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Temperature Control Strategy of Incubator based on RBF Neural Network PID

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Abstract

Taking the incubator temperature control system as the research object, the author studied the hardware structure of the incubator temperature control system and established the mathematical model of the temperature control system. Because the culture object is very sensitive to temperature changes, the traditional PID temperature control algorithm has slow response speed, weak anti-interference ability, and the control parameters are not easy to be set, the author adopts the strategy combining radial basis function (RBF) neural network and traditional PID to adjust the temperature of the incubator. In order to further improve the stability and dynamic response characteristics of the system, the LM algorithm was used instead of the gradient descent method to adjust the PID control parameters. The simulation results show that the control algorithm has faster response speed and stronger anti-interference ability, and can adjust the PID parameters in real time, which can meet the temperature control requirements of the incubator.

Keywords

Temperature control system; RBF neural network; PID control; LM algorithm.

1. INTRODUCTION

The incubator is a box device for cultivating microorganisms, animal and plant cells, and is a basic experimental equipment for scientific research departments such as biology, agriculture, medicine, and environmental protection. It is widely used in constant temperature culture and constant temperature reaction experiments [1]. Temperature is a key factor in these experiments, and the temperature response and accuracy directly affect the results of the experiment. At present, the temperature control of most incubators still uses the traditional PID algorithm, the response speed is slower, the degree of automation is lower, and the control parameters need to be based on the operator's practical experience. Therefore, this paper chooses a neural network PID control algorithm with self-learning ability to adjust its temperature.

In recent years, in the field of temperature control, neural network PID control algorithms have attracted more and more attention from domestic researchers. Literature [2] designed a BP neural network PID controller and applied it to the greenhouse temperature control system to improve the adaptive ability and robustness of greenhouse temperature control. Literature [3] proposed a PID temperature control system based on BP neural network self-tuning, which overcomes the defects of traditional PID control parameters and improves the control quality of the system. However, the BP neural network has a slow convergence rate and local minimum. Value, and its training time is longer, which will also affect the control quality of the system [4]. Therefore, this paper adopts the RBF neural network PID algorithm. For the problem of poor stability and slow response of the temperature control system, the LM (Levenberg-Marquardt)

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algorithm is used to adjust the PID control parameters to further improve the control quality of the system.

2. HARDWARE COMPOSITION OF THE INCUBATOR TEMPERATURE CONTROL SYSTEM

The incubator temperature control system mainly includes a microprocessor, a temperature sensor, an amplification and filtering circuit, an A/D converter, a driving circuit, a semiconductor refrigeration chip, a display screen and a keyboard. The microprocessor is the core of the temperature control system. It is used for the control of the whole system, the acquisition of sensor signals and the realization of the temperature control algorithm. The display is used to display the current temperature value, the keyboard is used to input the set temperature, and the temperature sensor is used to collect the temperature information in the incubator. The collected temperature information is transmitted to the microprocessor through the amplification circuit and the A/D converter processing, and the microprocessor analyzes and processes the data to calculate the current temperature, and then compares with the set temperature. If the current temperature is not equal to the set temperature, the microprocessor sends a control signal to the drive circuit to drive the semiconductor cooling chip to start heating or cooling, so that the temperature value in the incubator tends to the set temperature value [5,6]. Its hardware structure is shown in Figure 1.

