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Reinforcement Self-learning Fuzzy Neural Control of Three-axis Stabilized Spacecraft

Jia Jie[1], Xie Yu[1], Zhang Xiangyang[1] , Luo Xutao[2], Yong Yuanqin[2]
[1] Electronic Information Engineering College,Nanchang Hangkong University,Nanchang, China
Email: xieyu_121@163.com
[2] Northwestern Polytechnical University,Institute of Automation
Xi'an, China

Abstract—**This article introduce Reinforcement self-learning fuzzy neural control and put it into Attitude Control of Spacecraft System. It Simplifies and improves the Stucture of Reinforcement Fuzzy Neural Controller. Under the the premise of A certain degree of control accuracy , it decreases the number of the adjustment parameters which self-learning controller needed. The control algorithm which is able to learn online doen't require mathematical model of controlled object. In addition they Only use the reinforcement signals and don't need the Learning samples. They can be Robust for uncertainty of the non-parametric spacecraft. The simulation results also show that the control method is effective.**

Index Terms—**reinforcement self-learning; fuzzy neural control; three-axis; spacecraft**

I. INTRODUCTION

Since the spacecraft has the characteristics of strong-coupling, fast time-varying and nonlinear , therefore the design of spacecraft attitude control system is a complex task. With these uncertainties for spacecraft systems, it's difficult to establish the precise object mathematical model. This makes the traditional control methods have become increasingly unable to serve the control effect.

This paper has put reinforcement self-learning of fuzzy neural control [1]~[3]into attitude control system of spacecraft. It also simplifies and improves the structure of reinforcement fuzzy neural controller in literature [3].Use the T-S model to replace the Five-layer fuzzy neural controller in literature [3] and Learning algorithm of the controller. Reinforcement Fuzzy Neural Control of the Spacecraft Attitude has these Features: no need for mathematical model of controlled object and self-learning fuzzy neural controller at the time of training samples. Adjust the parameters of fuzzy neural controller online based on the evaluation of system output signals. If the output signal of system is "good", "reward" the adjusted parameters of fuzzy neural controller. If the output signal of system is "bad", "Punishment" the Adjusted parameters of fuzzy neural controller. Finally allow the output of system to achieve the desired output state. Therefore improve the control accuracy of the spacecraft attitude control and enhance robustness of the control system. The simulation results also verify the effectiveness of the control method.

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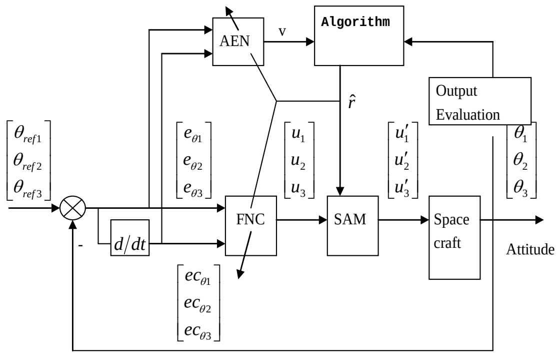

Figure 1. structure of Reinforcement self-learning fuzzy neural control system Spacecraft Attitude

II. REINFORCEMENT SELF-LEARNING OF THE FUZZY NEURAL CONTROL SYSTEM

The mathematical model of Spacecraft attitude stability is showed in literature [6]. For meeting flexible spacecraft attitude control requirements, the design uses reinforcement self-learning fuzzy neural control.

As the figure shows: θ_{ref1} 、 θ_{ref2} 、 θ_{ref3} express the expectations of the rolling angle, pitch angle, yaw angle separately. $e_{\theta i} = \theta_{refi} - \theta_i$ （$i = 1, 2, 3$） is the error of the attitude angle . $ec_{\theta i}$ （$i = 1, 2, 3$） is the changing rate of Attitude angle error . u_i （$i = 1, 2, 3$） Respectively express proposed control moment of the rolling axis, pitch axis, yaw axis which is the output of fuzzy neural controller FNC . u'_i （$i = 1, 2, 3$） is the actual control moment which is imposed to the spacecraft body. r is the external reinforcement signal. $\hat{r}$ is the Internal reinforcement signal. θ_1 、 θ_2 、 θ_3 express the actual rolling angle, pitch angle, yaw angle of Spacecraft respectively.

A. Posture assessment network AEN

1) structure of the AEN

AEN is an ordinary three-tier feed-forward network. The structure shows in Figure 2. Use $e_{\theta i}$ and $ec_{\theta i}$ ($i=1,\ 2,\ 3$) to assess the situation of the spacecraft attitude angle. Therefore Produce the Prediction value v of error signal r. a_{ij} 、 b_i 、 c_j （ i =1,2,…,6, j=1,2,…,18） are the weights between the first and second layer, the first and the third layer, the second and third layer .

