A Model Reference Adaptive Control Based on Fuzzy Neural Network for Some Weapon Ac Servo System

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Abstract. This paper presents a novel model reference adaptive control algorithm based on fuzzy neural network. This widely used method is utilized to adjust the parameters on line. The fuzzy neural network sliding mode controller, which integrates the fuzzy neural network with sliding mode controller, is put forward to control some weapon servo system with model uncertainties and parameters variation. Because this proposed algorithm combines excellences of FNN and sliding mode control, it has the ability to eliminate the drawbacks of traditional SMC, i.e. the chattering in the control signal and needing knowledge of bounds of uncertainties. Simulation results verify this proposed algorithm can reduce the plant’s sensitivity to parameter variation and disturbance.

Keywords: ac servo system; position control; fuzzy neural network

1. Introduction:

Servo system has been frequently applied in position control of multiple rockets thanks to their ability of serving large driving forces, rapid response and so on. However, as a typical servo system, this weapon controller possesses lots of nonlinearities caused by mechanical friction and distortion of transmission shaft. In addition, there are some uncertain factors such as outer disturbances and unmodeling factors. In order to realize high performance control servo system, we should identify mathematical model of controlled object, i.e. system identification. As for nonlinear and time varying system, we often use adaptive control tactics because of difficult identification. In this paper, fuzzy neural network theory is applied to ac servo system for artillery. At the same time, combining with excellences of sliding mode control, a novel type control algorithm is put forward. Via simulation validation, model uncertainty and impact moment affection can effectively be overcome. The system has fairly good robustness, dynamic and static control precision, achieving satisfying control effects.

2. Model of pmsm servo system:

Vector control of ac pmsm is a kind of tactics based on magnetic field oriented method. During model derivation, we have some assumptions as follows:

d. Ignoring saturation of central iron
b. Ignoring bow wave and waste of stagnant magnet
c. No damp roll thread in rotor and no damp effect in everlasting magnet
d. Counter electromotive force is sine

Based on assumptions above, we can get state-space equation under rotate axes as follows:

\[
\begin{bmatrix}
\dot{i}_d \\
\dot{i}_q \\
\dot{\omega}
\end{bmatrix} = \begin{bmatrix}
-R/L & \rho \omega & 0 \\
\rho \omega & -R/L & -p\psi_r/L \\
0 & p\psi_r/J & 0
\end{bmatrix} \begin{bmatrix}
i_d \\
i_q \\
\omega
\end{bmatrix} + \begin{bmatrix}
u_d/L \\
u_q/L \\
-T_i/J
\end{bmatrix}
\]

(1)

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where, $R$ is equivalent resistance of roll thread, $L$ is equivalent inductance, $p$ is the number of magnetic pole of electric motor, $\omega$ is mechanical angular velocity, $\psi_r$ is flux of every pair magnetic pole, $T_l$ is load torque, and $J$ is total moment of inertia at electric motor shaft.

In this paper, we use $i_d \equiv 0$ decoupled control, so we can get

$$\frac{di_q}{dt} = \begin{bmatrix} \frac{-R}{L} & -p\psi_r / L & 0 \\ p\psi_r / J & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} i_q \\ \omega \\ \theta \end{bmatrix} + \begin{bmatrix} u_q / L \\ -T_l / J \end{bmatrix}$$  \hspace{1cm} (2)

Take angle $\theta$ and angular velocity $\omega$ as state variables, and let

$$X = \begin{bmatrix} \omega \\ \theta \end{bmatrix}, \quad A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \quad B_1 = \begin{bmatrix} p\psi_r / J \\ 0 \end{bmatrix}, \quad B_2 = \begin{bmatrix} -1 \\ J \end{bmatrix}$$

Take output as follows:

$$Y = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} \omega \\ \theta \end{bmatrix}$$

Therefore, we can construct state-space equation of ac pmsm servo system as follows:

$$\begin{cases} \dot{X} = AX + B_1i_q + B_2T_l \\ Y = CX \end{cases}$$  \hspace{1cm} (3)

Where $A$ and $B$ represent nominal model, traditional control adopts integration of PI controller and linear state feedback controller. But this method can’t overcome bad effect of model parameters’ variation on performance. Therefore, a novel control algorithm is put forward to be applied to this weapon system. Simulation results show that this controller can make system have good following performance.

3. Design of SMC:

It is assumed that $\theta_d$ is the desired angle, and state variables are measurable and bound. The objective is to let $\theta$ track $\theta_d$ under condition of parameter variations and external disturbances. Define the tracking error $e_1 = \theta - \theta_d$, and the error vector

$$e = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix}$$  \hspace{1cm} (4)

Take

$$S = c_1e_1 + e_2$$  \hspace{1cm} (5)

Where $c_1, c_2$ are constants. The sliding surface is

$$S = c_1e_1 + e_2 = 0$$  \hspace{1cm} (6)

Set $\dot{S} = 0$, then the equivalent control can be got as follows:

$$u_{equ} = \frac{J}{p\psi_r} \left( \frac{T_l}{J} - c_1x_1 \right)$$  \hspace{1cm} (7)

Then we can get the control principle as follows:

$$u = u_{equ} + u_N = u_{equ} + K \text{sgn}(S)$$  \hspace{1cm} (8)

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4. Fuzzy neural network sliding mode control scheme:

In this paper, a novel idea, i.e. fuzzy neural network sliding mode control is put forward to be applied in weapon servo system. The control principle is depicted in Fig.1. The inputs of FNN are $S$ and $\dot{S}$, and the output is $K$.

5. Description of FC

The desired implement of fuzzy controller is as follows: according to the distance between state point and sliding mode line and its derivative, we can reason the output. The domains of $S$, $\dot{S}$ and $u$ are chosen as $[-5,5]$. The fuzzy sets of $S$, $\dot{S}$ and $u$ are chosen as [NB NM NS Z PS PM PB].

