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Research Article

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Design of radial basis function neural network controller for BLDC motor control system

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ABSTRACT

Brushless DC(BLDC) motors are widely used for many industrial applications, In view of the problem that it is difficult to tune the parameters and get satisfied control characteristics by using normal conventional PID controller. a online identification method based on Radial Basis Function(RBF) has been proposed in this paper. In this method, connection weight of neural network was revised in time according to the speed of motor and phase current, the duty cycle of pulse width modulation (PWM) was adjusted to control the speed of BLDC motor. Conventional PID and RBF neural network PID algorithm were respectively adopted to make a comparison. the control approach was validated with simulation at first and then was implemented with a DSP TMS320F28035. Matlab simulations and experiment results showed that the proposed approach has less overshoot, faster response, stronger ability of anti-disturbance than the conventional PID controller.

Key words: Radial Basis Function(RBF) Neural Network; Brushless DC Motor(BLDC Motor); Pulse Width Modulation (PWM); Brushless DC Motor(BLDC Motor)

INTRODUCTION

Brushless DC(BLDC) motor has several benefits such as: high power density, efficiency, power factor, silent operation, compact form, reliability, low maintenance, and better controllability. So far, BLDC motor has been widely used in CNC machine tools, electrical equipment, mining and other industrial applications fields. For BLDC motor the controller plays a very vital role in influencing its performance for applications concerning load variations[1-3].

The conventional proportional-integral-derivative (PID) controller is widely used in many control applications because of its simplicity and effectiveness, yet PID controller has its shortcomings, especially for the target which is nonlinear and uncertain. The parameters are fixed, which makes the controller inappropriate to complex nonlinear control systems. BLDC motor control system is a multi-variable, nonlinear, strong coupling system, it is difficult to achieve ideal control effect. Therefore, high performance control strategy must be robust and adaptive, so interest in emerging intelligent control systems for BLDC motor has increased significantly.

Some intelligent control algorithms have been applied in the control of BLDC motor. A genetic algorithm was used to find the optimum tuning parameters of the PID controller by taking integral absolute error[4,5]. PID self-tuning methods based on relay feedback technique were presented[6,7]. An adaptive fuzzy sliding-mode control system[8], which combines the merits of sliding mode control, the fuzzy inference mechanism and the adaptive algorithm, was proposed by Lin, F. J [9].Wang, C. H employed an observer based direct adaptive fuzzy-neural network controller with supervisory controller for a class of high order unknown nonlinear systems[10-11]. An adaptive PID control tuning was proposed to cope with the control problem for a class of uncertain chaotic systems with external disturbance[2]. Although the previous researches presented robust control in multi-rate or variable sampling, their controllers were complex and difficult to implement.

Neural network as an intelligent control algorithm, is known for its strong capacities of self-learning, self-adapting and self-organization, and it is suitable for the control of nonlinear systems. Radial basis function (RBF) neural network constitute a special network architecture that presents remarkable advantages over other neural network types including better approximation capabilities, simpler network structures and faster learning algorithms. RBF neural networks have found many applications in different scientific areas like pattern recognition, optimization, biological modeling and control.

This paper is organized in the following manner. In Section 2, mathematical model of BLDC motor is described. In Section 3, RBF neural network control theory is explained. PID controller based on RBF neural network is investigated in section 4. To verify the effectiveness of the proposed control method, the simulations and experiments are provided in Section 5. A brief conclusion is outlined in Section 6.

MATHEMATICAL MODEL OF BLDC MOTOR

The induction electromotive force of BLDC Motor is a trapezoidal wave which contained a larger number of harmonics, so it is difficult to analysis the operation characteristics of BLDC Motor precisely. Therefore, the following assumption of BLDC motor was given:

Windings of three-phase are symmetrical;
(2) The air-gap magnetic induction intensity in a trapezoidal distribution;
(3) Ignoring the influence of stator slot;
(4) Ignoring the influence of armature reaction on air gap flux;
(5) Ignoring the hysteresis and eddy current loss.
Typical mathematical model of BLDC motor is described by the following equations:

$$\begin{bmatrix} U_a \\ U_b \\ U_c \end{bmatrix} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \mathrm{p} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \tag{1}$$

Where, R is the resistance of each phase of the stator, L is the self-inductance of each phase, M is the mutual inductance between any two phases, U_a, U_b, U_c are the phase voltages, i_a, i_b, i_c are phase currents, e_a 、 e_b 、 e_c are trapezoidal back EMFs. p is differential operator, $\mathrm{p} = \mathrm{d}/\mathrm{d}t$ .The electromagnetic torque can be expressed as,

$$T_e = \frac{e_a i_a + e_b i_b + e_c i_c}{\omega} \tag{2}$$

Where, ω is the rotor speed. The torque balance equation is expressed as,

$$T_e = T_L + J\frac{\mathrm{d}\omega}{\mathrm{d}t} + B\omega \tag{3}$$

where T_L is the load torque, J is moment of inertia, B is damping of friction coefficient .

RBF NEURAL NETWORK

RBF Neural Network Model

RBF neural network was first proposed by J.Moody and C.Darken in the late 1980s. Theoretically, RBF neural networks can approximate any continuous function defined on a compact set to any prescribed degree of accuracy by sufficiently expanding the networks structure.

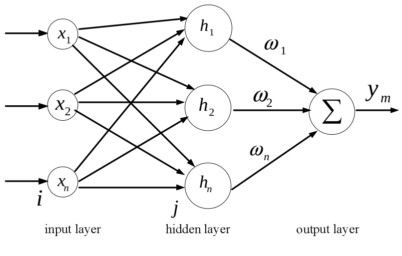


Fig 1 RBF Neural Network structure

Basic RBF neural network consists of three layers, namely input layer, hidden layer, and output layer. The nodes within each layer are fully connected to the previous layer. The input nodes are directly connected to the hidden layer neurons. The mapping from input layer to output layer is nonlinear, but the mapping from hidden layer to output layer is linear, Thus greatly accelerate the speed of learning, and avoid the local minimum problem. The structure of multi-input and single-output (MISO) RBF neural network is represented in Fig. 1.

In RBF neural network, the input vector is $x=[x_1,x_2,\cdots,x_n]^{\mathrm{T}}$, assuming radial basis vector is $h=[h_1,h_2,\cdots,h_n]^{\mathrm{T}}$, h_j is Gaussian function,

$$h_j=\exp(-\frac{\|x-c_j^2\|}{2b_j^2}),\ j=1,2,\cdots n \tag{4}$$

where c_j is the neuron's center and b_j is the center spread parameter. Here, we have used Gaussian transfer function for the hidden neurons. The weight from input layer to hidden layer is 1, the weight vector from hidden layer to output layer is $W=[w_1,w_2,\cdots,w_m]^{\mathrm{T}}$. For the neuron the output is:

$$y_m=\sum_{j=1}^{m}w_jh_j \tag{5}$$

The performance index function of identifier is

$$J=\frac{1}{2}(y(k)-y_m(k))^2 \tag{6}$$

According to the gradient descent method, node center, output weights and node base-width parameters are shown as the following formula:

$$\left.\begin{aligned}
&\Delta w_j(k)=\eta(y(k)-y_m(k))h_j\\
&w_j(k)=w_j(k-1)+\Delta w_j(k)+\alpha(w_j(k-1)-w_j(k-2))\\
&\Delta b_j(k)=\eta(y(k)-y_m(k))w_jh_j\frac{\|X-c_j\|^2}{b_j^3}\\
&b_j(k)=b_j(k-1)+\Delta b_j(k)+\alpha(b_j(k-1)-b_j(k-2))\\
&\Delta c_j(k)=\eta(y(k)-y_m(k))w_j\frac{x_j-c_{ji}}{b_j^2}\\
&c_{ji}(k)=c_{ji}(k-1)+\Delta\eta c_{ji}(k)+\alpha(c_{ji}(k-1)-c_{ji}(k-2))
\end{aligned}\right\}(7) \tag{7}$$

where η is the learning rate, α is momentum factor.

Jacobian algorithm is：

$$\frac{\partial y(k)}{\partial\Delta u(k)}\approx\frac{\partial y_m(k)}{\partial\Delta u(k)}=\sum_{j=1}^{m}w_jh_j\frac{c_{ji}-\Delta u(k)}{b_j^2} \tag{8}$$

RBF neural network PID tuning principle

The tuning principle based on RBF neural network PID diagram as shown in Figure 2.

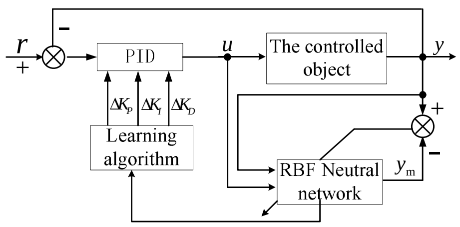


Fig 2 Tuning principle based on RBF neural network PID

This paper adopts the incremental PID controller, the control error is :

$$e(k)=y_d(k)-y(k) \tag{9}$$

PID inputs are:

$$\left.\begin{aligned} x_c(1) &= e(k) - e(k-1) \\ x_c(2) &= e(k) \\ x_c(3) &= e(k) - 2e(k-1) + e(k-2) \end{aligned}\right\} \tag{10}$$

Where $x_c(1)$ is the proportional term, $x_c(2)$ is the integral term, $x_c(3)$ is the differential term.
Neural network tuning index is:

$$E(k) = \frac{1}{2} e(k)^2 \tag{11}$$

PID control algorithm is

$$\begin{aligned} u(k) &= u(k-1) + K_P(e(k) - e(k-1)) + K_I e(k) + \\ &K_D(e(k) - 2e(k-1) + e(k-2)) \end{aligned} \tag{12}$$

We can get the adjustment quantity K_P 、K_I 、K_D with the gradient descent method, the adjustment quantity are:

$$\left.\begin{aligned} \Delta K_P &= -\eta \frac{\partial E}{\partial K_P} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial K_P} = \eta e(k) \frac{\partial y}{\partial \Delta u} x_c(1) \\ \Delta K_I &= -\eta \frac{\partial E}{\partial K_I} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial K_I} = \eta e(k) \frac{\partial y}{\partial \Delta u} x_c(2) \\ \Delta K_D &= -\eta \frac{\partial E}{\partial K_D} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial K_D} = \eta e(k) \frac{\partial y}{\partial \Delta u} x_c(3) \end{aligned}\right\} (13) \tag{13}$$

Where $\frac{\partial y}{\partial \Delta u}$ is the Jacobian information of controlled object, which can be obtained by identification of the neural network.

DESIGN OF BLDC MOTOR CONTROL SYSTEM BASED ON RBF NEURAL NETWORK

BLDC motor control system based on RBF neural network

The BLDC motor speed can be controlled accurately by controlling PWM duty cycle D, The input signals of RBF neural network are phase current and speed, output signal is duty cycle D, the input and output are applied in BLDC motor control system, it can change control parameters on-line and real-time. Neural network layers and number of neurons selection is designed according to the requirements of the system. Neural network revise the network weight vector and get the ideal duty cycle D according to the operation state of the system. Structure diagram of BLDC motor control system based on RBF neural network as shown in Figure 3. The system adopts double closed loop control, the inner loop is current loop, the outer loop is speed loop.

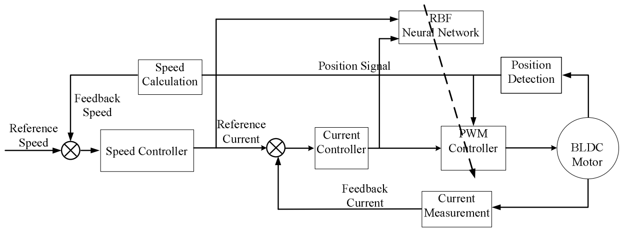


Fig3 Structure diagram of BLDC motor control system based on RBF neural network

Control algorithm system flow

According to the RBF neural network algorithm, the process of BLDC motor control system is as follows:
To initialize the parameters of RBF neural network according to the initialization process, set connection weight a random number between [-0.5,0.5], set the threshold value of duty D [0,1], the duty cycle error threshold is 0.02.

To start the system, and then sample phase current and speed of BLDC motor. The activation function of hidden layer nodes is S type function:

$$f(s) = a + \frac{b}{1 + e^{-ds}}$$

Where a , b , d is constant, the S type function can meet the control requirements of the electric drive control system.

To send sampled phase current i_a, i_b, i_c and speed n to RBF neural network, correct the network weight vector in real time according to the operation status of the motor; In accordance with the phase current, speed and output D values of neural network, Correct PWM in real time to control the motor speed. compare actual value duty D with threshold value, if the error e_k is less or equal to error threshold value e_k^*, speed control signal is output. Return to step (1) and restart if it has not met the end condition.

To end the algorithm if it has met the end condition, namely the error signal e_k is less than or equal to the error threshold e_k^*,. Otherwise, return to step (1).

In the whole control process, input signals are sent to network, the weight vector of RBF neural network is modified in real time until the output duty cycle D is ideal and the desired speed is achieved.

SIMULATION AND EXPERIENT RESULTS

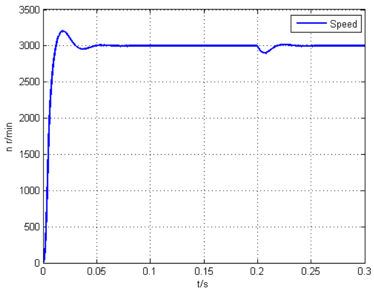
Simulation test

To test the system performance, a simulation model of BLDC motor was established in MATLAB, the simulation model adopted conventional PID control and RBF neural network PID control respectively, The BLDC motor parameters are given in Table 1.

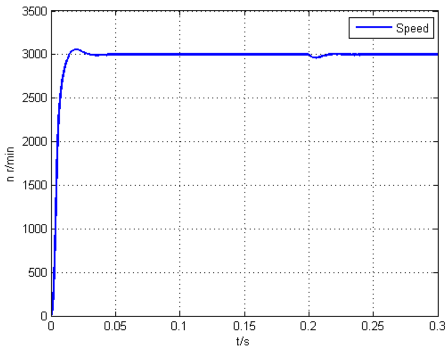
Table.1 Selected specifications of BLDC Motor

Parameters	Value
Stator phase resistance R (ohm)	3
Stator phase inductance L (H)	0.01
Voltage Constant (V/rpm)	0.08
Torque Constant (N.m / A)	0.7
Moment of Inertia (kg.m2/rad)	0.001
Friction factor (N.m/(rad/sec))	0.0007
Pole pairs	4

Simulation results of speed response of BLDC motor using conventional PID controller and the proposed RBF neural network PID controller is shown in Fig.4. In simulation, reference speed was 3000 r/min, load torque constant was 2 N.m at the beginning and changed to 4 N.m at 0.2 s.



(a)



(b)

Fig.4 Simulation Waveform (a) Speed Response Using Conventional PID Controller (b) Speed Response Using RBF neural network PID Controller

When conventional PID controller is used, the drive attains the reference speed in 0.02 s, the overshoot is about 8%, the adjustment time is 0.06 s, the steady-state error is about 2 r/min. When RBF neural network PID controller is used, reference speed is reached in 0.02s, the overshoot is 2.5%, the adjustment time is 0.03 s, the steady-state error is 2 r/min.

From the results shown above, the steady state error is same for both controllers, the drive system will have superior rise time and settling time characteristics with the proposed controller, the vital performance indexes are in favor of proposed controller only.

To ascertain the performance of the proposed controller, simulation results is obtained for varying load conditions. The load torque increase from 2 N.m to 4 N.m at 0.2s. Fig. 4 shows the response for varying load conditions. From the response plots shown above, if the conventional PID controller is used, the speed decrease 2.4%, recovery time is about 0.04s; if the proposed RBF neural network PID controller is used, speed decrease 1%, recovery time is 0.02s.

From the above results, the proposed RBF neural network PID controller for the BLDC motor is superior in all aspects when compared with conventional PID controller. When the load increased, the proposed controller produce less undershoot and recovery time, it indicates that the proposed controller is suited for the driver employed for varying load conditions.

Experimental test
The BLDC motor control system hardware structure based on DSP TMS320F28035 is shown in Fig.5, All functions including data acquisition, processing and control are achieved by TMS320F28035. Peripheral circuits consist of power driver, inverter circuit, Hall signal circuit, current sampling and CAN communication circuit, and so on. Real photo of control system is given in Fig.6.

The computer communicates with BLDC motor controller through CAN communication cable, the system transfers the experimental data to the computer, the data is saved in computer, the data can be drawn in waveform. Oscilloscope waveform of current and PWM signals are shown in Fig.7.

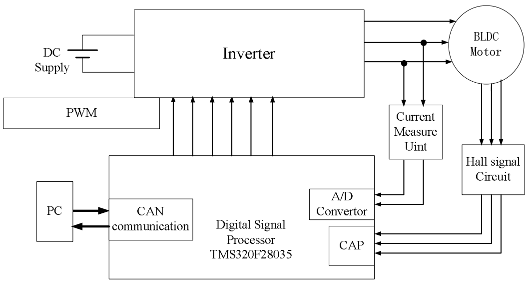


Fig.5 BLDC Motor Control System Hardware Structure

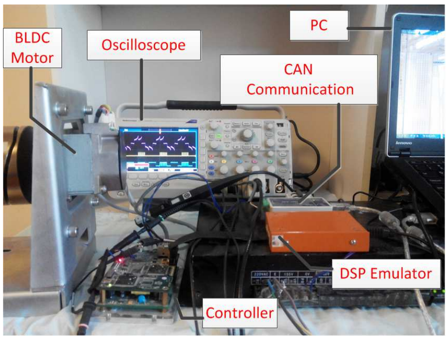


Fig.6 Real photo of BLDC Motor Control System

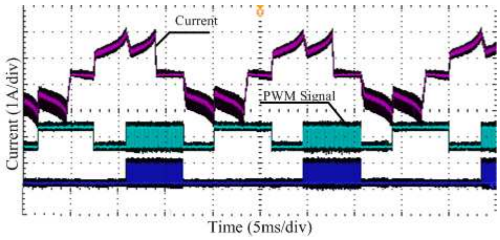
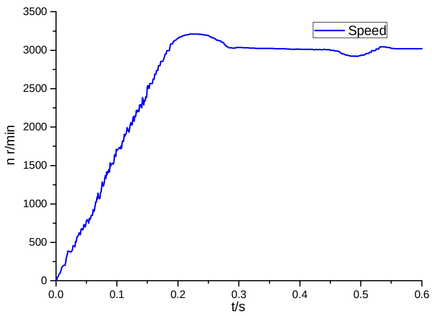


Fig.7 Current and PWM Signals

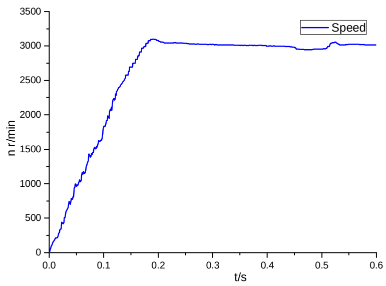
BLDC motor speed varies with constant load. Initially the motor run at 0 r/min, then the speed is changed to 3000 r/min at constant load. Speed response is obtained while changing the speed for both the controllers. With the help of Fig.8, the parameters of speed responses are summarized.

From the comparison of the controller performances, if the conventional PID controller is used, the settling time is 0.19 s, the overshoot is about 7%, adjusting time is about 0.28 s, the steady-state error is about 10 r/min. If the RBF neural network PID controller is used, the settling time is 0.17 s, the overshoot is 3%, adjusting time is 0.2 s, the steady-state error is about 4 r/min.

From the above verification and comparison, it is proved that proposed RBF neural network PID controller gives better performance when compared to the conventional PID controllers.



(a)



(b)

Fig.8 Experimental Waveform (a) Speed Response using Conventional PID controller (b) Speed Response using RBF neural network PID Controller

The load is suddenly changed at constant speed. The performances of the controllers are analyzed at this situation. The motor speed maintains constant at this condition and the load vary. Initially, 2 N.m load is applied to the motor. Then the load change from 2 N.m to 4 N.m. Based on the speed response graphs shown in Fig.8, the results are summarized.

If conventional PID controller is used, when the load is changed, the speed decrease 3%, recovery time is about 0.1 s. If the RBF neural network PID controller is used, when the load is changed, the speed decrease 1.5%, recovery time is about 0.08 s.

From the above comparisons, the experimental results further validate the proposed RBF neural network PID controller can improve the dynamic performance of the system.

CONCLUSION

The conventional PID controller is difficult to meet the performance requirements of BLDC motor, this paper proposed a control strategy of RBF neural network PID. The RBF neural network PID controller is successfully implemented in the BLDC motor drive system, its performance has been investigated both experimentally and by simulation when the system is subjected to step change in reference speed and sudden load disturbance. Various control system parameters for both controllers have been measured, analyzed and compared. The comparison shows clearly that the proposed controller gives better performances.

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