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Research on UAV Adaptive Control Method Based on Genetic Programming

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Abstract: In order to improve the non-linear PID control effect of a small unmanned aerial vehicle (UAV) flight, an adaptive PID height controller based on genetic programming is proposed. Firstly, the structure of the PID controller is introduced and the GP algorithm is applied in view of its characteristics of clear mapping relationship and strong non-linear fitting ability. The flight state parameters and the optimal control parameters are taken as the sample data of input and output respectively, and the intuitive functional relationship between the flight state parameters of UAV and the PID control parameters is obtained. Finally, the online adaptive tuning of the control parameters is realized. The simulation results show that the proposed PID neural network controller has faster response, smaller overshoot, higher precision, better robustness and stronger adaptive ability than the traditional PID controller, which can meet the requirements of autonomous flight.

Key Words: PID control; adaptive control; genetic programming; nonlinear system

1 Introduction

In recent years, UAVs have shown potential application prospects and scientific significance of academic research in many fields. UAVs have been applied to remote sensing, transport, search and rescue missions, see [1]. Longitudinal control is an important part of UAV flight control system, especially in low-height flight, UAVs often rely on accurate height control and height maintenance. However, during the flight, UAVs are vulnerable to atmospheric disturbance and change the expected height, which will not only affect the task completion, but also cause serious consequences.

Classical PID controller is applied widely in UAV flight control because of its simple structure, good stability and strong robustness. The key of PID controller is the tuning of P, I, D three parameters. PID control performance and robustness are determined by these three parameters. However, in practical application, most of the controlled systems are affected by the external environment, which makes the model and parameters of the controlled system change in real time. The original setting parameters can only be applied to the original timing system structure and parameters, which cannot adapt to the change of the system. With the development of artificial intelligence, people have conducted a lot of research on the adaptive PID controller by using the method of artificial intelligence, see e.g., [2].

The classical PID control method is actually based on the preset parameter values to determine the current situation of the controlled object, and then according to the experience and some logical reasoning mechanism, the parameters or parameter variations of the PID controller are obtained, and the iterative calculation is carried out continuously, so as to obtain satisfactory results and set PID parameters. The preset parameter values are usually derived from empirical knowledge. If these empirical values are set unreasonable, the expected control results cannot be obtained, see e.g., [3, 4, 5].

Fuzzy PID control method summarizes the tuning experience and technical knowledge into fuzzy rule model, and uses fuzzy reasoning to realize self-tuning of PID parameters. Taking error E and error change E_C as input, the requirements of E and E_C at different times for PID parameter self-tuning can be met, and the PID parameters can be modified in real time by using fuzzy control rules. However, the extraction of expert experience in fuzzy PID control method is difficult, and the selection of membership function of process variables has a great influence on the system, see e.g., [6, 7, 8].

The PID control method based on neural network can adjust the three control parameters of the PID controller corresponding to the neuron output parameters of the training output layer in real time, so as to realize the effective control of the controlled object. However, the structure of neural network PID control method is complex, and the difficulty and cost of realization are relatively large. Moreover, it has the inherent shortcomings of ordinary neural network: slow convergence, many uncertain parameters, and easy limitation such as local minimum, see e.g., [9, 10, 11].

Comprehensive analysis of the above methods, this paper combines the good nonlinear function approximation ability of genetic programming and the characteristics of explicit results (see e.g., [12, 13]), and designs a height adaptive control strategy of UAV based on genetic programming. The structure of the height controller is still derived from the classical PID control strategy, but it is integrated with the adaptive control idea. The genetic programming is used to replace the complex parameter identification process in the adaptive method, and the explicit expression of the control parameters can be obtained after offline learning, which makes the structure of the whole control system clearer and helps to realize the engineering. At the same time, the control parameters are adjusted in real time according to different motion characteristics of UAV during flight, and the relatively intuitive parameter controller structure is used to achieve the ideal control effect.

2 Controller Designing Approach

2.1 Overall Structure

The structure of UAV height control system is shown in Figure 1. The implementation process of the system can be divided into the following two steps:

(1) Using sample data offline training control parameter regulator. With the change of flight state of UAV during flight, PID control parameters will also change accordingly,

but in general, the mapping relationship from flight state to control parameters is not linear, and the change rule is often difficult to describe by mathematical formulas. Therefore, this paper uses genetic programming learning to obtain the nonlinear mapping relationship from flight state to control parameters, so as to obtain the control parameter regulator.

