Research on the Application of Neural Network PID in Quadcopter Aircraft

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Abstract: As a highly maneuverable and flexible unmanned aerial vehicle, quadcopters have broad application prospects in both civilian and military fields. However, due to their complex dynamic characteristics, nonlinearity, and strong coupling, achieving stable and precise control of quadcopters is a challenging task. Traditional control methods often fail to meet the control performance requirements for such complex nonlinear systems. Neural networks provide a new approach to solving control problems in complex systems due to their powerful learning and adaptive capabilities. Neural networks can improve the performance of control systems by learning from large amounts of data, capturing the dynamic characteristics of the system, and adjusting control strategies online. Combining neural networks with PID control is expected to fully leverage the advantages of both. Neural networks can adjust the parameters of PID controllers in real-time, enabling them to better adapt to the complex dynamic changes and external disturbances of quadcopter aircraft. This fusion control method brings new possibilities for improving the control performance of quadcopter aircraft. This study explores the application of neural network PID in quadcopter aircraft to achieve stable and precise control, laying the foundation for its widespread promotion in practical applications.

Keywords: Rotorcraft; Fuzzy Neural Network; BP-PID; BP Neural Network; PID

1. Introduction

A quadcopter is an unmanned aerial vehicle with four rotors. Its structure is simple, usually consisting of four symmetrically distributed rotors, fuselage, motors, electronic governors, sensors, and controllers. Strong maneuverability, capable of vertical takeoff and landing, hovering, forward, backward, left, right, and various complex flight movements. It can be used in multiple fields such as aerial photography, monitoring, rescue, agricultural crop protection, logistics and distribution[1,2].

1.1 History

The development of quadcopters can be traced back to 1907, when the Breguet brothers designed and manufactured the first manned quadcopter. However, this aircraft had a short flight duration and relied entirely on human physical control, resulting in poor performance in all aspects.

After the 1990s, with the maturity of research on microelectromechanical systems (MEMS), several gram MEMS inertial navigation systems were developed and applied, providing the possibility for the production of automatic controllers for multi rotor aircraft. However, due to insufficient computing power and high data noise in early calculators, the application of miniature automatic controllers was limited. It was not until around 2005 that a truly stable automatic controller for multi rotor unmanned aerial vehicles was produced.

The MD4-200 quadcopter system launched by German company Microdrones GmbH in 2006 pioneered the application of electric quadcopters in professional fields. Its MD4-1000 quadcopter, launched in 2010, has achieved success in the global professional drone market.

In 2010, the French company Parrot released the world's first popular quadcopter aircraft, AR. Dragon. As a high-tech toy, it has the advantages of being lightweight, flexible, safe, and easy to control. It can also hover through sensors and transmit camera images to mobile phones using WIFI.

In February 2012, Professor V. Kumar from the University of Pennsylvania showcased the flexibility and formation collaboration capabilities of quadcopters at the TED conference, demonstrating the inherent potential of multi rotor technology.

In early 2012, China's DJI launched the Phantom all-in-one machine, which, like AR. Drone, is easy to control, beginner friendly, and affordable for ordinary consumers. Compared to the AR. Drone quadcopter aircraft, the Phantom has certain wind resistance, positioning function, and load-bearing capacity, and can also carry small cameras. At that time, using Gopro sports cameras to shoot extreme sports became a trend, so the Phantom drone quickly became popular as soon as it was launched.

In March 2016, DJI launched the Phantom 4, which features forward facing dual cameras with obstacle perception capabilities and real-time autonomous obstacle avoidance through image recognition based visual tracking. It is the world's first fourth generation intelligent visual drone.

With the continuous advancement of technology, quadcopters have been widely used in various fields such as aerial photography, monitoring, rescue, and agricultural crop protection, and are still constantly developing and innovating.

1.2 Working Principle

A quadcopter aircraft controls its attitude and motion by adjusting the rotational speed of its four rotors. The four rotors are divided into two groups, with two rotors on the diagonal rotating in the same direction and two adjacent rotors rotating in opposite directions to counteract the reverse torque[3].

When the four rotors have the same rotational speed, the aircraft achieves vertical ascent or descent; By changing the rotational speed of different rotors, unbalanced lift is generated, thereby achieving changes in attitude such as pitch (forward/backward tilt), roll (left/right tilt), and yaw (horizontal rotation). For example, increasing the speed of the first two rotors while decreasing the speed of the last two rotors will cause the aircraft to tilt forward and fly forward.

