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ADAPTIVE NEURAL NETWORK DECENTRALIZED CONTROL FOR LARGE SCALE SYSTEM WITH INPUT SATURATION

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ABSTRACT

A new method of adaptive neural network decentralized control is designed for a relevant large scale system with input saturation, it is not necessary for this method to assume that relevant items satisfy the function upper bound of high order or low order, cancel the constraint condition for known upper bound of the unknown continuous function and controlled gain of the system. It is not necessary to handle controlled gain with unknown directions by virtue of Nussbum function, only using a neural network can simultaneously approximate unknown function, unknown gains, and unknown relevant items. It can be known by using the Lyapunov theoretical analysis that the designed method can guarantee the control system to obtain overall situation stability, simulation results display that the control method is valid and feasible.

Keywords: *Neural Network; Input Saturation; Decentralized Control; Global Stability; Large Scale System*

1. INTRODUCTION

In recent 20 years, relevant research achievements on designing fuzzy decentralized controller [1],[6] and neural network decentralized controller[2],[3],[4] for large scale system have been emerging. According to order difference of the upper bound qualified function in relevant items, current research achievements can be briefly classified into two categories, one is to assume that the upper bound of relevant item is first order polynomial function [1][5], another two are to assume that the upper bound of relevant item is high order polynomial function [7], thereby, the current research achievements on decentralized control are not applicable to large scale system that relevant items do not satisfy one order or high order constraint. In addition, current achievement normally assume qualified function is solely influenced by subsystem status or tracking error of subsystem when processing independent variables of qualified function for relevant items [1],[7], or assume that independent variables of qualified function for relevant items are directly determined by system output[2][5], for the large scale system of relevant items formed by all system variables, these research achievements are not applicable as well. Simultaneously, majority of the current achievements focus upon researches on the large scale system with linear input [1],[2],[3],[4],[5],
[6], however, we know the inputs of many systems are non-linear [8],[9], therefore, it is

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rather necessary to research decentralized control of large scale system with the non-linear input. Furthermore, current research achievements generally assume unknown function and controlled gain of large scale system has known upper and lower bound [2][3], and controlled gain symbol is already known [2], under many circumstances, it is very difficult to confirm the bound of unknown function and controlled gain, and the symbol of controlled gain. Focusing on the system with unknown symbol of controlled gain, the design of traditional adaptive fuzzy/neural network controller is normally processed by virtue of Nussbum function [10].

This article designs a new adaptive neural network decentralized control method by the concentration on saturation input large scale system, on the basis of above research achievements. This method has following advantages compared with current achievements: 1. it is not necessary to assume that relevant items satisfy the upper bound of high or low order function. 2. Cancel the constraint condition for upper bound of the unknown continuous function and controlled gain of the system. 3. Cancel assumptions that controlled gain has bound and known direction, and there is no need to use Nussbum function can realize the design of control system with unknown control gain direction. 4. The upper bound of saturation input is unknown. 5. Use one neural network to simultaneously approximate unknown function, unknown gain and unknown relevant item, significantly reducing the design difficulty. It can be learned from theoretical analysis that the design method can guarantee overall global stability of the control system, while simulation results verify the validity and feasibility of the control method.

2. DESCRIPTION OF RESEARCH OBJECT

The number i subsystem of large scale system is as follows:

$$\begin{cases} \dot{x}_{i,1} = x_{i,2} \\ \vdots \\ \dot{x}_{i,n_i} = f_i(\boldsymbol{x}_i) + g_i p_i(u_i) + d_i(\boldsymbol{x}_1,\cdots,\boldsymbol{x}_N) \\ y_i = x_{i,1} \end{cases} \tag{1}$$

Among, $\boldsymbol{x}_i = (x_{i,1},\cdots x_{i,n_i})^T = (y_i,\cdots,y_i^{(n_i-1)})^T \in R^{n_i}$ $(1 \le i \le N)$, u_i, y_i is separately the status, input and output of subsystem, p_i is saturation function by independent variable u_i, $d_i(\boldsymbol{x}_1,\cdots,\boldsymbol{x}_N)$ means the mutual relevance among the subsystems, $f_i(\boldsymbol{x}_i)$, $g_i > 0$ is separately unknown continuous function and unknown controlled gain of subsystem. $p_i(u_i)$ is defined by the following expression:

$$p_i(u_i) = \begin{cases} sign(u_i)u_{iH}, |u_i| \ge u_{iH} \\ u_i, \ |u_i| < u_{iH} \end{cases} = q_i(u_i) + \tau_i(u_i) \tag{2}$$

Among, $u_{iH} > 0$ is unknown upper bound of u_i, $q_i(u_i) = u_{iH}\tanh(\frac{u_i}{u_{ih}})$, $\tau_i(u_i) = p_i(u_i) - q_i(u_i)$, that is $|q_i(u_i)| \le u_{iH}$, $|\tau_i(u_i)| \le u_{iH} - u_{iH}\tanh(1) \stackrel{\Delta}{=} \tau_i$.

Hypothesis 1: desired trajectory $\boldsymbol{Y}_{di} = (y_{di}, \dot{y}_{di},$

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$\cdots, y_{di}^{(n_i-1)})^T$ is continuously bounded, and $\boldsymbol{Y}_{di} \in \boldsymbol{\Omega}_{di} = \{\|\boldsymbol{Y}_{di}\| \le Y_i\}$.

Hypothesis 2: $|d_i(\boldsymbol{x}_1,\cdots,\boldsymbol{x}_N)| \le \sum_{j=1}^{N} D_{ij}(\boldsymbol{x}_j)$, among, $\boldsymbol{X} = (\boldsymbol{x}_1,\cdots,\boldsymbol{x}_N)^T$, $D_i(\boldsymbol{x}_i)$ is unknown continuous function.

Note $e_{i,1}(t) = x_{i,1} - y_{di}$, $\boldsymbol{e}_i(t) = (e_{i,1}, e_{i,2}, \cdots, e_{i,n_i})^T$, $v_i = -y_{di}^{(n_i)} + k_{i,1}e_{i,2}(t) + \cdots + k_{i,n_i-1}e_{i,n_i}$, make

$$s_i(t) = \left(\frac{d}{dt} + \lambda_i\right)^{n_i-1} e_{i,1} = \sum_{j=1}^{n_i-1} k_{i,j}e_{i,j} + e_{i,n_i} \tag{3}$$

Among, $k_{i,j} = C_{n_i-1}^{j-1}\lambda_i^{n_i-j}\ (j = 0,1,\cdots n_i-1)$, $\lambda_i > 0$ is design parameter, that is

$$\dot{s}_i(t) = v_i + f_i(\boldsymbol{x}_i) + g_i(\boldsymbol{x}_i)p_i(u_i) + d_i(\boldsymbol{x}_1,\boldsymbol{x}_2,\cdots,\boldsymbol{x}_N,t) \tag{4}$$

Lemma 1: if s_i is satisfies expression (3), following conclusions can be established:

1) when $s_i = 0$, $e_{i,1} \to 0$;

2) when $|s_i| \le s, \boldsymbol{e}_i(0) \in \Omega_s, \boldsymbol{e}_i(t) \in \Omega_s$, $\forall t > 0$;

3) when $|s_i| \le s, \boldsymbol{e}_i(0) \in \Omega_s, \exists T = \dfrac{n_i - 1}{\lambda_i}$, make $\boldsymbol{e}_i(t) \in \Omega_s, \forall t \ge T$, among,

$$\Omega_s = \left\{\boldsymbol{e}_i(t) \middle| |e_{i,j}| \le 2^{j-1}\lambda_i^{j-n_i}s,\ j = 1,2,\cdots,n_i\right\}.$$

The following will use radial basis function neural network (RBF) to approach unknown continuous non-linear function of the system:

$f(\boldsymbol{Y}) = \boldsymbol{W}^T S(\boldsymbol{Y}) + \delta(\boldsymbol{Y})$, among, $\boldsymbol{Y} \in \Omega_Y \subset R^m$ is input variable, l is the number of node, $\boldsymbol{W} = (w_1,\cdots,w_l)^T \in R^l$ is unknown ideal adjustable weight vector, $S(\boldsymbol{Y}) = (s_1(\boldsymbol{Y}),\cdots, s_l(\boldsymbol{Y}))^T \in R^l$ is radial basis function, where

$$s_i(\boldsymbol{Y}) = \exp\left(\frac{-(\boldsymbol{Y}-j_i)^T(\boldsymbol{Y}-j_i)}{c_i^2}\right), \quad i = 1,2,\cdots,l$$

$j_i(\boldsymbol{Z}) = (j_{i1}(\boldsymbol{Z}), j_{i1}(\boldsymbol{Z}),\cdots, j_{im}(\boldsymbol{Z}))^T$. For given constant $\delta > 0$, when l is large enough, $|\delta(\boldsymbol{Y})| \le \delta$ establishes.

3. CONTROLLER DESIGN AND ANALYSIS OF SYSTEM STABILITY

Theorem 1: controlled large scale system (1) satisfied above assumption conditions 1, 2, the controller and the parameter adaptive laws of on-line adjustment are designed as the following expression (5-7), then it can guarantee closed-loop large scale system (1) globally uniformly and ultimately bounded, and the tracking error converged to zero.

$$u_i = -[h_i(x_i)+1]s_i - \hat{\boldsymbol{W}}_i^T S_i(\bar{\boldsymbol{x}}_i) - \hat{\delta}_i(\bar{\boldsymbol{x}}_i) \tag{5}$$

$$\dot{\hat{\boldsymbol{W}}}_i = \begin{cases} r_i S_i(\bar{\boldsymbol{x}}_i)s_i, \|\hat{\boldsymbol{W}}_i\| < M_{W_i}, \\ \text{或}\|\hat{\boldsymbol{W}}_i\| = M_{W_i}, \hat{\boldsymbol{W}}_i^T S_i(\bar{\boldsymbol{x}}_i)s_i \le 0 \\ r_i S_i(\bar{\boldsymbol{x}}_i)s_i - r_i\dfrac{\hat{\boldsymbol{W}}_i\hat{\boldsymbol{W}}_i^T}{\|\hat{\boldsymbol{W}}_i\|^2}S_i(\bar{\boldsymbol{x}}_i)s_i, \\ \|\hat{\boldsymbol{W}}_i\| = M_{\hat{W}_i}, \hat{\boldsymbol{W}}_i^T S_i(\bar{\boldsymbol{x}}_i)s_i > 0 \end{cases} \tag{6}$$