(2) The control parameter regulator is inserted into the control system to realize adaptive control. In the process of UAV flight, the parameter regulator adjusts the control parameters in real time and online according to the current flight state, so that the height control effect of the controller on the controlled object (UAV) is optimal.

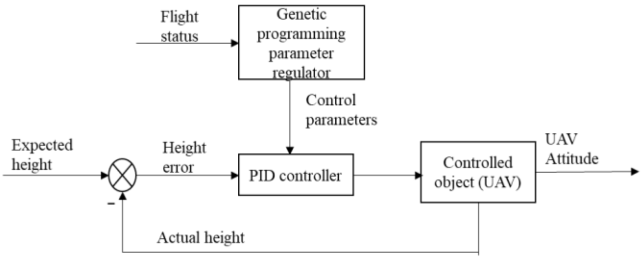

Fig.1 System structure

2.2 PID Controller

The height control system is mainly used to assist the aircraft to achieve the expected height flight, which belongs to the specific function of the aircraft longitudinal flight control system. The common functions include height following and height maintaining. The main process of longitudinal flight control of fixed-wing aircraft is to control the pitch attitude or longitudinal trajectory through the pitch angle of the elevator.

In the actual flight process, the control system controls the UAV to fly at the desired flight height by adjusting the elevator pitch angle δ_e. When the actual flight height H_r of the UAV is greater than the predetermined flight height H_m, the pitch angle of the elevator is deflected downward, resulting in negative pitching moment, making the UAV bow and reducing the flight height of the UAV; Similarly, when H_r is less than H_m, the pitch of the elevator should be deflected upward, resulting in a positive pitching moment, which makes the UAV head up and increases the flight height of the UAV, see e.g., [14, 15]. In order to speed up the response speed of the control system and avoid the oscillation of the control system, the UAV is stabilized at a specified height at a faster speed. On the basis of the proportional control, the differential term and the integral term are introduced, and the PID controller with the height error as the input term is constructed:

$$\begin{aligned}\Delta\delta_e(k) &= K_p \Delta H(k) + K_i T \sum_{j=0}^{k} \Delta H(j) \\ &+ K_d \frac{\Delta H(k) - \Delta H(k-1)}{T} \qquad (1) \\ \Delta H(k) &= H_m(k) - H_r(k)\end{aligned}$$

In the formula, $\Delta\delta_e$ is the pitch angle of elevator. K_p, K_i and K_d are the control parameters of proportional term, integral term and differential term respectively. In the flight process, corresponding to different flight states, the control parameters have different optimal values. ΔH is the height error between the actual flight height H_r and the predetermined flight height H_m.

3 Parameter Regulator Training

This paper selects genetic programming algorithm as the training algorithm of parameter regulator. Because it can achieve good training effect, and easy to implement in software, in addition to its training results are explicit function expression, in engineering implementation and theoretical analysis are more intuitive, can greatly reduce the complexity of the control system.

3.1 Genetic Programming

Genetic programming is a new evolutionary algorithm based on genetic algorithm. The biggest difference between genetic programming and genetic algorithm is its individual gene structure (data coding structure). In the genetic algorithm, the individual's gene structure is binary or real-valued encoding, while in the genetic planning, the individual's gene adopts the tree structure, which can be adjusted to form different individual genes.

Figure 2 shows the genetic structure of individuals in genetic planning. In the figure, symbols +, −, *, / are operators; Variables x_1, x_2, x_3, x_4 and constants 3, 7, 20 are terminators; The combination of operator and terminator $(x_1+3)/(x_2-x_3)-7 \times 20/x_4$ is the individual genetic structure of genetic planning. Thus, the final result of genetic programming is an explicit computer program, the quantitative relationship between variables can be described in a clear expression.