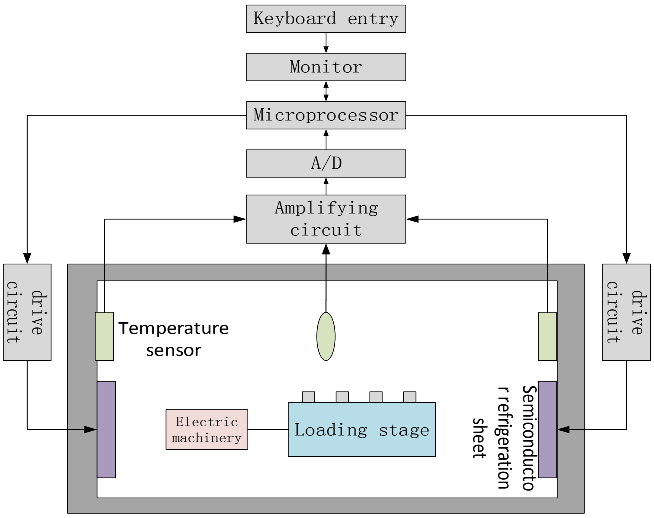

Fig 1. Hardware structure diagram of incubator temperature control system

3. INCUBATOR TEMPERATURE CONTROL MODEL

Assuming that the incubator is a concentrated parameter object, the internal air has the same temperature in any radial section, and we ignore the heat loss, the heat absorbed by the air in the incubator is equal to the heat released by the semiconductor cooling fins on both sides, and its static the equilibrium equation is

$$K_s = K_c \tag{1}$$

Its dynamic equilibrium equation is

$$\mathrm{Q} = \frac{2\lambda A(K_s - K_c)}{b} \tag{2}$$

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From the basic theorem of thermodynamics, the instantaneous heat flow formula can be derived as:

$$Q = CV\rho \frac{dK}{dt} \tag{3}$$

The heat transfer from the sides of the incubator to the middle of the tank can be seen as a free heat transfer from the infinity plane to the space, so:

$$CV\rho \frac{dK_c}{dt} = \frac{2\lambda A}{b}(K_s - K_c) \tag{4}$$

By transforming and deforming the above formula, the heat transfer transfer function of the temperature and intermediate temperature on both sides of the incubator can be obtained as follows:

$$G(S) = \frac{K_C(S)}{K_S(S)} = \frac{2\lambda A / b}{CV\rho s + 2\lambda A / b} \tag{5}$$

There is a hysteresis in the heat transfer process, so the hysteresis link $e^{-\tau s}$ should be added to the transfer function, so the transfer function is:

$$G(S) = \frac{K}{1+Ts} e^{-\tau s} \tag{6}$$

Where $K = 1, T = CV\rho b / 2\lambda A.$

In equations (1) to (6), K_S represents the temperature on both sides of the incubator, K_C represents the temperature in the middle of the incubator, b represents the thickness of the gas, λ represents the thermal conductivity, C represents the specific heat capacity of the air, and ρ represents the air density inside the incubator, A indicates the cross-sectional area of the incubator, and ΔK indicates the temperature difference between the temperature on both sides of the incubator and the middle.

4. DESIGN OF RBF NEURAL NETWORK PID CONTROLLER

4.1. Radial Basis Function Neural Network Structure

The radial basis function neural network includes three layers of input layer, hidden layer and output layer [7,8]. The input layer contains n nodes, which are used to transmit input information to the hidden layer. The hidden layer contains m nodes. The selection of nodes depends on the specific situation. The activation function of the hidden layer is a Gaussian function, its role is to spatially transform the input data. The output layer contains a node, which role is to sum up the output of hidden layer linearly. The detailed structure is shown in Figure 2. The RBF neural network is a locally approximating network with fast learning speed and can avoid local minima, so it is feasible to apply it in real-time temperature control [9, 10].

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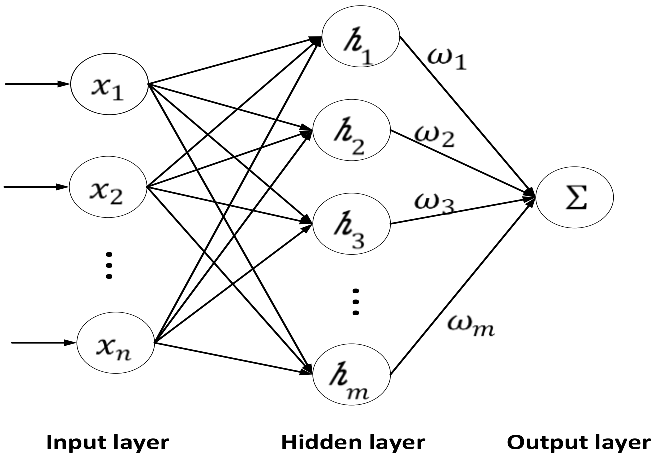