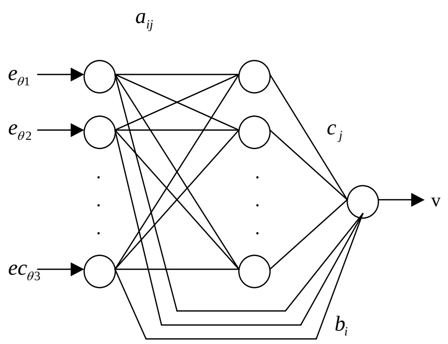

Figure 2. Network structure of AEN

(1)The first layer: The layer has six neurons. Output:

$$x_i = e_{\theta i} \qquad x_{(i+3)} = ec_{\theta i} \qquad i=1,\ 2,\ 3$$

(2) The second layer: The layer has eighteen neurons.

Output: $$y_{j(t,t+1)} = g[\sum_{i=1}^{6} a_{ij(t)} \cdot x_{i(t+1)}] \qquad (1)$$

$$g(s) = \frac{1}{1+\exp(-s)} \qquad (2)$$

$y_{j(t,t+1)}$ Represent coefficient at the time of t

Output （ $e_{\theta i}$ $ec_{\theta i}$ ） is the time of t+1 . That is, work after update .

(3) The third layer: The layer has one neurons.

$$v_{(t,t+1)} = \sum_{i=1}^{6} b_{i(t)} x_{i(t+1)} + \sum_{j=1}^{18} c_{j(t)} y_{j(t,t+1)} \qquad (3)$$

2) Learning method of AEN

The program which modifies Weights of the network uses a reward and punishment method. So adjust the network weights a_{ij} 、 b_i 、 c_j , With internal reinforcement signals, Which the learning rate $\beta > 0$, $\beta_h > 0$.

$$a_{ij(t+1)} = a_{ij(t)} + \beta_h \hat{r}_{(t+1)} y_{j(t,t)} (1 - y_{j(t,t)}) sign(c_{j(t)}) x_{i(t)} \qquad (4)$$

$$b_{i(t+1)} = b_{i(t)} + \beta\, \hat{r}_{(t+1)} x_{i(t)} \qquad (5)$$

$$c_{j(t+1)} = c_{j(t)} + \beta\, \hat{r}_{(t+1)} y_{j(t,t)} \qquad (6)$$

III. Fuzzy Neural Network FNN_i

B. structure of FNN_i

(1) Input layer: This layer has two neurons. Input Attitude angle errors $e_{\theta i}$ (x1) and error rate $ec_{\theta i}$ (x2) respectively.

(2) Fuzzy layer: This layer a total of 10 neurons. The output x_i is the membership of Fuzzy set $A_i^j(x_i)$.

$$A_i^j(x_i) = e^{-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}} \quad i=1,2\ ,\ j=1,2,\ldots,5, \qquad (7)$$

m_{ij} and σ_{ij} represent the mean and variance of Membership function .

This paper uses Normal distribution of the membership function Rather than the Triangular membership function in Literature [3]. Therefore, in the reverse study the function is differentiable everywhere.

(3) Rules layer: The general form of fuzzy rules is R^l : if $x_1 = A_1^l$ and $x_2 = A_2^l$ then $u = c_l$. l =1,2,…,25

This layer a total of 10 neurons. The out put is activation degree β_l .

$$\beta_l = A_1^l \cdot A_2^l \qquad (8)$$

(4) Output layer: This layer only one neuron.

$$u = \frac{\sum_{l=1}^{25} \beta_l c_l}{\sum_{l=1}^{25} \beta_l} \qquad (9)$$

C. Learning method of FNN_i

Use to represent the transfer parameter vector, which is Membership function parameters m_{ij} 、 σ_{ij} and concluding part of numerical c_l .Learning goal is to make the largest v. When we use Gradient method ,the Incremental of Parameter vector p is Δp . Learning rate $\eta > 0$, $\hat{r}_{(t)}$ is Internal reinforcement signal. Because v is the output of AEN network, it can only be Calculated by $\partial v / \partial u$ Approximationly.

$$\Delta p = \eta\, \hat{r}_{(t)} \frac{\partial v}{\partial u} \frac{\partial u}{\partial p} \qquad (10)$$

$$\frac{\partial v}{\partial u} \approx \frac{dv}{du} \approx \frac{v_{(t)} - v_{(t-1)}}{u_{(t)} - u(t-1)} \quad (11)$$

(1) For the concluding part values of the rules c_l.

$$\frac{\partial u}{\partial c_l} = \partial\left(\frac{\sum_{l=1}^{25} \beta_l c_l}{\sum_{l=1}^{25} \beta_l}\right) \Bigg/ \partial c_l = \frac{\beta_l}{\sum_{l=1}^{25} \beta_l} \quad (12)$$

$$c_{l(k+1)} = c_{l(k)} + \eta\, \hat{r}_{(k)} sign\left(\frac{v_{(k)} - v_{(k-1)}}{u_{(k)} - u_{(k-1)}}\right) \cdot \frac{\beta_l}{\sum_{l=1}^{25} \beta_l} \quad (13)$$

(2) The premise of the rules, Input membership function parameters m_{ij} 、 σ_{ij} is similar to above Adjusting algorithm. To get the partial derivatives of Output u to the activation degree β_l and membership degree A_i^j :

$$\frac{\partial u}{\partial \beta_l} = \frac{c_l \sum_{l=1}^{25} \beta_l - \sum_{l=1}^{25} \beta_l c_l}{(\sum_{l=1}^{25} \beta_l)^2} = \frac{c_l - u}{\sum_{l=1}^{25} \beta_l} \quad (14)$$

$$\frac{\partial \beta_l}{\partial A_1^l} = A_2^l \qquad \frac{\partial \beta_l}{\partial A_2^l} = A_1^l$$

Therefore:

$$\frac{\partial u}{\partial p} = \frac{\partial u}{\partial A_i^j} \cdot \frac{\partial A_i^j}{\partial p} = \left(\sum_{A_i^j \in Ant(R_k)} \frac{\partial u}{\partial \beta_k} \cdot \frac{\partial \beta_k}{\partial A_i^j}\right) \cdot \frac{\partial A_i^j}{\partial p} \quad (15)$$

R_k represents Fuzzy rules of A_i^j which is Contained in Precondition from (15). Therefore, the mean m_{ij} and variance σ_{ij} of the learning formula is:

$$m_{ij(k+1)} = m_{ij(k)} + \eta \hat{r}_{(k)} sign\left(\frac{v_{(k)} - v_{(k-1)}}{u_{(k)} - u_{(k-1)}}\right) \cdot \frac{\partial u_{(k)}}{\partial A_i^j} \cdot e^{-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}} \cdot \left(\frac{2(x_i - m_{ij})}{\sigma_{ij}^2}\right) \quad (16)$$

$$\sigma_{ij(k+1)} = \sigma_{ij(k)} + \eta\, \hat{r}_{(k)} sign\left(\frac{v_{(k)} - v_{(k-1)}}{u_{(k)} - u_{(k-1)}}\right) \cdot \frac{\partial u_{(k)}}{\partial A_i^j} \cdot e^{-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}} \cdot \left(\frac{2(x_i - m_{ij})^2}{\sigma_{ij}^3}\right) \quad (17)$$

D. *SAM Algorithm*

According to the internal reinforcement signal $\hat{r}_{(t-1)}$, use the probability density function (18) to get Actual control torque u_i' which imposes to the spacecraft. Take $p_{(u_i')} = 0.9$ in simulation.

$$p_{(u_i')} = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(u_i' - m)^2}{2\sigma^2}}, \quad m = u_{i(t)} \quad \sigma = e^{-\hat{r}_{(t-1)}} \quad (18)$$

Ⅳ. SIMULATION RESEARCH

This design has done the simulation study of the proposed adaptive fuzzy algorithm . In simulation ,the initial value of Spacecraft Attitude is $\theta_{ci} = 0.1^0$, $\omega_{ci} = 0.01^0 / s$, ($i = 1, 2, 3$) , expectations of Posture is $\theta_{refi} = 0^0$, $\omega_{refi} = 0^0 / s$, ($i = 1, 2, 3$) . The initial value of AEN network weights are set to random numbers ranging in [-0.1 0.1].Learning rate $\beta = \beta_h = 0.1$, The Discount rate is $\delta = 0.9$. When FNN_i ($i = 1, 2, 3$)Network is self-learning , the input value of membership function parameters is fixed. Only change the concluding part value of Rules c_l .It's learning rate is $\eta = 0.001$. In order to be compared, this design has done the simulation work which pluses the interference situation by PD control and reinforcement of self-learning fuzzy neural control method separately.

Figure 3- Figure 5 shows that changes in spacecraft attitude angle θ with interference (solid line for the reinforcement of self-learning fuzzy neural control, dotted line for the PD control).

Figure 6 to figure 7 is Simulation of spacecraft angular velocity curve in the three situation., shows that changes in spacecraft angular velocity ω with interference. Figure 8 to figure 9 is the Simulation curve of the first-order modal coordinates Flexible.

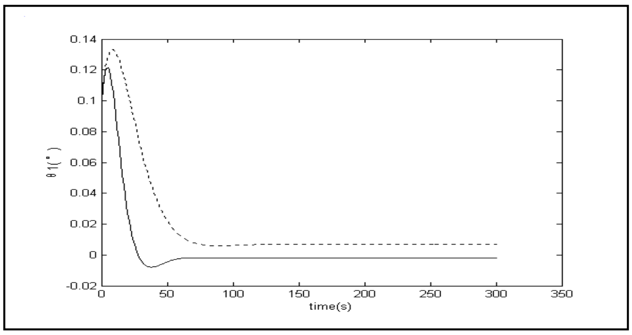

Figure 3. Changes in Rolling angle θ_1

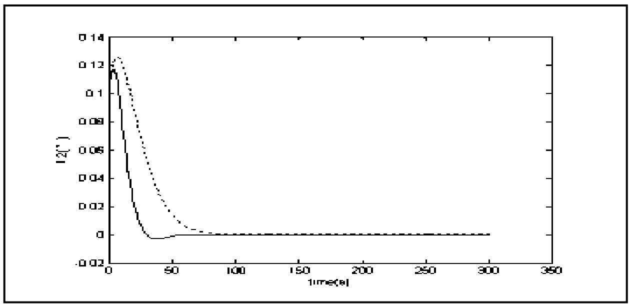

Figure 4. Changes in pitch angle θ_2

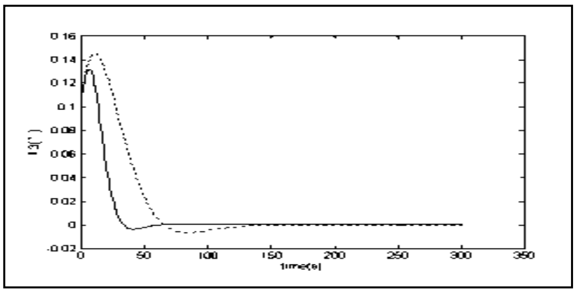

Figure 5. Changes in Yaw angle θ_3

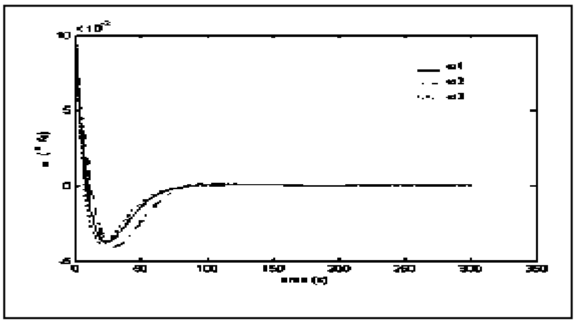

Figure 6. Reinforcement of self-learning fuzzy neural control

Ⅴ. CONCLUSION

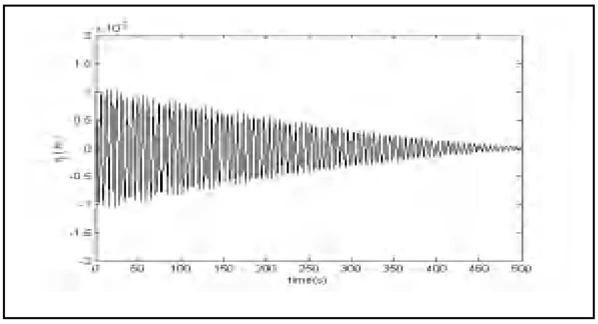

Figure 7. PD control

This program introduces Reinforcement self-learning fuzzy neural control and put it into Attitude Control of Spacecraft System. It Simplifies and improves the structure of Reinforcement Fuzzy Neural Controller. Under the premise of A certain degree of control accuracy, it decreases the number of the adjustment parameters. These supply the conditions of projects in future. The control algorithm does not need mathematical model of controlled object .It can learn online and only need Reinforcement signal rather than Learning samples. The program has robustness for the non-parametric uncertainty of the spacecraft.

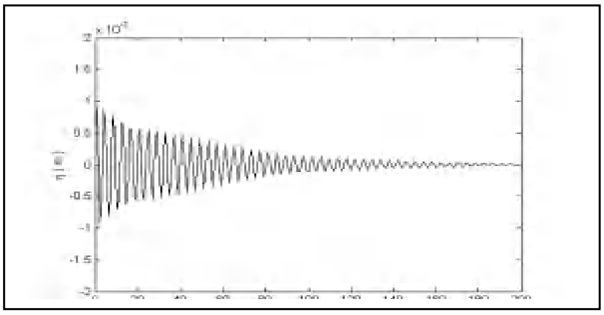

Figure 8. Reinforcement of self-learning fuzzy neural control

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