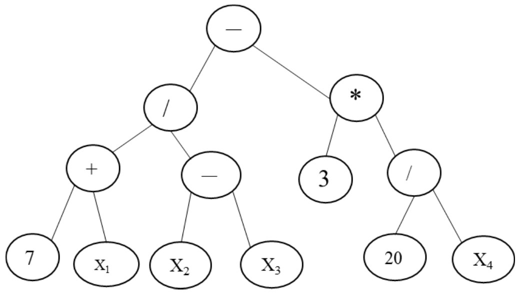

Fig.2 Gene structure of GP's individual

Gene crossover occurs between two independent individuals. It's function is to exchange gene information within the population. The specific operation is to select two individuals from the group, two individual selection process independent. During the exchange, a node is randomly selected from each individual's structure as the intersection, so a subtree with the intersection as the root is generated, which includes all the subtrees below the intersection. In special cases, the subtree is only a leaf node. Then exchange two individual subtrees. and then two individual subtrees are exchanged. Figure 3 describes the process of crossover between two individual genes.

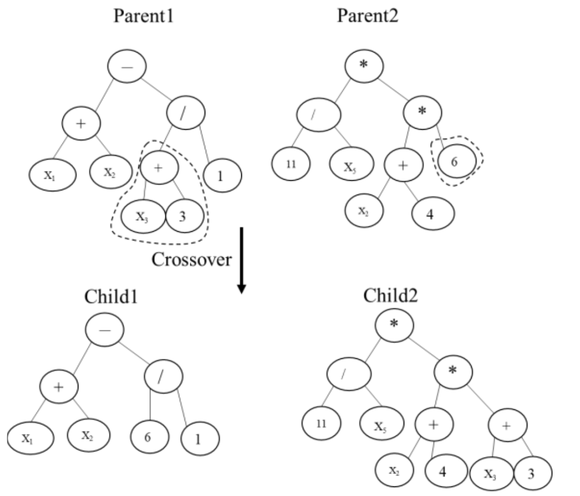

Fig. 3 The cross operation

Similar to genetic algorithm, gene mutation in genetic programming is carried out in individual units. A node is randomly selected from the structure of a single individual as a mutation point, and an operator / terminator is randomly selected to replace the operator / terminator at the mutation point. Figure 4 describes the process of individual gene mutation.

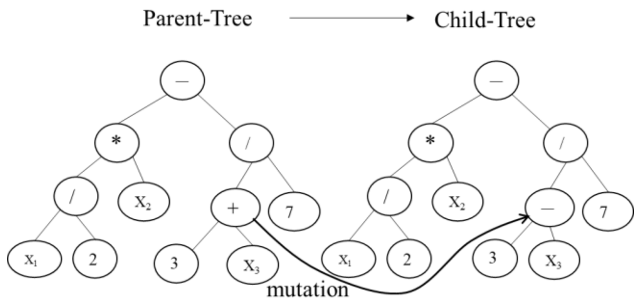

Fig. 4 The mutation operation

The algorithm flow of genetic programming is as follows:

(1) Setting main parameters: setting population size and evolution algebra, determining operator set and terminator set, and setting probabilities of various genetic operations, such as crossover probability and mutation probability.

(2) Generation of initial population: The initial population is generated by random method, and the initial population with high diversity is obtained.

(3) Evaluation of individuals: The fitness function is used to calculate the fitness value of each individual gene in the group.

(4) Termination judgment: determine whether the current population meets the selection conditions of the optimal solution, if satisfied, return to the optimal solution, if not satisfied, continue the following steps until finding the optimal solution or reaching the maximum number of evolutions of the population.

(5) Generation of offspring: individual genes are selected according to the fitness level and probability for mutation and crossover operation to generate new offspring population. After the generation of progeny population, jump to step 3 to continue the cycle.

3.2 Training Dataset

The task of genetic programming is to establish a nonlinear relationship from the flight state of the UAV to the control parameters. Therefore, it is necessary to obtain sufficient training data sets for training parameter regulators. When describing the flight state, the state variables which are easy to obtain and have obvious influence on the motion state of the UAV should be selected. Therefore, the flight Mach number Ma and the angle of pitch are selected as the state variables to describe the flight state when training the parameter regulator. The relationship between the state variables and the control parameters can be expressed as:

$$\left.\begin{array}{l} K_p = f_p\left(Ma,\alpha\right) \\ K_i = f_i\left(Ma,\alpha\right) \\ K_d = f_d\left(Ma,\alpha\right) \\ Ma \in \left[1,2\right] \\ \alpha \in \left[-10,10\right] \end{array}\right\} \tag{2}$$

In the formula, the value range of (Ma, α) forms the state space of missile flight state, obtains a series of discrete status points (Ma_j, α_j) in the state space, and obtains the corresponding optimal control parameter set (K_p, K_i, K_d) by using parameter tuning method, which constitutes the data set required for training parameter regulator. Some training data are shown in table 1.

Table 1 Part of training data set

Status (Ma,α)	K_p	K_i	K_d
(1.0, -10)	6.756	2.254	5.817
(1.2, -4)	2.612	2.312	6.514
(1.4, 0)	4.228	2.124	6.556
(1.6, 4)	2.082	1.954	7.718
(1.8, 7)	7.947	2.069	6.567
(2.0, 10)	7.442	1.661	7.521

3.3 Training Process

Using the given data set to train the parameter regulator, the key parameters of genetic programming are set as table 2.

Table 2 Parameters of GP

Parameters	Value
Population Size	100
Stop generation	100
Minimum tree depth	3
Maximum tree depth	7
Mutation probability	0.2
Crossover probability	0.85
Fitness function	least-square method
Operator set	+, -, ×, ÷, sin, cos, ^
Terminator set	Ma, α, randnum

The fitness function in Table 2 is:

$$F_i = \sum_{j=0}^{m} \left| f\left(Ma_j, \alpha_j\right) - K_j \right|^2 \left(i = 1, \cdots, n\right) \quad (3)$$

In the formula: F_i is the fitness value of the first individual in the population; f is the individual generated by genetic programming, that is, in Equation (2), (Ma_j, α_j) is the independent variable, and the control parameter K is the output; K_j is the optimal control parameter corresponding to (Ma_j, α_j) in the training dataset.

The training process of control parameter K_p is shown in Figure 5. It can be seen from the figure that the fitness value tends to be stable in the 57rd generation.

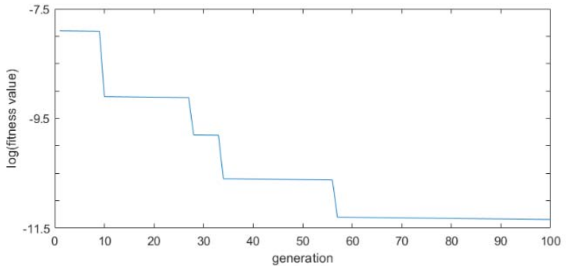

Fig.5 Fitness values of K_p

The parameter K_p regulator trained by genetic programming algorithm is:

$$\begin{aligned} K_p = &\left(1.3501\cos\left(\sin\alpha + 4.790\right) + 0.7453\right) Ma \\ &-0.2501\cos\left(4.236\sin\left(\sin\alpha\right) + 46\right) \\ &+1.0754\left(Ma + 0.0536\alpha^2\right) \\ &-0.1473\cos\left(\cos\alpha + 10.706\right) \\ &+1.8439\cos\left(0.36Ma + \alpha\right) \\ &-0.0672Ma \end{aligned} \quad (4)$$

After the same training process, the parameters K_i and K_d regulator are:

$$\begin{aligned} K_i = &\ 0.20574\sin\left(\sin\alpha\right) \\ &+0.5773\sin\left(Ma^2 + 0.8846\right) \\ &-0.3426\sin\left(\sin\alpha + Ma\right) \\ &+0.0315\sin\left(0.13Ma + 0.0042Ma\alpha^2\right) \\ &+0.3642\sin\left(0.168\alpha\right) \\ &+0.2868 \end{aligned} \quad (5)$$

$$\begin{aligned} K_d = &\ 0.0023\mathrm{M}a\alpha \\ &+7.25\sin Ma \\ &-0.265\cos\left(\sin(Ma \cdot \cos\alpha)\right) \\ &-0.3443Ma(0.051\alpha - \cos\alpha) \\ &-0.265\sin(\sin\alpha) \\ &-0.0391\sin(\alpha - Ma) \end{aligned} \quad (6)$$

Figure 6 intuitively shows the range and transformation trend of the three control parameter regulators in the state space.