The stable flight of quadcopter aircraft relies on various sensors (such as accelerometers, gyroscopes, magnetometers, etc.) to perceive attitude and position information, and feedback this information to the controller. The controller calculates appropriate control instructions based on preset control algorithms, adjusts the motor speed, and achieves stable flight control.

The working principle of quadcopter aircraft is based on aerodynamics and motor control. The four rotors are distributed in a cross shape, and the adjacent two rotors rotate in opposite directions. In fact, various movements and posture adjustments are mainly achieved through the following methods[4]:

(1) Vertical motion: When the rotational speed of the four rotors is the same and increases or decreases, the total lift generated is greater or less than the weight of the aircraft, thereby achieving ascent or descent.

(2) Forward and backward motion: Increasing the speed of the two rear rotors while decreasing the speed of the two front rotors will cause the aircraft to tilt forward, generating a forward force component and achieving forward flight; Otherwise, fly backwards.

(3) Left and right movement: Increase the speed of the left two rotors while decreasing the speed of the right two rotors. The aircraft will tilt to the right, generating a force to the right and achieving rightward flight; Otherwise, fly to the left.

(4) Yaw motion (horizontal rotation): When the rotational speed of the two rotors on the diagonal increases and the rotational speed of the other two rotors on the diagonal ecreases, a torque difference is generated, causing the aircraft to rotate around the vertical axis and achieve yaw motion.

In order to achieve stable flight, quadcopters are usually equipped with various sensors such as accelerometers, gyroscopes, magnetometers, etc., to measure the attitude, angular velocity, acceleration, and other information of the aircraft. These sensors provide data feedback to the flight controller, which adjusts the speed of each motor in real time ccording to preset algorithms and control strategies to maintain the stable attitude of the aircraft and fly along the predetermined trajectory.

2 Neural Network PID

The working principle of neural network PID controller mainly includes the following aspects:

Firstly, traditional PID controllers regulate system deviations through three stages: proportional, integral, and derivative. However, its parameters are often difficult to accurately set when facing complex and ever-changing systems.

Neural networks have powerful learning and adaptive abilities. In the neural network PID controller, the neural network part is responsible for learning the dynamic characteristics of the system and adjusting the parameters of the PID controller (proportional coefficient, integral coefficient, and differential coefficient) based on the learning results.

Specifically, neural networks use the system's inputs (such as the deviation between set values and actual output values) and outputs (control variables) as training data. Through continuous training, neural networks gradually master the operating rules of the system.

In the control process, when there is a deviation in the system, the neural network calculates the appropriate PID parameter adjustment based on the current deviation and its learning of the system's past behavior. Then, the adjusted PID parameters are used to calculate the control variables and applied to the controlled object to reduce deviations.

This process continues to loop, allowing PID parameters to adapt to changes in the system in real time, thereby achieving more accurate and stable control effects.

In summary, the neural network PID controller combines the learning ability of neural networks with the basic framework of PID control to improve the control performance of complex systems【5-6】.

2.1 PID Control

PID control (Proportional Integral Derivative Control) is a classic control strategy widely used in industrial control and automation fields.

Proportional (P) control: The output of the controller is proportional to the input error signal. When there is a deviation in the system, proportional control will immediately generate a control effect proportional to the deviation. The larger the proportional coefficient, the stronger the control effect, but an excessively large proportional coefficient may lead to system instability and overshoot.

Integral (I) control: The output of the controller is proportional to the integral of the input error signal. As long as there is an error in the system, the integral control effect continues to accumulate, causing the output to continuously increase or decrease until the error is zero, at which point the integral effect will stop. The integral effect can eliminate the steady-state error of the system, but excessive integral effect will slow down the response speed of the system and increase overshoot.

Differential (D) control: The output of the controller is directly proportional to the differential of the input error signal. At the moment when the deviation signal changes, differential control will have a significant control effect, helping to accelerate the response speed of the system, reduce overshoot, overcome oscillation, and make the system tend to be stable; But it has an amplifying effect on noise interference, and excessive differential control is detrimental to the system's anti-interference ability.

In practical applications, by adjusting the values of proportional coefficients, integral coefficients, and differential coefficients (Kp, Ki, Kd), the control system can achieve desired performance indicators such as fast response, small overshoot, and high steady-state accuracy. The PID controller has a simple structure, good stability, reliable operation, and easy adjustment, and has achieved good control effects in many industrial process control and motion control systems.

The control process of PID classical control algorithm can be summarized as follows: 1. Obtaining feedback signals of the controlled object from the sensors of the rotary wing aircraft; 2. Feed the error signal between the expected value and the actual value into the PID controller; 3. The classic PID controller calculates the output signal of the control based on the parameters of the proportional, integral, and derivative stages; 4. Control the output signal to enter the actuator of the controlled object, completing the adjustment of the controlled object. Thus, the goal of continuously reducing the error between the expected value and the actual value can be achieved, ultimately making the control effect of the system more accurate[7].

The basic principle is shown in Figure 1.

2.2 Neural Network PID Control

Neural Network PID is a control method that combines neural networks with traditional PID control. The traditional PID controller achieves control of the system through a combination of proportional, integral, and derivative stages, but its parameter tuning usually relies on experience or trial and error methods, and its control effect may not be ideal for complex nonlinear and time-varying systems. Neural networks have characteristics such as self-learning, adaptability, and nonlinear mapping ability. Applying neural networks to PID control can automatically identify the parameters of the controlled process and tune the PID control parameters in real-time to adapt to changes in the controlled process.

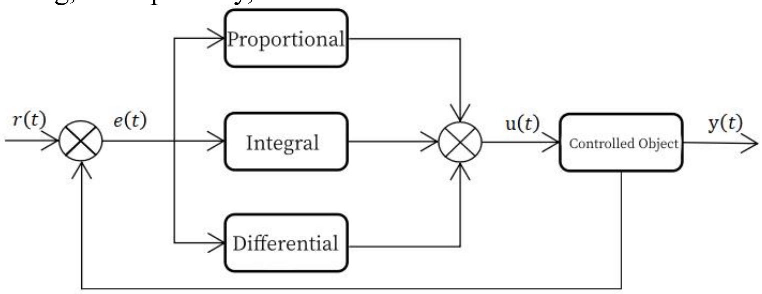

Figure 1. PID controller structure

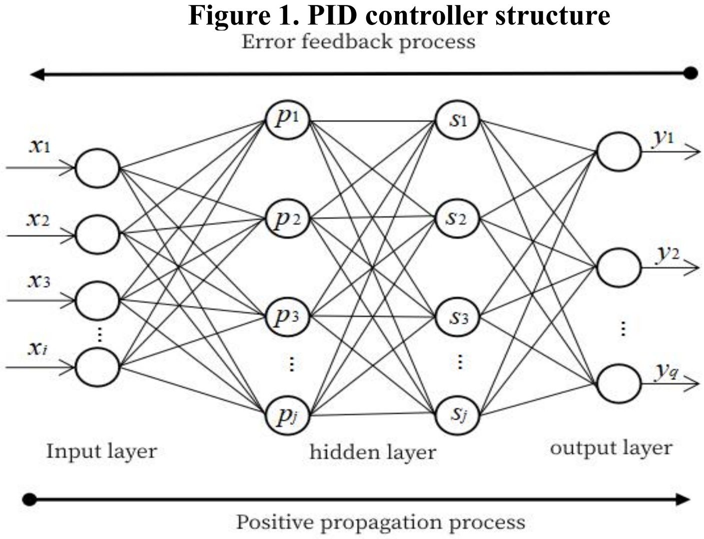

Figure 2. Basic Structure of BP Neural Network

2.2.1The working principle of BP neural network

Common methods for tuning PID parameters based on neural networks include BP neural networks, etc. Taking BP neural network tuning PID parameters as an example, its controller structure usually includes two parts: the lower part is the classical PID control loop. The upper part is a BP network. The input of the network is control error, and the output is proportional, integral, and derivative parameters.

BP (Back Propagation) neural network is a multi-layer feedforward network trained by error backpropagation, and is currently one of the most widely used neural network models. The basic structure of BP neural network includes input layer, hidden layer, and output layer. The input layer neurons are responsible for receiving external input information; The hidden layer is responsible for processing and transforming input information; The output layer is responsible for outputting the processing results. The learning process of BP neural network consists of two processes: forward propagation of signals and backward propagation of errors. In the process of forward propagation, input information is processed layer by layer through the hidden layer and transmitted to the output layer. If the output layer does not receive the expected output, it enters the backpropagation process.

In backpropagation, the output error is propagated layer by layer through the hidden layer to the input layer in some form, and the error is shared among all neurons in each layer to obtain the error signal of each neuron. This error signal serves as the basis for correcting the weights of each neuron. The process of adjusting the weights of each layer in the forward propagation of signals and the backward propagation of errors is a repetitive process. The process of continuously adjusting weights is the learning and training process of the network. Training continues until the error in the network output is reduced to an acceptable level, or until a predetermined number of learning iterations are reached, The basic structure and workflow are shown in Figure 2[8].

During the training process, the backpropagation algorithm is used to derive the learning rules (i.e. iterative formulas) for each layer, continuously adjusting the weights of the network to enable the controller to automatically optimize PID parameters based on the system's operating conditions.

Compared to traditional PID controllers, neural network PID controllers have stronger adaptability and robustness, and can better handle control problems of complex systems such as nonlinear and time-varying systems.

For example, in a PID control based on BP neural network tuning proportional, integral, and derivative, the input layer can be:

$$e(k) = r(k) - \mathrm{y}(k) \qquad (1)$$

(Among them, $r(k)$ is the control input, and$y(k)$ is the system output), The error at the current moment; The input of the hidden layer is:

$$net_i^{(1)}(k) = \sum\nolimits_{j=0}^{m} w_{ij}^{(1)} x_j(k) \qquad (2)$$

Among them, $w_{ij}^{(1)}$ is the connection weight from the input layer to the i-th hidden layer node, $x_j(k)$ is the j-th input of the input layer, m is the number of input layer nodes。

The input of the output layer is:

$$net_l^{(2)}(k) = \sum\nolimits_{i=1}^{q} w_{li}^{(2)} O_i^{(1)}(k) \quad (3)$$

Among them, $w_{li}^{(2)}$ is the connection weight from the hidden layer to the l-th output layer node, $O_{\mathrm{i}}^{(1)}(k)$ is the output of the i-th hidden layer node, q is the number of hidden layer nodes.

By continuously adjusting the weights $w_{ij}^{(1)}$ and $w_{li}^{(2)}$, the system's output can track the control input as closely as possible, thereby achieving adaptive tuning of PID parameters.

In practical applications, it is necessary to select appropriate neural network structures and training algorithms based on specific controlled objects and control requirements, and conduct sufficient debugging and optimization to achieve ideal control effects. Meanwhile, the computational complexity of neural network PID controllers is relatively high, which may require certain computing resources and time.

2.2.2 Selection of BP Neural Network Architecture Framework

The BP neural network framework for selecting optimal regions can play a certain optimization role in the neural network controller of rotary wing aircraft. When selecting the structural framework of BP neural network, several aspects should be considered:

(1). Number of input layer nodes

The number of input layer nodes depends on the feature dimension of the input data., The input layer is set to 4 neurons, respectively

To specify the input $r(k)$, actual input $y(k)$, error $e(k)$, and constant factor 1 used to stabilize the BP neural network.

(2) Number of hidden layers

Usually, you can try 1-2 hidden layers first.

(3) Number of hidden layer nodes

The number of hidden layer nodes is determined using empirical methods, selecting as few hidden layer nodes as possible to avoid overfitting in the neural network.

(4) Number of output layer nodes

It depends on the task objectives. The output layer is set to three neurons based on the three parameters KP, KI, KD in the PID control algorithm

(5) Activation function

The input layer generally does not use activation functions. The commonly used activation functions for hidden layers include Sigmoid function, Tanh function, ReLU function, etc. The Sigmoid function can compress the output of neurons to a range of 0-1; The Tanh function compresses the output between -1 and 1; The ReLU function is computationally simple and helps alleviate gradient vanishing problems in deeper networks. The activation function of the output layer depends on the task type, for example, in binary classification problems, the output layer can use the Sigmoid function; In multi classification problems, the Softmax function is commonly used; In regression problems, activation functions are generally not used or linear activation functions are used.

For the BP neural network controller in this article, Tanh function and Sigmoid function are selected for the hidden layer and output layer, respectively.

(6) Learning rate

The learning rate controls the update speed of neural network weights. A slow learning rate can lead to slow updates. Excessive learning rate leads to unstable weight updates. Choose a fixed learning rate of 0.2 here

2.3.3 The calculation process of BP neural network algorithm

The calculation process of BP neural network includes forward propagation stage and backward propagation stage[9].

Positive propagation stage:

(1) The input layer accepts input data and passes it to the hidden layer

(2) For each neuron in the hidden layer and output layer, calculate its input weighted sum, where is the weight connecting the neuron and the neuron, and is the output of the neuron.

(3) Calculate the output of neurons using Tanh function and Sigmoid function based on the hidden layer and output layer, respectively

Backpropagation stage:

(1) Calculate the error of the output layer: Calculate the error based on the actual output and expected output.

(2) Backpropagate the error to the hidden layer and calculate the error term for each neuron.

(3) Update weights based on the error term, where is the learning rate and is the error function

Application of Neural Network PID in quadcopter Aircraft

The neural network PID controller has strong adaptability and can automatically adapt to the changes and uncertainties of the controlled object. By using the learning ability of the neural network, the PID parameters can be adjusted in real time to achieve better control effects. Capable of handling nonlinear systems, with good control performance for complex nonlinear systems, and able to effectively handle nonlinear characteristics. Strong anti-interference ability, with a certain degree of suppression ability against noise and interference in the system, improving the stability and robustness of the system. High optimization performance can achieve more precise control, reduce overshoot, shorten adjustment time, and improve the dynamic and steady-state performance of the system.

Neural network PID has a wide range of applications in quadcopter aircraft, mainly reflected in its ability to accurately control the pitch, roll, and yaw attitude of quadcopters, ensuring stability in various environments and working conditions; Position control can achieve precise control of the horizontal position (such as X and Y axis directions) and vertical position (Z-axis direction) of the aircraft, and can be used to complete tasks such as fixed-point hovering and flying along a predetermined trajectory; The improvement of anti-interference ability is achieved by adjusting control strategies in real time to reduce the impact of interference on flight stability and accuracy; Adapt to complex environments and optimize control parameters based on environmental characteristics when flying in complex geographical environments such as mountainous areas, urban canyons, etc; Adaptation to load changes and collaborative control.

In summary, neural network PID provides strong support for the stable, precise, and intelligent control of quadcopter aircraft, promoting its widespread application and development in many fields[10].

4. Conclusion

The application of neural network PID in quadcopter aircraft is mainly aimed at solving the time-varying and nonlinear problems of quadcopter unmanned aerial vehicle systems, in order to achieve more accurate attitude control.

Compared to traditional PID control methods, neural network PID controllers have some significant advantages. For example, it has stronger adaptability and anti-interference ability. Through the learning ability of neural networks, it can automatically adjust PID parameters to adapt to the characteristic changes of quadcopter aircraft under different operating conditions, while having better suppression effects on noise and interference in the system.

In practical applications, researchers first need to establish rigid body kinematic and dynamic models of quadcopter drones. Based on these models, use tools such as MATLAB Simulink to build attitude simulation control models. Then, the neural network PID control algorithm is compared with other control algorithms such as traditional PID and cascade PID to evaluate its control effect on the three attitude angles (pitch angle, roll angle, yaw angle) of the drone.

The experimental results show that the neural network PID control algorithm performs better in adjusting transition time and system static error. For example, its adjustment transition time is significantly shortened compared to other algorithms, and the static error of the system after stable output is also significantly reduced. This means that this control algorithm can achieve higher control accuracy while having better static and dynamic characteristics. For example, a study proposed a drone attitude control algorithm based on neural network PID, and the results showed that the transition time of the algorithm was reduced from 4 seconds to 1 second, and the static error of the system after stable output was only 0.5%.

However, neural network PID controllers also have some limitations, such as high computational complexity, requiring a large amount of computing resources and time for training and real-time parameter adjustment; It has a certain demand for training data and relies on sufficient training data to accurately learn system characteristics; Its model structure is relatively complex, which increases the difficulty of design and debugging; And compared to traditional PID controllers, its working principle and decision-making process are difficult to explain and understand. However, overall, in application scenarios such as quadcopters that require high control accuracy and adaptability, neural network PID controllers have important application value and potential.

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