Fig 2. Structure Diagram of Radial Basis Function Neural Network

In Figure 2, $X=[x_1,x_2,\dots,x_n]^T$ is the input vector, h_j is the output of the jth neuron in the hidden layer, ie

$$h_j=\exp\left(-\frac{\|X-C_j\|^2}{2{b_j}^2}\right), j=1,2,\dots,m \tag{7}$$

In the equation (7), $C_j=[c_{j1},c_{j2},\dots,c_{jn}]^T$ is the center point vector of the jth hidden layer neuron. b_j is the Gaussian function width of the hidden layer neuron j.

The weight vector of the network is $W=[w_1,w_2,\dots,w_m]^T$

The output of the RBF network is:

$$y_m(k)=w_1h_1+w_2h_2+\cdots+w_mh_m \tag{8}$$

The performance indicator function of neural network identification is:

$$J=\frac{1}{2}[y(k)-y_m(k)]^2 \tag{9}$$

The output weight, node base width, and node center are adjusted using the gradient descent method. The algorithm is as follows:

$$\begin{cases}\Delta w_j=\eta\left[y(k)-y_m(k)\right]h_j\\ w_j(k)=w_j(k-1)+\Delta w_j+\alpha\left[w_j(k-1)-w_j(k-2)\right]\\ \Delta b_j=\eta\left[y(k)-y_m(k)\right]w_jh_j\dfrac{\left\|X-C_j\right\|^2}{b_j^3}\\ b_j(k)=b_j(k-1)+\Delta b_j+\alpha\left[b_j(k-1)-b_j(k-2)\right]\\ \Delta c_{ji}=\eta\left[y(k)-y_m(k)\right]w_j\dfrac{x_j-c_{ji}}{b_j^2}\\ c_{ji}(k)=c_{ji}(k-1)+\Delta c_{ji}+\alpha\left[c_{ji}(k-1)-c_{ji}(k-2)\right]\end{cases} \tag{10}$$

In the equation (10), α is a momentum factor, and η is a learning rate, $\alpha,\eta\in[0,1]$.

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4.2. RBF-PID Control System Design

The RBF neural network PID incubator temperature control system consists of three parts. The first part is the RBF neural network. The neural network takes u(k), y(k), y(k-1) as input and y_m as the output. After the network identification, the weighting coefficient, the node width and the center vector are corrected by the gradient descent method; The second part is the LM algorithm part, which uses the LM algorithm instead of the gradient descent method to adjust the PID controller parameters k_p、k_i、k_d [11]; The third part is the traditional PID controller, which directly controls the incubator temperature control system after receiving the dynamically adjusted PID control parameters. Its block diagram is shown in Figure 3:

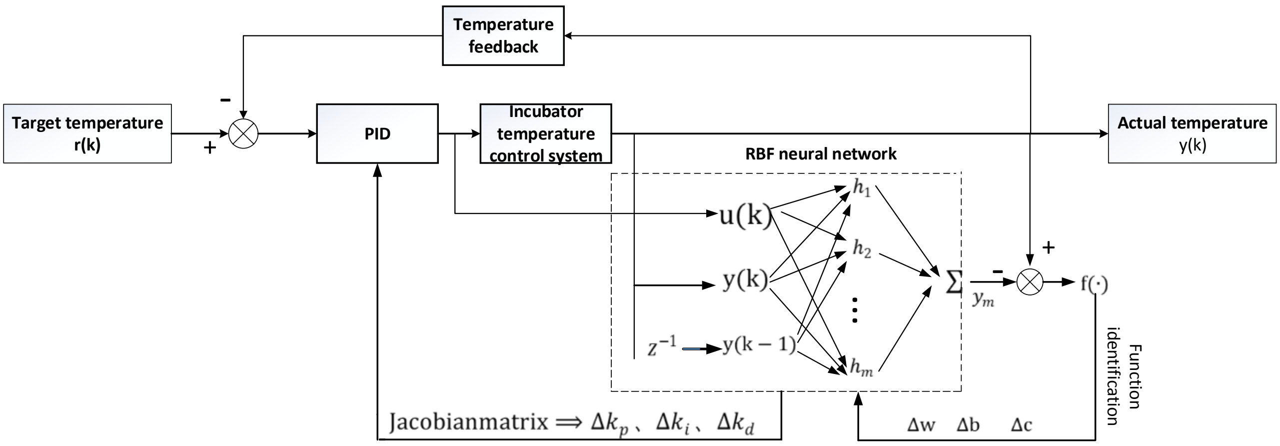

Fig 3. Temperature control System of incubator Based on RBF Neural Network PID

In this paper, the incremental PID calculation method is adopted, and the control error is

$$e(k) = r(k) - y(k) \tag{11}$$

The three inputs of the PID controller are:

$$\begin{cases} x_P = e(k) - e(k-1) \\ x_I = e(k) \\ x_D = e(k) - 2e(k-1) + e(k-2) \end{cases} \tag{12}$$

The control algorithm is

$$u(k) = u(k-1) + k_p x_P + k_i x_I + k_d x_D \tag{13}$$

In order to further improve the stability and response speed of the temperature control system, the LM algorithm is used to calibrate the PID parameters. The LM algorithm has both the local characteristics of the Gauss-Newton method and the global characteristics of the gradient descent method. It makes full use of the Jacobian information obtained by the network identifier. Therefore, the convergence speed is faster and the dynamic response characteristics are stronger [12].

The LM algorithm is as follows:

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$$\Delta x = -[J^T(x)J(x) + \mu I]^{-1}J(x)E(x) \tag{14}$$

Where Δx represents the amount of change in the weight and the threshold, μ>0, and I is an identity matrix.

Let the the composition vector of weight and the threshold of the kth correction be x(k), then:

$$x(k+1) = x(k) + \Delta x \tag{15}$$

The error indicator function is:

$$E(x) = \frac{1}{2}\sum_{i=1}^{N} e_i^2(x) \tag{16}$$

The Jacobian matrix is:

$$J(x) = \begin{pmatrix} \frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \cdots & \frac{\partial e_1(x)}{\partial x_n} \\ \frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \cdots & \frac{\partial e_1(x)}{\partial x_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial e_N(x)}{\partial x_1} & \frac{\partial e_N(x)}{\partial x_2} & \cdots & \frac{\partial e_N(x)}{\partial x_n} \end{pmatrix} \tag{17}$$

The above algorithm is used to adjust the control parameters, taking $K=\left[k_p, k_i, k_d\right]$, then:

$$\begin{cases} \frac{\partial e(k+1)}{\partial k_P} = \frac{\partial y(k+1)}{\partial \Delta u(k)} \frac{\partial \Delta u(k)}{\partial k_P} = \frac{\partial y(k+1)}{\partial \Delta u(k)} x_P \\ \frac{\partial e(k+1)}{\partial k_I} = \frac{\partial y(k+1)}{\partial \Delta u(k)} \frac{\partial \Delta u(k)}{\partial k_I} = \frac{\partial y(k+1)}{\partial \Delta u(k)} x_I \\ \frac{\partial e(k+1)}{\partial k_D} = \frac{\partial y(k+1)}{\partial \Delta u(k)} \frac{\partial \Delta u(k)}{\partial k_D} = \frac{\partial y(k+1)}{\partial \Delta u(k)} x_D \end{cases} \tag{18}$$

Then:

$$\Delta k = -\left[\left(\frac{\partial e(k+1)}{\partial K}\right)^T \left(\frac{\partial e(k+1)}{\partial K}\right) + \mu I\right]^{-1} \frac{\partial e(k+1)}{\partial K} e(k) \tag{19}$$

In the equation (19), since $[J^T(x)J(x) + \mu I]$ is positive definite, the solution of the equation (19) always exists. $\partial y / \partial u$ in equation (18) is the Jacobian information of the temperature control system. As long as $\partial y / \partial u$ is obtained, the PID control parameters can be obtained.