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6. Description of FNN

A three-layer FNN is shown in Fig.2.

Gaussian core function is expressed as follows:
where,  \( u_j \) is the \( j \)th output of hidden layer nodes, and \( u_j \in [0,1], X = (x_1, x_2, \cdots, x_n)^T \) are output samples. \( C_j \) is central value of Gaussian core function, \( \sigma_j \) is standard constant and \( N_n \) is the number of hidden layer nodes. Then, we get
\[
y_i = \sum_{j=1}^{N_n} \omega_j u_j - \theta = W_i^T U, \quad i = 1, 2, \cdots, m
\]
where,
\[
W_i = (\omega_1, \omega_2, \cdots, \omega_{N_n}, -\theta)^T, \quad U = (u_1, u_2, \cdots, u_{N_n}, 1)^T
\]

Learning process of RBF neural network can be decomposed into two stages. At first, according to all input samples, central value of Gaussian core function \( C_j \) and standard constant \( \sigma_j \) are decided. Then, when parameters of hidden layer are decided, by use of the least two multiply theorem, weight value \( W_i \) of output layer is decided.

Theorem1: Given arbitrary \( \varepsilon > 0 \), for any \( L_2 \) type function \( f: \mathbb{R}^n \rightarrow \mathbb{R}^m \), there exists an RBF neural network, it can approach \( f \) in arbitrary \( \varepsilon \) square error.

This theorem indicates that RBF neural network can approximate arbitrary continuous nonlinear function as BP neural network.

7. Identification algorithm:

Identification structure of RBF neural network is depicted as Fig.3.

In RBF network structure, \( X = [x_1, x_2, \cdots, x_n]^T \) is input vector of network. Assume radial base \( H = [h_1, h_2, \cdots, h_m]^T \), where \( h_j \) is Gaussian base function:
\[
h_j = \exp\left(-\frac{\|X - c_j\|^2}{2b_j^2}\right) \quad j = 1, 2, \cdots, m
\]

Where, central vector of the \( j \)th node is expressed as follows:
\[
c_j = (c_{j1}, c_{j2}, \cdots, c_{jn})
\]
Assume radial width vector of network is as follows:

$$B = [b_1, b_2, \cdots, b_m]^T$$  \hspace{1cm} (14)

Here, $b_j$ is radial width parameter of node $j$, and $b_j > 0$. The weight vector of network is as follows:

$$W = [\omega_1, \omega_2, \cdots, \omega_m]^T$$  \hspace{1cm} (15)

Output of RBF neural network is expressed as follows:

$$y_m(t) = \omega_1 h_1 + \omega_2 h_2 + \cdots + \omega_m h_m$$  \hspace{1cm} (16)

Performance index function of RBF neural network is as follows:

$$E = \frac{1}{2} [y(t) - y_m(t)]^2$$  \hspace{1cm} (17)

According to gradient descending method, iteration algorithms of output weight, node center and node base width parameter are expressed respectively as follows:

$$\omega_j(t) = \omega_j(t-1) + \eta[y(t) - y_m(t)]h_j + \alpha(\omega_j(t-1) - \omega_j(t-2))$$  \hspace{1cm} (18)

$$\Delta b_j = \frac{[y(t) - y_m(t)]\omega_j h_j \|X - c\|^2}{b_j^3}$$  \hspace{1cm} (19)

$$b_j(t) = b_j(t-1) + \eta \Delta b_j + \alpha(b_j(t-1) - b_j(t-2))$$  \hspace{1cm} (20)

$$\Delta c_{ji} = \frac{[y(t) - y_m(t)]\omega_j x_{ji} - c_{ji}}{b_j^2}$$  \hspace{1cm} (21)

$$c_{ji}(t) = c_{ji}(t-1) + \eta \Delta c_{ji} + \alpha(c_{ji}(t-1) - c_{ji}(t-2))$$  \hspace{1cm} (22)

Where, $\eta$ is learning rate and $\alpha$ is momentum factor.

8. Design of FNNSMC

Fuzzy neural network, which incorporates excellences of fuzzy logic control and neural network control.

In order to obtain the inference control, BP algorithm is used to train parameters of FNN. Where, FNN is used to satisfy the conditions of sliding mode controller. We use neural networks in parallel to realize equivalent control and corrective control terms of sliding mode control.

RBF neural network is utilized to learn the output and tune weights online to make feedback control output approximate zero, which makes neural network controller be leading. The value of the sliding mode function $s$ can be gained from the prediction error vector $e$. Then the derivation $s$ and $\dot{s}$ are fed back to the regulation function to assure the existence of sliding mode surface, i.e. $s \cdot \dot{s} < 0$.

9. Simulation results

In order to verify the validation of the proposed algorithm, the simulation experiment is carried out on orientation servo system. At the same time, in order to compare with traditional PID algorithm, simulation results under PID controller are shown as Fig.4, Fig.5 and Fig.6 respectively. The results under fuzzy neural network sliding mode controller are shown as Fig.7, Fig.8 and Fig.9 respectively. From the figures, we can find that when we use FNNSMC, the performance is better than PID controller. When we use the new algorithm proposed in this paper, we find that step response error curve is almost zero when the system reaches steady state, slope response error curve is less than 1mil and sine response error curve is less than 3mil, which fulfill the requests of the performance index.

Fig.4 error curve of 500mil step response

Fig.5 error curve of $36^0/s$ slope response

Fig.6 error curve of $1042\sin(7.86t)(\text{mil})$ sine response

Fig.7 error curve of 500mil step response

Fig.8 error curve of $36^0/s$ slope response

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11. References:


