation and Systems*, 2021, 19(02): 698-711.
- [40] Zuo Z, Ru P. Augmented 1L adaptive tracking control of quadrotor unmanned aircrafts[J]. *IEEE Transactions on Aerospace and Electronic Systems*, 2014, 50(04): 3090-3101.
- [41] Zhao Guang-lei, GAO Ru-shuai, Chen Jian-nan. Adaptive Predetermined Performance Control of Quadrotor UAV with Actuator Faults [J]. *Control & Decision*, 2021, 36(09): 2103-2112.
- [42] Hardy R L. Multiquadric equations of topography and other irregular surfaces [J]. *Journal of Geophysical Research Atmospheres*, 1971, 76(8):1905-1915.
- [43] Hou Yuan-bin, DU Jing-yi, WANG Mei. *Neural Network [M]*. Xidian University Press, 2007:19-21.
- [44] Moody J, Darken C, Fast learning in networks of locally-tuned processing units [J]. *Neural Computation*, 1989, 1(2):281-294.
- [45] Liu Jin-Jun. *Research on Improvement and Application of RBF Neural Network [D]*. Lanzhou University, 2008, 12-19.
- [46] Chai Tian-you, Wang Xiao-bo. Application of RBF Neural Network in Accelerated Cooling Control System [J]. *Acta Automatica Sinica*, 2000, 26(2): 219-225.
- [47] Giduthuri S B, Sundaram S, Sequential projection-based metacognitive learning in a radial basis function network for classification problems [J]. *IEEE Transactions on Neural Networks and Learning Systems*, 2013, 24(2):194-206.
- [48] Feraz A, William S A, Predicting single-neuron activity in locally connected networks [J]. *Neural computation*, 2012, 24(10):2655-2677.
- [49] Cristian A, Isabel M, Universal approximation by radial basis function networks of delarte translates [J]. *Neural Networks*, 2013, 46:299-305.
- [50] Zhang R, Xu Z B, Huang G B, Wang D H, Global convergence of online BP training with dynamic learning rate [J]. *IEEE Transactions on Neural Networks and Learning Systems*, 2012, 23(2):330-341.
- [51] Chen B D, Zhao S L, Zhu P P, José C P, Quantized kernel recursive least squares algorithm [J]. *IEEE Transactions on Neural Networks and Learning Systems*, 2013, 24(9): 1484-1491.
- [52] Xie T T, Yu H, Hewlett J, Rozycki P, Wilamowski B M, Fast and efficient second-order method for training radial basis function networks [J]. *IEEE*

- Transactions on Neural Networks and Learning Systems, 2012, 23(4):609-619.
- [53] Peng J X, Li K, George W I, A novel continuous forward algorithm for RBF neural modelling [J]. IEEE Transactions on Automatic Control, 2007, 52(1):117-122.
 - [54] Serkan K, Turker I, Alper Y, Moncef G, Evolutionary artificial neural networks by multi-dimensional particle swarm optimization [J]. Neural Networks, 2009, 22(10):1448-1462.
 - [55] Oliver B, Manuel K, Bernhard S, Evolutionary optimization of radial basis function classifiers for data mining applications [J]. IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics, 2005, 35(5): 928-947.
 - [56] Tatt H O, Nor A M I, Adaptive evolutionary artificial neural networks for pattern classification [J]. IEEE Transactions on Neural Networks, 2011, 22(11):1823-1836.
 - [57] Pedro L, Hossein K, Concha B, Roberto S, A review on evolutionary algorithms in bayesian network learning and inference tasks [J]. Information Sciences, 2013, 233(1):109-125.
 - [58] Reynolds C W f.Herd and Schools: A Distributed Behavioral Model [J]. Computer Graphics, 1987, 21(4): 25-34.
 - [59] Heppner F, U Grenander. A stochastic nonlinear model for coordinated bird flocks [M]. Washington D C: AAAS Publications, 1990:1-98.
 - [60] Kennedy J, Eberhart R. Particle Swarm Optimization [J]. In: Proceeding of IEEE International Conference on Neural Networks, Piscataway, NJ: IEEE CS, 1995: 1942-1948.
 - [61] Eberhart R, Kennedy J. A new optimizer using particle swarm theory [J]. In: Proceeding of the 6th International Symposium on Micro Machine and Human Science, NJ: IEEE CS, 1995:39-43.
 - [62] SESHAGIRI S, KHALIL H K. Output feedback control of nonlinear systems using RBF neural networks[J]. IEEE Transactions on Neural Networks, 2000, 11(1): 69-79.
 - [63] SUN R H, ZHENG Z, XING J Z, et al. Design of quadrotor PID control system based on RBF neural networks[J]. Automation App lication, 2018(5): 3-4 (in Chinese) .
 - [64] HAN Y Z, HUA R. RBF neural network adaptive sliding mode control for quadrotor aerial vehicle[J]. Electronics Optics & Con trol, 2017, 24(11): 22-27 (in Chinese) .
 - [65] LIN X, WANG Y, LIU Y. Neural network-based robust terminal sliding-mode control of quadrotor[J]. Asian Journal of Control, 2022, 24(1): 427-438.
 - [66] HAO H Y, WANG X J. Method of tracking maximum power point of photovoltaic system based on improved PSO-RBF sliding mode control[J]. Chinese Journal of Power Sources, 2020, 44(8): 1148- 1151 (in Chinese) .
 - [67] FU X W, HU Y. Three-dimensional path planning based on im proved PSO algorithm[J]. Electronics Optics & Control, 2021, 28(3): 86-89 (in Chinese) .