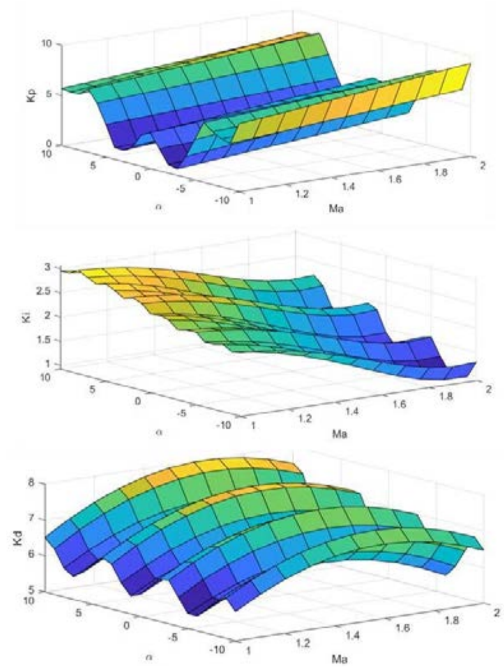

Fig.6 Control parameters (K_p, K_i, K_d) in state space (Ma, α)

4 Simulation Verification

In order to test the control effect of the system, the parameter regulator obtained by offline training is put into the control system. In the process of UAV flight, the parameter regulator can calculate the optimal control parameter groups (K_p, K_i, K_d) in real time according to the Mach number Ma and pitch angle of the current UAV flight to adjust the elevator pitch angle and control the flight height of the UAV.

Figure 7 and figure 8 are the unit step response of traditional PID height keeping system and adaptive PID height keeping system respectively. In order to compare and analyze, Fig. 7 adopts the traditional PID control method, and selects better PID parameters to control the system. Compared with Fig. 7, Fig. 8 shows that the adaptive PID control method based on genetic programming is obviously superior to the traditional PID control method. The former accelerates the response time of the system, greatly reduces the overshoot of the system, and improves the dynamic and static performance of the system.

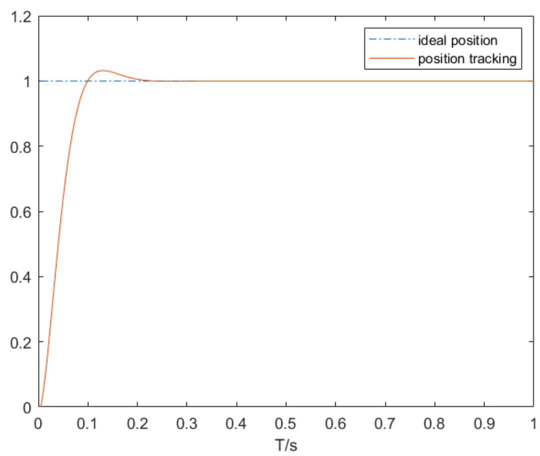

Fig. 7 Step response of traditional PID control loop

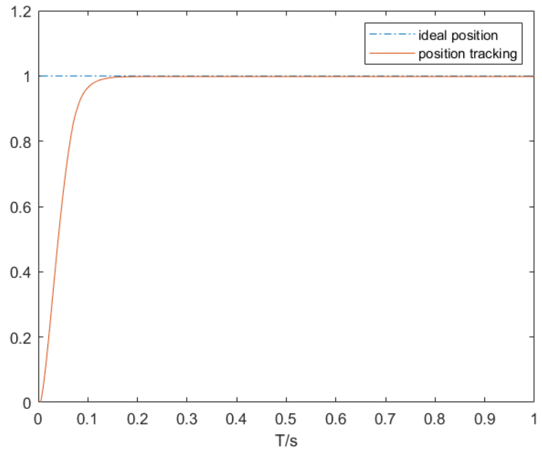

Fig 8 Step response of adaptive PID control loop

5 Conclusion

In this paper, a PID adaptive control method for longitudinal height control of UAV is designed, which is suitable for the control of nonlinear and time-varying objects such as UAV. The simulation results show that the performance of the controller using this control method is significantly improved compared with that of the conventional PID controller. The response is fast, the overshoot is small, and the steady-state accuracy is high. The dynamic and static performance of the system are greatly improved, which can meet the requirements of autonomous flight. Compared with other PID adaptive control methods, the adaptive adjustment of the extended parameters can be applied to the control system with more parameters to be adjusted and more complex structure (that is, strong nonlinear characteristics). At the same time, the method can directly obtain the expression of control parameters from the results of off-line training, which is convenient for software implementation to improve the response speed of the system and has strong adaptability to the nonlinear changes of parameters in the system.

However, there are too few state variables selected in the design method of this paper, only considering the flight speed and pitch angle of UAV, which has certain limitations on the adjustment of parameters. In the next research process, the characteristic parameters affecting the flight state are considered as much as possible to further improve the accuracy of PID parameter tuning.

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