An artificial neural network controller based on MPSO-BFGS hybrid optimization for spherical flying robot

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Abstract. Spherical flying robot can perform various tasks in the complex and varied environment to reduce labor costs. However, it is difficult to guarantee the stability of the spherical flying robot in the case of strong coupling and time-varying disturbance. In this paper, an artificial neural network controller (ANNC) based on MPSO-BFGS hybrid optimization algorithm is proposed. The MPSO algorithm is used to optimize the initial weights of the controller to avoid the local optimal solution. The BFGS algorithm is introduced to improve the convergence ability of the network. We use Lyapunov method to analyze the stability of ANNC. The controller is simulated under the condition of nonlinear coupling disturbance. The experimental results show that the proposed controller can obtain the expected value in shorter time compared with the other considered methods.

1. Introduction

Because of simple structure, low manufacturing cost, strong adaptability to environment and flexible mobility [1], spherical aircraft are being paid more and more attention by organizations and researchers. With the development of MEMS manufacturing process and artificial intelligence technology [2] – [5], spherical flying robot has played an important role and shows great advantage in the field of agricultural photogrammetry, terrain exploration, mountain rescue and military scouting [6]. At present, there are some basic problems in spherical flying vehicles, including underactuated, nonlinear, time-varying, strong coupling and so on [7], [8]. As one of the key technologies to solve these control problems, autonomous control has been the focus of research in this field. Hatamleh et al. [9] described a parameter estimation method to improve the robustness of flight control under uncertain system parameters. Islam et al. [10] has studied a robust adaptive tracking algorithm to solve modeling error and uncertain disturbance. Aiming at solving coupling and underactuated problems in the control, Zhao et al. [11] proposed a nonlinear robust tracking control scheme based on RISE and I&I method. Diao et al. [12] study on a continuous time-varying adaptive controller based on underactuated vehicles. Peng et al. [13] designed a backstepping sliding mode controller based on RBF neural network to enhance the robustness of the flight height control. Xiong et al. [14] introduced a full drive subsystem controller based on TSMC algorithm to realize the high precision tracking control of position and attitude In order to the complexity and singularity problem caused by attitude representation, Lee [15] proposed a robust adaptive controller based on SO(3) to achieve a track of height and angular velocity in the case of unknown rigid body inertia matrix. Lin et al. [16] put forward an intelligent controller based on recursive wavelet neural network, which can realize the vehicle’s motion control under the condition of control force attenuation and wind disturbance. WANG et al.
[17] studied a neural network adaptive inverse model control method to deal with the parameter variation and external disturbance. In this paper, we propose an artificial neural network controller based on MPSO-BFGS hybrid optimization algorithm for the motion control of spherical flying robot. Firstly, in order to solve the learning object of the controller, the dynamics of robot is analyzed and its motion model is established. Secondly, an artificial neural network is constructed according to the motion model. Finally, in order to improve the learning efficiency and generalization ability of the network, a hybrid optimization algorithm based on MPSO and BFGS is used to select and update weights of the network. The simulation results show that the proposed controller can obtain the expected control in shorter time than the considered controller in the presence of disturbance parameters and coupling.

2. Dynamic model of spherical flying robot

The spherical flying robot is mainly composed of carbon fiber mesh shell, propeller, air separator and power device as shown in Figure 1. Servo motor, energy management system and control system are located in the power device. The two main propellers are used to realize the lift control of robot, and the four auxiliary propellers realize the attitude control by adjusting the rotational speed. We analyse the external force of spherical flying robot by using Newton-Euler equation. The specific expression can be written as:

\[ F = G_o + f + T_o \]  \hspace{1cm} (1)
\[ \Delta b = \mu_b + \delta_b \times \mu_b \]  \hspace{1cm} (2)

The translational equation of spherical flying robot is obtained:

\[ \dot{\mu}_b = -\delta_b \times \mu_b + \frac{G_o + f + T_o}{m} \]  \hspace{1cm} (3)

The rotation of spherical flying robot satisfies the theorem of moment of momentum, as shown in equation (10). Considering the good symmetry of the sphere, the moment of inertia matrix can be written by equation (11).

\[ J \delta_b + \delta_b \times J \delta_b = M \]  \hspace{1cm} (4)

The resultant moment of force relative to the center of robot’s mass is

\[ M = M_c + M_f \]  \hspace{1cm} (5)

\( M_c \) indicates the outer moment of rotors acting on the spherical flying robot, \( M_f \) represents the aerodynamic drag torque of robot body. In summary, the dynamic equation of spherical flying robot is as follows:
\[
\begin{align*}
\dot{u} &= vr - wq - g \sin \varphi + \frac{f_x + T_{ox}}{m} \\
\dot{v} &= wp - ur + g \cos \varphi \sin \gamma + \frac{f_y + T_{oy}}{m} \\
\dot{w} &= uq - vp + g \cos \varphi \cos \gamma + \frac{f_z + T_{oz}}{m} \\
\dot{\alpha} &= p + \tan \varphi \sin \gamma \ q + \tan \varphi \ cos \gamma \ r \\
\dot{\beta} &= q \ cos \gamma - r \sin \gamma \\
\dot{\omega} &= \frac{q \sin \gamma + r \cos \gamma}{\cos \varphi} \\
I_x \dot{p} &= (I_y - I_z) q r + M_{cx} + M_{fx} \\
I_y \dot{q} &= (I_z - I_x) r p + M_{cy} + M_{fy} \\
I_z \dot{r} &= (I_x - I_y) p q + M_{cz} + M_{fz}
\end{align*}
\]  

(6)

3. Artificial neural network controller

The proposed artificial neural network controller structure is shown in Figure 2. The controller includes feedback decision control, fusion tuning function and neural network to realize the flight control law. The control law is used to stabilize the output power of spherical robot by compensating the nonlinear dynamic disturbance of the system. Current attitude informations of robot are fed back to the decider after EKF filtering. The angular rate obtained by the differential and input datas are transformed into the training sets of neural network through the fusion function. Net learn data with its neuron compensation function to approximate the dynamic disturbances of spherical flying robot system. This neural network controller can be trained offline to construct the network structure and obtain the optimal control performance by automatically adjusting the parameters during the flight. The controller consists of five feedforward layers. \( E = [\psi ; \theta] \) is the training data vector of controller, \( \psi = [\psi_1, \psi_2, \ldots, \psi_n]^T \) is the adjusting angle vector of control system, \( \theta = [\theta_1, \theta_2, \ldots, \theta_n]^T \) represents the feedback value of the current robot attitude data after noise reduction. The definition of \( \psi_i \) and \( \theta_i \) is as follows. \( \psi_i = [\alpha_i, \beta_i, \omega_i] \), \( \theta_i = [\alpha_i', \beta_i', \omega_i'] \), where \( \alpha, \beta, \theta \) respectively represents pitch angle, tilt angle and roll angle.

The \( 2n \) neurons of network input layer are used to input \( \psi \) and \( \theta \). Its hidden layer is divided into three layers. The first layer has \( 6n \) neurons which are used to store the angular vector members from the input layer. The neurons in this layer use linear activation function \( f_i(x) = \mu_i x \), where \( \mu_i \) is suppression parameter vector for correcting the overflow of peak data. The second layer has \( 9n \) neurons. There are three kinds of neuron activation functions in this layer, namely, the stable control activation function, the error compensation activation function, and the overshoot control activation function. And the third layer has \( 3n \) neurons.

The output layer has \( n \) neurons. The neuron activation function is a vector conversion function, which is used to the conversion of the hidden layer’s data format.
4. Simulation

The simplified control model of spherical flying robot is defined as:

\[
\theta_i(k) = 0.6 \times \theta_i(k-1) + 0.5 \times \theta_{i+1}(k-1) + \frac{c_{ti}(k-1)}{c_{ti}(k-1)^2 + c_{ti}(k-1)} \times I_0 + 0.3 \times c_{ti+1}(k-1)^3 \times I_0
\]

\[
\theta_{i+1}(k) = 0.5 \times \theta_{i+1}(k-1) + 0.4 \times \theta_{i+2}(k-1) + \frac{c_{ti+1}(k-1)}{c_{ti+1}(k-1)^2 + c_{ti+1}(k-1)} \times I_0 + 0.7 \times c_{ti}(k-1)^3 \times I_0
\]

\[
\theta_{i+2}(k) = 0.8 \times \theta_{i+2}(k-1) + 0.5 \times \theta_i(k-1) + \frac{c_{ti+2}(k-1)}{c_{ti+2}(k-1)^2 + c_{ti+2}(k-1)} \times I_0 + 0.2 \times c_{ti+1}(k-1)^3 \times I_0
\]

Where \(i = 1, 2 \ldots n\). \(I_0 = [1, 1, 1]\); \(\theta_i(k) = [\alpha_i(k), \beta_i(k), \omega_i(k)]\), which represents the feedback angle signal of robot system in the k-th sampling period; \(c_{ti}(k)\) represents the control signal of robot system in the k-th sampling period. In order to facilitate the analysis and visualization, \(\alpha(k)\)' is regarded as observation object. Set \(i=1\), the simulation parameters of the model are as follows: (1) The initial value of the control is \([0,0,0]\); (2) The output value of the system is \(\alpha' = [0.7, 0.4, 0.6]\); (3) The learning rate of network is set to 0.001; (4) The sampling period is set to 0.0001s~0.0005s.

To illustrate the advantages of the controller, three different methods are used to control the motion of system. The first is the simulation results of control system through the traditional neural network. As shown in Figure 3 to 5, the simulation results show that the actual output is close to the target output, the control quantity of the system is stable and the error tends to 0. In a word, the controller can have some effect on the control of the system.

Secondly, the simulation results of PSO optimization neural network controller are presented. As shown in Figure 6 to 8, the simulation results show that the output of this method is close to the target output and the learning speed is better than the first two methods.

Finally, in the Figure 9 to 11, the simulation results of MPSO-BFGS neural network controller are presented.
5. Conclusion
In this paper, an artificial neural network controller based on MPSO-BFGS hybrid optimization algorithm is proposed for the motion control of a spherical flying robot. The experimental results show that the ANNC is superior to other considered methods. The controller can obtain the expected output in shorter control period. However, due to the combination of the MPSO and BFGS algorithm, it results in occupying so many computing resources. One of the considered methods is to simplify the algorithm and optimize the corresponding hardware layer, which is the focus of future research work.

6. Reference
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