PROJECT MANAGEMENT

The methodology employed in this project was grounded in a structured and methodical approach designed to effectively manage the complexities associated with the development and testing of the PSO-RBF neural network adaptive sliding mode controller for quadrotor UAVs. The research was systematically divided into clearly defined phases: beginning with an extensive literature review, followed by dynamic modeling, controller design, optimization, and culminating in validation through simulation. Each phase was meticulously planned and executed, ensuring that the project progressed logically and efficiently, with each step building on the foundations laid by the previous one.

The methods utilized throughout the project combined both qualitative and quantitative approaches. The qualitative aspect was primarily centered on a comprehensive literature review, which identified significant gaps in existing control strategies and provided a foundation for the design of the new controller. On the quantitative side, high-fidelity simulations played a crucial role in rigorously testing the controller under various conditions to ensure it met the required performance criteria. The integration of Particle Swarm Optimization (PSO) for fine-tuning the Radial Basis Function (RBF) network parameters was a critical component of the quantitative methods, allowing for precise adjustments that optimized the controller's performance in dynamic environments.

The project leveraged several advanced tools and techniques, which were pivotal to its success. MATLAB/Simulink served as the primary software platform for dynamic modeling, simulation, and analysis. The implementation and testing of the RBF neural network and PSO algorithms within this environment provided a robust framework for the development and validation of the controller. Additionally, statistical analysis tools were employed to assess the performance data, ensuring that the results were both reliable and meaningful, thus enhancing the overall rigor of the research.

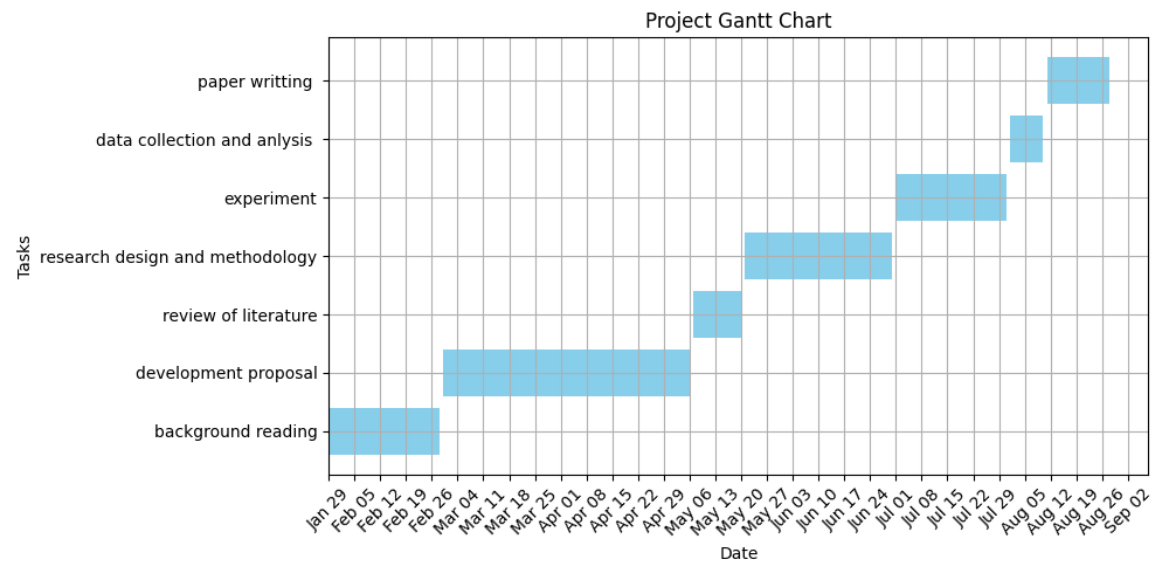
Upon reviewing the tools and techniques employed, it is clear that their selection was largely effective, enabling a comprehensive exploration of the research problem. MATLAB/Simulink proved to be an invaluable tool, offering the flexibility and computational power necessary to model complex UAV dynamics and simulate the controller's performance across various scenarios. The combination of PSO and RBF techniques was particularly successful, providing a powerful mechanism for optimizing the controller. However, the reliance on simulation tools, while effective for theoretical validation, limited the scope for real-world validation, highlighting an area for potential future improvement.