5. SIMULATION AND EXPERIMENT

In order to verify the control effect of the algorithm, the system simulation model was built in the Simulink environment of Matlab, as shown in Figure 4, and the simulation verification was carried out.

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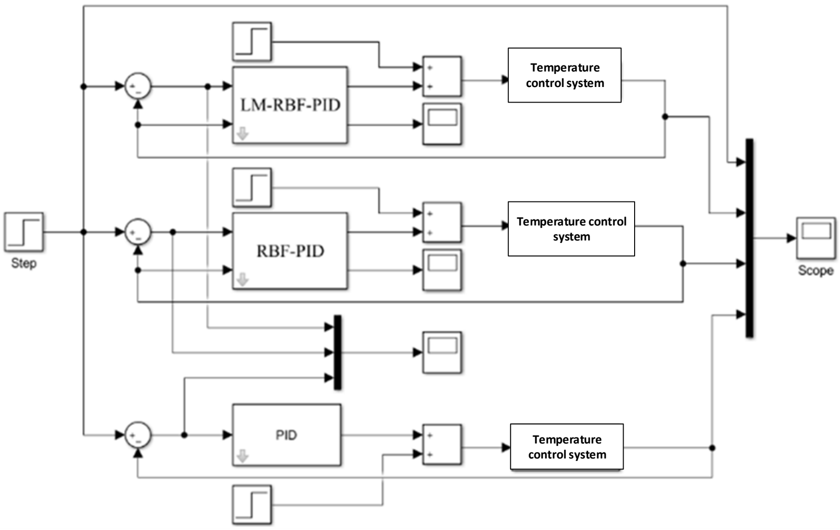

Fig 4. System simulation model diagram

In the simulation process, the network structure is selected 3-6-1, the learning rate of the network is selected as η=0.45, the learning rate of PID control parameters is $\eta_2 = 0.2$, the control parameter of LM algorithm is μ=1, and the interference signal is added to the system at 2000s. The response curve of the system is shown in Figure 5. The error curve of the system is shown in Figure 6. The simulation results show that compared with the traditional PID algorithm and the RBF-PID algorithm, the control algorithm of this paper has better response characteristics and its anti-interference ability is also improved.