Reflecting on the project's execution, the methodology and tools selected were appropriate and aligned with the research objectives. The phased approach facilitated structured progress, and the use of advanced techniques like PSO for optimization was instrumental in achieving robust results. Nevertheless, the project was not without its challenges. Significant technical difficulties arose due to hardware issues with my HP Omen 9 series laptop, which suffered from a manufacturing defect leading to critical failures in both the motherboard and hard drive. These hardware malfunctions introduced substantial delays and impeded the ability to fully demonstrate the project as initially planned.

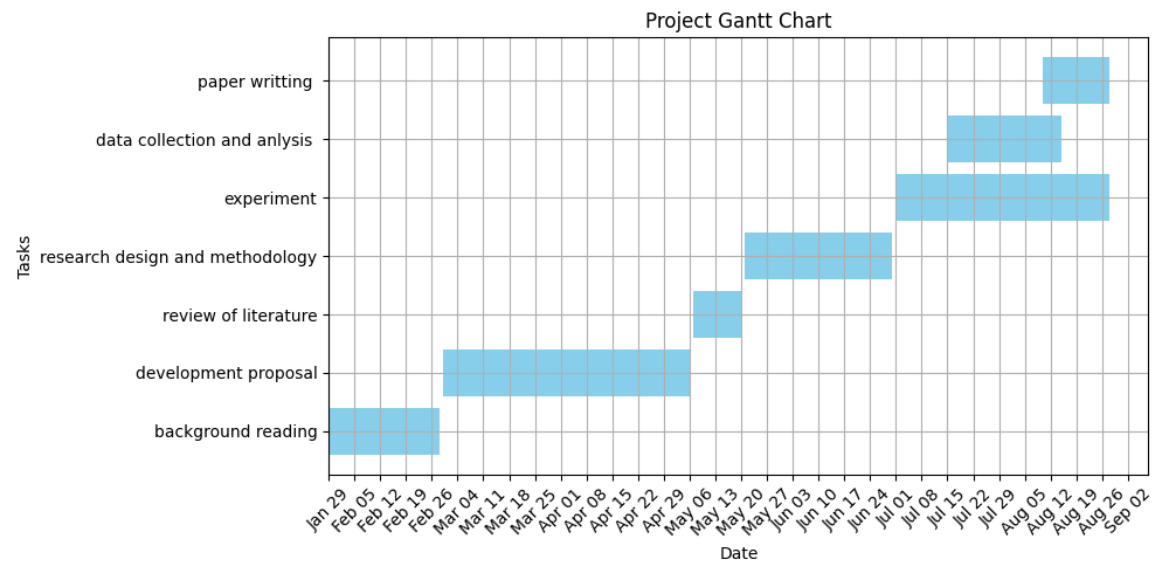
Despite these setbacks, I was able to salvage key data and results that were critical to the completion of the project. By leveraging backup strategies and focusing on the most essential aspects of the research, I managed to finalize the report, albeit with some compromises. The inability to conduct additional real-time tests and demonstrations due to the hardware issues did limit the project's scope, but the core objectives were still met, and the findings were documented comprehensively. The experience underscored the importance of contingency planning and resilience in project management, and the lessons learned from these challenges will undoubtedly inform future research endeavors.

In conclusion, while the project encountered significant obstacles due to hardware failures related to the HP Omen 9 series, which affected both the motherboard and hard drive, the overall methodology and approach remained sound. The project's objectives were largely achieved through the robust methods, tools, and

techniques employed, and the flexibility to adapt to unexpected challenges. Although the scope of the project was constrained by these technical difficulties, the final report effectively reflects the key findings and contributions of the research, demonstrating a successful completion under challenging circumstances.



Gantt Chart 1 The Gantt chart of the completed project plan



Gantt chart 2 The actual Gantt chart of the completed project

ETHICS FORM

ETHICS FORM – STEM MSc STUDENTS ONLY			
APPLICATION FOR ETHICAL APPROVAL			
In order for research to result in benefit and minimise risk of harm, it must be conducted ethically. The University follows the OECD Frascati manual definition of research activity: "creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications". As such this covers activities undertaken by members of staff, postgraduate research students, and both taught postgraduate and undergraduate students working on dissertations/projects. The individual undertaking the research activity is known as the "principal researcher". This form must be completed and approved prior to undertaking any research activity.			
SECTION A: About You (Principal Researcher)			
1	Full Name:	Aq	
2	Student Number:	2304716	
3	Email address:	2304716@student.uwtsd.ac.uk	
4	Programme of Study:	Software Engineering and Artificial Intelligence	
5	Director of Studies/Supervisor:	Gareth Jones	
SECTION B: Internal and External Ethical Guidance Materials			
Please list the core ethical guidance documents that have been referred to during the completion of this form (including any discipline-specific codes of research ethics, location-specific codes of research ethics, and also any specific ethical guidance relating to the proposed methodology). Please tick to confirm that your research proposal adheres to these codes and guidelines. You may add rows to this table if needed.			
1	UWTSd Research Ethics & Integrity Code of Practice	☒	
2	UWTSd Research Data Management Policy	☒	
3		☐	
SECTION C: Details of Research Activity			
1	Indicative title:	Quadrotor Control Algorithm Based On Optimized PSO-RBF Neural Network Adaptive Sliding Mode Control	
2	Proposed start date:	01.07.2024	Proposed end date: 28.08.2024
3	Introduction to the Research (maximum 300 words in each section) Ensure that you write for a <u>Non-Specialist Audience</u> when outlining your response to the three points below: - Purpose of Research Activity - Proposed Research Question - Aims of Research Activity - Objectives of Research Activity		