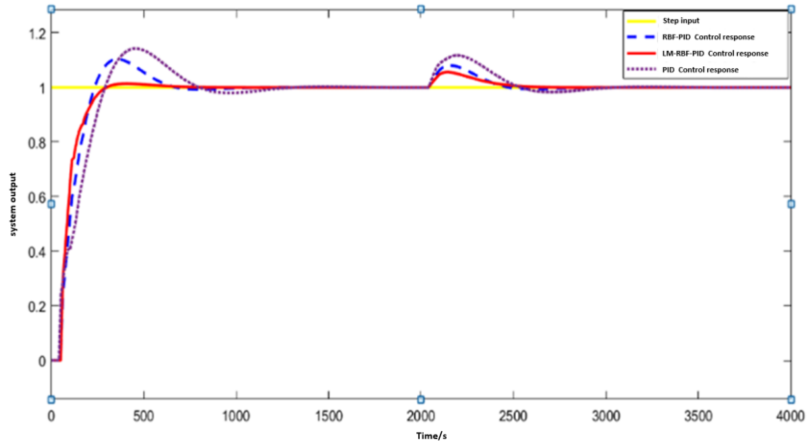

Fig 5. Response Curve of Control System

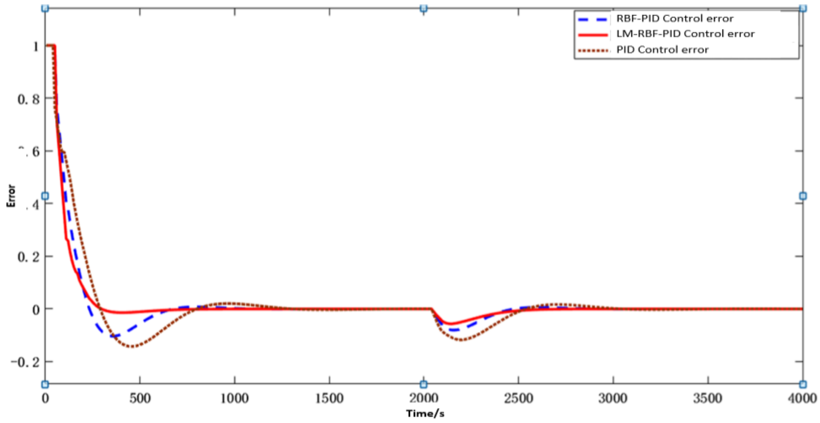

Fig 6. Error descent curve

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In order to further verify the practical feasibility of the algorithm, the PT1000 temperature sensor is used to collect the temperature in the incubator in real time, and the thermoelectric cooling sheet TEC1-12706 is used for heating or cooling. The acquired signals are conditioned by the high-performance instrument op amps AD8221 and LTC1867 A/D converters, The low-power STM32 microprocessor is selected as the core of the temperature control system, and Labview2016 is used as the software development platform for experiments, The collected temperature data is transmitted to the computer via the RS232 serial port, and the computer's Labview program further analyzes and processes the collected temperature [13]. The set temperature is 32 ° C, the ambient temperature is 22 ° C, the upper temperature limit is set to 33 ° C, the lower temperature limit is set to 31 ° C, the temperature data is collected every 30 s, after 150 minutes of experimental test, the experimental results are shown in Figure 7. The system reaches the set temperature in 9 minutes, and then fluctuates up and down at 32 °C. The temperature fluctuation error is basically less than 0.5 °C, which can meet the temperature control requirements of the incubator.

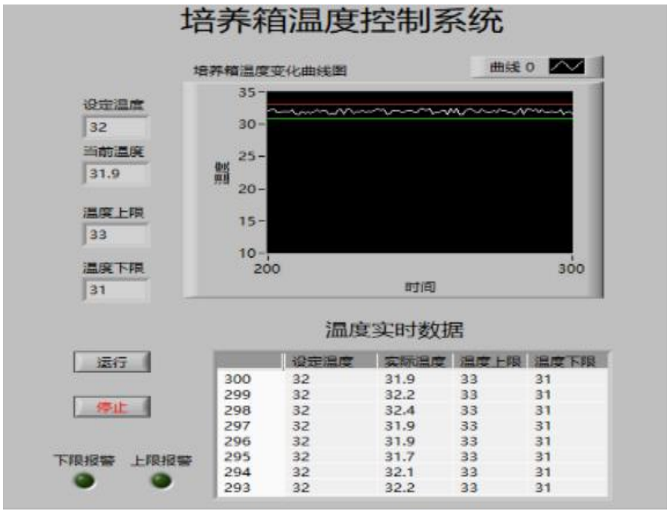

Fig 7. Screenshots of Experimental Test Procedures

6. CONCLUSION

Because microorganism, animal and plant cells are very sensitive to temperature change, there are nonlinear and time-varying uncertainties in the temperature control process of incubator, and the traditional PID control algorithm has long response time, poor anti-interference ability and difficult to adjust control parameters, we use RBF neural network PID algorithm to adjust the temperature of incubator. In order to further improve the stability and dynamic response speed of the temperature control system, the LM algorithm was used instead of the gradient descent method to adjust the PID control parameters. Through simulation and experimental analysis, the control quality of the RBF neural network PID control algorithm is significantly better than the traditional PID control algorithm. The algorithm can significantly improve the stability and dynamic response speed of the incubator temperature control system. And its anti-interference ability has also been enhanced, basically meeting the temperature control requirements of the incubator. It provides a novel and effective control method for the temperature control of the incubator and has certain application value.

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