November 2021
1 Ethical Approval Form – Engineering Students Only

ETHICS FORM – STEM MSc STUDENTS ONLY

	Demonstrate, briefly, how Existing Research has informed the proposed activity and explain - What the research activity will add to the body of knowledge - How it addresses an area of importance.
3	Purpose of Research Activity In this project, a modified PSO-RBF neural network adaptive sliding mode controller for quadrotor is proposed. The global optimization ability of the improved PSO algorithm was applied to find the center value, width and connection weight of RBF neural network neurons, which further improved the approximation speed of RBF neural network to the quadrotor model and approached the uncertain state of the quadrotor model in the sliding mode controller faster. (this box should expand as you type)
4	Research Question particle swarm optimization (PSO) algorithm, as a global optimization algorithm, is often applied to the path planning of quadrotor, but rarely applied to the stability and anti-disturbance control of quadrotor. (this box should expand as you type)
5	Aims of Research Activity The approximation speed of the RBF neural network to the quadrotor model is improved, and the uncertain state of the quadrotor model in the sliding mode controller is approached faster. (this box should expand as you type)
6	Objectives of Research Activity In preparation for the physical testing of the quadrotor (this box should expand as you type)
	Proposed data collection methods (maximum 600 words) Provide a brief summary of all the methods that may be used in the research activity to collect data, making it clear what specific techniques may be used. If methods other than those listed in this section are deemed appropriate later, additional ethical approval for those methods will be needed. You do not need to justify the methods here, but should instead describe how you intend to collect the data necessary for you to complete your project.
7	This should describe how you intend to collect data. It should not include a discussion of the theoretical basis for your data collection methods. Please note, that if you intend to collect any audio/video recordings of interviews with participants then these will be classified as Personal Data under GDPR/DPA2018. If you intend to use these then note this in section H. The input data are the designed simulated quantities, and the output data are derived from the MATLAB calculation results. (this box should expand as you type)

SECTION D: Scope of Research Activity

	Will the research activity include:	YES	NO
1	Use of a questionnaire or similar research instrument?	☐	☒
2	Use of interviews?	☐	☒
3	Use of focus groups?	☐	☒
4	Use of participant diaries?	☐	☒
5	Use of video or audio recording?	☐	☒
6	Use of computer-generated log files?	☐	☒

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7	Participant observation with their knowledge?	☐	☒
8	Participant observation without their knowledge?	☐	☒
9	Access to personal or confidential information without the participants' specific consent?	☐	☒
10	Administration of any questions, test stimuli, presentation that may be experienced as physically, mentally or emotionally harmful / offensive?	☐	☒
11	Performance of any acts which may cause embarrassment or affect self-esteem?	☐	☒
12	Investigation of participants involved in illegal activities?	☐	☒
13	Use of procedures that involve deception?	☐	☒
14	Administration of any substance, agent or placebo?	☐	☒
15	Working with live vertebrate animals?	☐	☒
16	Procedures that may have a negative impact on the environment?	☐	☒
17	Other primary data collection methods. Please indicate the type of data collection method(s) below.	☐	☒
	Details of any other primary data collection method: (this box should expand as you type)		

If you have ticked NO to every question then the research activity is (ethically) low risk and you may skip section E and continue to section F.

If YES to any question, then no research activity should be undertaken until full ethical approval has been obtained.

SECTION E: Intended Participants

	Who are the intended participants?	YES	NO
1	Students or staff at the University?	☐	☐
2	Adults (over the age of 18 and competent to give consent)?	☐	☐
3	Vulnerable adults?	☐	☐
4	Children and Young People under the age of 18? (Consent from Parent, Carer or Guardian will be required)	☐	☐
5	Prisoners?	☐	☐
6	Young offenders?	☐	☐
7	Those who could be considered to have a particularly dependent relationship with the investigator or a gatekeeper?	☐	☐
8	People engaged in illegal activities?	☐	☐
9	Others. Please indicate the participants below, and specifically any group who may be unable to give consent.	☐	☐
	Details of any other participant groups: Complete this only if your participants cannot give consent. This includes animals (this box should expand as you type)		

Participant numbers and source

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	Provide an estimate of the expected number of participants. How will you identify participants and how will they be recruited?		
10	How many participants are expected?	Ballpark figures are fine, but make sure that you explain how you will identify and contact your participants. (this box should expand as you type)	
11	Who will the participants be?	(this box should expand as you type)	
12	How will you identify the participants?	(this box should expand as you type)	
Information for participants:			
		YES	NO
13	Will you describe the main research procedures to participants in advance, so that they are informed about what to expect?	☐	☐
14	Will you tell participants that their participation is voluntary?	☐	☐
15	Will you obtain written consent for participation?	☐	☐
16	Will you explain to participants that refusal to participate in the research will not affect their treatment or education (if relevant)?	☐	☐
17	If the research is observational, will you ask participants for their consent to being observed?	☐	☐
18	Will you tell participants that they may withdraw from the research at any time and for any reason?	☐	☐
19	With questionnaires, will you give participants the option of omitting questions they do not want to answer?	☐	☐
20	Will you tell participants that their data will be treated with full confidentiality and that, if published, it will not be identifiable as theirs?	☐	☐
21	Will you debrief participants at the end of their participation, in a way appropriate to the type of research undertaken?	☐	☐
22	If NO to any of above questions, please give an explanation		
	You should be able to tick YES for all of these questions. If not, then explain why not in this box. (this box should expand as you type)		
Information for participants:			
		YES	NO
24	Will participants be paid?	☐	☐
25	Is specialist electrical or other equipment to be used with participants?	☐	☐
26	Are there any financial or other interests to the investigator or University arising from this study?	☐	☐
27	Will the research activity involve deliberately misleading participants in any way, or the partial or full concealment of the specific study aims?	☐	☐
28	If YES to any question, please provide full details		
	You should be able to tick NO for most of these questions. For any cases that you have ticked YES then provide details in this box. If you are using cameras/voice recorders to record interviews then please state that in this box. (this box should expand as you type)		

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SECTION F: Anticipated Risks

1	Outline any anticipated risks that may adversely affect any of the participants, the researchers and/or the University, and the steps that will be taken to address them.		
1	Risks to participants For example: sector-specific health & safety, emotional distress, financial disclosure, physical harm, transfer of personal data, sensitive organisational information. If you have identified in section D that there are no participants then enter N/A and go skip to question 3.		
2	<table border="1"> <tr> <td data-bbox="379 474 845 582"> Risk to participants: N/A <i>(this box should expand as you type)</i> </td> <td data-bbox="845 474 1323 582"> How you will mitigate the risk to participants: N/A <i>(this box should expand as you type)</i> </td> </tr> </table>	Risk to participants: N/A <i>(this box should expand as you type)</i>	How you will mitigate the risk to participants: N/A <i>(this box should expand as you type)</i>
Risk to participants: N/A <i>(this box should expand as you type)</i>	How you will mitigate the risk to participants: N/A <i>(this box should expand as you type)</i>		
2	If research activity may include sensitive, embarrassing or upsetting topics (e.g. sexual activity, drug use) or issues likely to disclose information requiring further action (e.g. criminal activity), give details of the procedures to deal with these issues, including any support/advice (e.g. helpline numbers) to be offered to participants. Note that where applicable, consent procedures should make it clear that if something potentially or actually illegal is discovered in the course of a project, it may need to be disclosed to the proper authorities.		
3	Risks to the investigator For example: personal health & safety, physical harm, emotional distress, risk of accusation of harm/impropriety, conflict of interest.		
4	<table border="1"> <tr> <td data-bbox="379 815 845 1048"> Risk to the investigator: There are always risks. Do not write NA. Emotional disturbance, the time period to complete the project is short and the completion pressure is high. <i>(this box should expand as you type)</i> </td> <td data-bbox="845 815 1323 1048"> How you will mitigate the risk to the investigator: Seek counseling from a mentor. <i>(this box should expand as you type)</i> </td> </tr> </table>	Risk to the investigator: There are always risks. Do not write NA. Emotional disturbance, the time period to complete the project is short and the completion pressure is high. <i>(this box should expand as you type)</i>	How you will mitigate the risk to the investigator: Seek counseling from a mentor. <i>(this box should expand as you type)</i>
Risk to the investigator: There are always risks. Do not write NA. Emotional disturbance, the time period to complete the project is short and the completion pressure is high. <i>(this box should expand as you type)</i>	How you will mitigate the risk to the investigator: Seek counseling from a mentor. <i>(this box should expand as you type)</i>		
4	University/institutional risks For example: adverse publicity, financial loss, data protection.		
5	<table border="1"> <tr> <td data-bbox="379 1093 845 1209"> Risk to the University: There are always risks. Do not write NA. NA <i>(this box should expand as you type)</i> </td> <td data-bbox="845 1093 1323 1209"> How you will mitigate the risk to the University: NA <i>(this box should expand as you type)</i> </td> </tr> </table>	Risk to the University: There are always risks. Do not write NA. NA <i>(this box should expand as you type)</i>	How you will mitigate the risk to the University: NA <i>(this box should expand as you type)</i>
Risk to the University: There are always risks. Do not write NA. NA <i>(this box should expand as you type)</i>	How you will mitigate the risk to the University: NA <i>(this box should expand as you type)</i>		
5	Environmental risks For example: accidental spillage of pollutants, damage to local ecosystems.		
6	<table border="1"> <tr> <td data-bbox="379 1254 845 1391"> Risk to the environment: You may write NA if there are no research-related environmental risks. Driving to the university does not count as a risk. NA <i>(this box should expand as you type)</i> </td> <td data-bbox="845 1254 1323 1391"> How you will mitigate the risk to environment: NA <i>(this box should expand as you type)</i> </td> </tr> </table>	Risk to the environment: You may write NA if there are no research-related environmental risks. Driving to the university does not count as a risk. NA <i>(this box should expand as you type)</i>	How you will mitigate the risk to environment: NA <i>(this box should expand as you type)</i>
Risk to the environment: You may write NA if there are no research-related environmental risks. Driving to the university does not count as a risk. NA <i>(this box should expand as you type)</i>	How you will mitigate the risk to environment: NA <i>(this box should expand as you type)</i>		

SECTION G: Feedback, Consent and Confidentiality

If you have identified in section D that there are no participants then enter skip this section and continue to section H.

1	Feedback What de-briefing and feedback will be provided to participants, how will this be done and when?
2	You don't need to email your participants with your final report. A good alternative is to set up an email address that they will be able to contact for further details or results. <i>(this box should expand as you type)</i>

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2	Informed consent Describe the arrangements to inform potential participants, before providing consent, of what is involved in participating. Describe the arrangements for participants to provide full consent before data collection begins. If gaining consent in this way is inappropriate, explain how consent will be obtained and recorded in accordance with prevailing data protection legislation.
	If you are using a paper questionnaire then you should have the participants sign an appropriate consent form. These forms will count as personal data and should be noted as such in section J. If you are using an online questionnaire, then you should have a screen before the questions start that acts as a consent form, informing participants that by clicking on the NEXT button they are providing consent. (this box should expand as you type)
3	Confidentiality / Anonymity Set out how anonymity of participants and confidentiality will be ensured in any outputs. If anonymity is not being offered, explain why this is the case.
	Do not collect names unless you really need them. Do not name participants or organisations in any research publications (including the thesis) without their explicit permission. (this box should expand as you type)

SECTION H: Data Protection and Storage

	Does the research activity involve personal data (as defined by the General Data Protection Regulation 2016 "GDPR" and the Data Protection Act 2018 "DPA")?	YES	NO
1	"Personal data" means any information relating to an identified or identifiable natural person ('data subject'). An identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person. Any video or audio recordings of participants is considered to be personal data.	☐	☒
	If YES, provide a description of the data and explain why this data needs to be collected:		
2	This includes audio/video data of participants, but can also include IP addresses and usernames. Names, addresses and emails also count, as do consent forms. (this box should expand as you type)		
	Does it involve special category data (as defined by the GDPR)?	YES	NO
3	"Special category data" means sensitive personal data consisting of information as to the data subjects' – (a) racial or ethnic origin, (b) political opinions, (c) religious beliefs or other beliefs of a similar nature, (d) membership of a trade union (within the meaning of the Trade Union and Labour Relations (Consolidation) Act 1992), (e) physical or mental health or condition, (f) sexual life, (g) genetics, (h) biometric data (as used for ID purposes).	☐	☒
	If YES, provide a description of the special category data and explain why this data needs to be collected:		
4	What counts as 'sensitive' will differ between cultures. Any information on behaviour that is not in accordance with cultural norms would count as sensitive personal data. (this box should expand as you type)		

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	Will data from the research activity (collected data, drafts of the thesis, or materials for publication) be stored in any of the following ways?	YES	NO
5	Manual files (i.e. in paper form)?	☐	☒
6	University computers?	☐	☒
7	Private company computers?	☐	☒
8	Home or other personal computers?	☐	☒
9	Laptop computers/ CDs/ Portable disk-drives/ memory sticks?	☒	☐
10	"Cloud" storage or websites?	☐	☒
11	Other – specify:	☐	☒
12	For all stored data, explain the measures in place to ensure the security of the data collected, data confidentiality, including details of backup procedures, password protection, encryption, anonymisation and pseudonymisation:		
	If possible, save your data on computers that are secure and regularly backed up. Many cloud services only provide GDPR-compliant storage for business customers. An example of suitable text is given below. All data will be kept in password protected cloud storage on the University Office 365 system which will not be shared. Audio/visual data will be transcribed and would be shown to participants to check accuracy of reporting. Any USB sticks used to store or transfer data will be password protected. All participants will be given a unique identifier to ensure confidentiality and this list will be kept securely in the password protected folder. (this box should expand as you type)		

Data Protection			
	Will the research activity involve any of the following activities?	YES	NO
13	Electronic transfer of data in any form?	☐	☒
14	Sharing of data with others at the University outside of the immediate research team?	☐	☒
15	Sharing of data with other organisations?	☐	☒
16	Export of data outside the UK or importing of data from outside the UK?	☐	☒
17	Use of personal addresses, postcodes, faxes, emails or telephone numbers?	☐	☒
18	Publication of data that might allow identification of individuals?	☐	☒
19	If YES to any question, please provide full details, explaining how this will be conducted in accordance with the GDPR and Data Protection Act (2018) (and/or any international equivalent):		
	This includes data such as drafts of your thesis as well as experimental or survey data. An example of suitable text is given below. All data will be encrypted and kept in password protected cloud storage on the University Office 365 system which will not be shared. Any USB sticks used to store or transfer data will be password protected. All data transfers will be encrypted and password protected. All participants will be given a unique identifier to ensure confidentiality and this list will be kept securely in the password protected folder. The data will be stored until the completion of the project and then deleted. In accordance with the DPA2018, participants will have the right to ask to see what data is held relating to them, and this data will be deleted immediately if the participant requests this, in which case the data will not be used in the project.		

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	(this box should expand as you type)	
20	List all who will have access to the data generated by the research activity:	
	Normally the principal researcher, possibly also the supervisor and, if the project has an industrial partner, a representative of that partner. Possibly also external examiner or second marker?	
	(this box should expand as you type)	
21	List who will have control of, and act as custodian(s) for, data generated by the research activity:	
	Usually the principal researcher.	
	(this box should expand as you type)	
22	Give details of data storage arrangements, including security measures in place to protect the data, where data will be stored, how long for, and in what form.	
	All data will be encrypted and kept in password protected cloud storage on the University Office 365 system which will not be shared. Any USB sticks used to store or transfer data will be password protected, and will be reformatted at the end of the project in order to destroy the data. The data will be stored until the completion of the project and then deleted.	
	(this box should expand as you type)	
22	Confirm that you have read the UWTSD guidance on data management (see https://www.uwtsd.ac.uk/library/research-data-management/)	☒
23	Confirm that you are aware that you need to keep all data until after your research has completed or the end of your funding	☒

SECTION I: Declaration

	The information which I have provided is correct and complete to the best of my knowledge. I have attempted to identify any risks and issues related to the research activity and acknowledge my obligations and the rights of the participants.	
	In submitting this application I hereby confirm that I undertake to ensure that the above named research activity will meet the University's Research Ethics and Integrity Code of Practice which is published on the website: https://www.uwtsd.ac.uk/research/research-ethics/	
1	Signature of applicant:	Aq. Tang
2	Director of Studies/Supervisor:	
3	Signature:	
		Date: 01.06.2024

FOR INTERNAL USE ONLY:

	Ethical approval given	
1	Signature of assessor:	Date:
2	Name:	
3	Role:	

LOGBOOK

Week 1 (Jul 01 - Jul 07):

This week was dedicated to finalizing the data collection and analysis phase of the project. After conducting extensive simulations, I focused on compiling and synthesizing the data, ensuring that the results were robust and consistent. The statistical analysis was completed, providing clear insights into the performance of the PSO-RBF neural network adaptive sliding mode controller. I also began drafting the initial sections of the final report, particularly the analysis and discussion segments.

Week 2 (Jul 08 - Jul 14):

The focus of this week was on continuing with the writing process. I worked on expanding the results and discussion sections, drawing connections between the simulation outcomes and the objectives set out at the beginning of the project. The methodology and literature review sections were also refined, integrating the latest insights and ensuring that all references were accurately cited. Feedback from initial drafts was incorporated, improving the clarity and depth of the analysis.

Week 3 (Jul 15 - Jul 21):

During this week, I concentrated on polishing the report. I paid particular attention to the discussion and conclusion sections, ensuring that the implications of the research were clearly articulated. The report now reflects the full scope of the research, from the initial problem formulation to the final outcomes. I also prepared the final figures and tables, ensuring they effectively communicated the key findings. The draft was reviewed to identify any gaps or areas requiring further clarification.

Week 4 (Jul 22 - Jul 28):

This week presented significant challenges due to unexpected hardware failures with my HP Omen 9 series laptop. The motherboard and hard drive issues disrupted the final stages of the project, preventing me from conducting additional real-time tests and demonstrations. Despite this setback, I focused on salvaging as much data as possible. I made necessary adjustments to the report, ensuring

that all essential analyses and conclusions could still be supported by the existing data. The primary objective became completing the report with the available resources.

Week 5 (Jul 29 - Aug 04):

Given the ongoing hardware issues, I dedicated this week to finalizing the report under challenging conditions. Despite the limitations, I managed to complete the writing, ensuring that all sections were coherent and well-integrated. The inability to perform additional tests was noted in the report, with an explanation provided for how the hardware failure impacted the project's scope. The final draft was reviewed for completeness and accuracy, with particular attention paid to ensuring that the conclusions were well-supported by the data.

Week 6 (Aug 05 - Aug 11):

This week was spent preparing the final report for submission. I conducted a thorough review of the entire document, focusing on consistency, accuracy, and overall presentation. Given the constraints imposed by the hardware failure, I ensured that the report clearly communicated the challenges faced and how they were managed. Despite the inability to demonstrate the project as initially planned, I highlighted the key findings and contributions of the research, ensuring that the report still met academic standards.

Week 7 (Aug 12 - Aug 18):

The report was submitted this week. Following the submission, I reflected on the overall project, particularly the unforeseen challenges posed by the hardware issues. The experience underscored the importance of contingency planning and resilience in research projects. I began drafting a set of recommendations for future work, focusing on areas where further research and testing could enhance the PSO-RBF controller's performance and applicability.

Week 8 (Aug 19 - Aug 25):

This week was dedicated to finalizing the recommendations for future research. I emphasized the need for real-world testing of the PSO-RBF controller to validate its performance beyond simulations. Additionally, I suggested further optimization

of the PSO algorithm and the exploration of alternative hybrid approaches. The recommendations were designed to guide future research efforts, building on the foundation established by this project.

Week 9 (Aug 26 - Aug 28):

In the final days of this period, I completed my reflections on the project and compiled them into a comprehensive conclusion for the report. The focus was on summarizing the key achievements, acknowledging the challenges, and outlining the contributions made by the research. Despite the technical difficulties, I concluded the project with a sense of accomplishment, having successfully navigated the challenges to deliver a completed report.

GLOSSARY

Adaptive Sliding Mode Control (SMC):

A robust control technique designed to handle uncertainties and external disturbances in dynamic systems. It forces the system states to converge to a predefined sliding surface, ensuring stability and robustness.

Dynamic Modeling:

The process of creating a mathematical representation of a system's behavior, which, in this project, involves capturing the complex, nonlinear dynamics of a quadrotor UAV using Newton-Euler equations.

Empirical Validation:

The process of verifying a model or hypothesis through observation and experiment. In this project, it involves testing the PSO-RBF neural network adaptive sliding mode controller through simulations to validate its performance.

Literature Review:

A comprehensive survey of existing research and studies in a particular field. For this project, it involved analyzing existing control strategies for quadrotor UAVs to identify gaps and inform the development of a new control approach.

MATLAB/Simulink:

A high-level programming platform used for mathematical modeling, simulation, and analysis. It was used extensively in this project for developing and testing the quadrotor UAV model and the PSO-RBF controller.

Particle Swarm Optimization (PSO):

A computational algorithm inspired by the social behavior of birds flocking or fish schooling, used to optimize the parameters of complex systems. In this project, it was applied to optimize the parameters of the RBF neural network.

PSO-RBF Neural Network Adaptive Sliding Mode Controller:

A hybrid control strategy developed in this project, combining Particle Swarm Optimization (PSO) with a Radial Basis Function (RBF) neural network within an adaptive sliding mode control framework. It is designed to handle the nonlinear and dynamic challenges of controlling quadrotor UAVs.

Quadrotor UAV:

A type of unmanned aerial vehicle (UAV) with four rotors, known for its agility and ability to hover. The subject of this project, which focused on improving control strategies for such vehicles.

Radial Basis Function (RBF) Neural Network:

A type of artificial neural network that uses radial basis functions as activation functions. It is particularly effective for approximating nonlinear functions and was a key component of the control strategy developed in this project.

Real-World Testing:

The process of validating a system or model under real operating conditions, as opposed to simulations. Although constrained by hardware issues, real-world testing is essential for confirming the practical applicability of the control strategy.

Robustness:

The ability of a control system to maintain performance in the presence of uncertainties or disturbances. This project aimed to enhance the robustness of quadrotor UAV control through the PSO-RBF controller.

Sensitivity Analysis:

A technique used to determine how different values of an independent variable affect a particular dependent variable under a given set of assumptions. In this project, it was used to assess the impact of various parameters on the performance of the PSO-RBF controller.

Simulation Testing:

The use of a computer model to test the behavior of a system under various conditions. This project utilized simulation testing to validate the effectiveness of the PSO-RBF controller in managing the dynamic behavior of quadrotor UAVs.

Stability Margins:

Quantitative measures of how close a system is to instability. In this project, stability margins were assessed using tools like Bode and Nyquist plots to ensure the UAV control system remains stable under different operating conditions.

Traditional PID Controller:

A classical control method that uses proportional, integral, and derivative terms to control a system. It was used as a baseline in this project to compare with the more advanced PSO-RBF neural network adaptive sliding mode controller.

Uncertainties:

In the context of control systems, these refer to unknown or unpredictable

variations in the system's dynamics or the environment. The PSO-RBF controller was designed to manage such uncertainties effectively.

Wind Gusts:

Sudden increases in wind speed, which can significantly affect the stability and control of a UAV. This project included testing the controller's robustness against wind gusts in simulation environments.

Wireless Communication Delays:

Potential delays in signal transmission in UAV systems, which can impact control performance. This project's simulations included considerations of such delays to ensure the controller's effectiveness in practical scenarios.

Zero-Crossing Detector:

A component often used in control systems to detect the points at which a signal changes sign (crosses zero). This concept is related to the sliding mode control implemented in the project.