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$$\dot{\hat{\delta}}_i = \begin{cases} \eta_i s_i, |\hat{\delta}_i| < M_{\hat{\delta}_i} 或 |\hat{\delta}_i| = M_{\hat{\delta}_i}, \quad \hat{\delta}_i s_i \le 0 \\ 0, |\hat{\delta}_i| = M_{\hat{\delta}_i}, \hat{\delta}_i s_i > 0 \end{cases} \quad (7)$$

Among,

$$h_i(\bar{\boldsymbol{x}}_i) = \frac{1}{\varepsilon}\sqrt{1 + M_{W_i}^2 |S_i(\bar{\boldsymbol{x}}_i)|^2 + M_{\delta_i}^2}\ , \varepsilon > 1$$

$M_{W_i}, M_{\delta_i}, M_{G_i} > 0$ is designable known parameter, $\hat{\boldsymbol{W}}_i, \hat{\delta}_i$ is estimate value of $\boldsymbol{W}_i^*, \delta_i$, and $\tilde{\delta}_i = \delta_i - \hat{\delta}_i, \tilde{\boldsymbol{W}}_i = \boldsymbol{W}_i^* - \hat{\boldsymbol{W}}_i$, $r_i, \eta_i > 0$ are adaptive rates of parameter.

Demonstration: Suppose the closed-loop system is unstable, that is for $\forall \varepsilon > 1$, $|s_j| \ge \varepsilon > 1, j = 1 \cdots N$.

Make $V_1 = \sum_{i=1}^{N} s_i^2$, that is

$$\dot{V}_1 = \sum_{i=1}^{N} (g_i p_i(u_i) s_i + (v_i + f_i(\boldsymbol{x}_i) + d_i(\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N) s_i)$$

$$\le \sum_{i=1}^{N} \{u_i s_i + [g_i(q_i(u_i) + \tau_i(u_i)) - u_i] s_i + v_i s_i + f_i(\boldsymbol{x}_i) s_i + \sum_{j=1}^{N} D_{ij}(\boldsymbol{x}_j) s_i\}$$

$$\le \sum_{i=1}^{N} \{u_i s_i + v_i s_i + f_i(\boldsymbol{x}_i) s_i + [|g_i| u_{iH} + |u_i| + |g_i| \tau_i] |s_i| + \sum_{j=1}^{N} D_{ij}(\boldsymbol{x}_j) s_i\}$$

$$\le \sum_{i=1}^{N} \{u_i s_i + v_i s_i + f_i(\boldsymbol{x}_i) s_i + s_i^2 + \frac{(|g_i| u_{iH} + u_{i\max} + |g_i| \tau_i)^2}{2} s_i + [\frac{N}{2} \sum_{j=1}^{N} D_{ij}^2(\boldsymbol{x}_j)] s_j\}$$

$$\le \sum_{i=1}^{N} \{u_i s_i + s_i^2 + [v_i + f_i(\boldsymbol{x}_i) + \frac{(|g_i| u_{iH} + u_{i\max} + |g_i| \tau_i)^2}{2} + \frac{N}{2} \sum_{j=1}^{N} D_{ji}^2(\boldsymbol{x}_i)] s_i\} \quad (8)$$

As $F_i = f_i(\boldsymbol{x}_i) + \frac{(|g_i| u_{iH} + u_{i\max} + |g_i| \tau_i)^2}{2} + v_i + \frac{N}{2} \sum_{j=1}^{N} D_{ji}^2(\boldsymbol{x}_i)$ is continuous function, where $u_{i\max} > 0$ will be gave in the follow-up design, therefore, it can use RBF neural network to approximate,that is $F_i = \boldsymbol{W}_i^{*T} S_i(\bar{\boldsymbol{x}}_i) + \delta_i(\bar{\boldsymbol{x}}_i)$,

$\bar{\boldsymbol{x}}_i = (\boldsymbol{x}_i, y_{di}^{n_i}, \boldsymbol{e}_i)$, w_i^{*T} is optimal approximation parameter, $\delta_i(\bar{\boldsymbol{x}}_i)$ is approximation error, and satisfied $|\delta_i(\bar{\boldsymbol{x}}_i)| \le \delta_i$, $\delta_i > 0$ is unknown constant. Therefore,

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$$\begin{aligned}\dot{V}_1 &\le \sum_{i=1}^{N}\{u_i s_i + s_i^2 + [\boldsymbol{W}_i^{*T} S_i(\bar{\boldsymbol{x}}_i) + \delta_i(\bar{\boldsymbol{x}}_i)]s_i\} \\ &\le -\sum_{i=1}^{N}\{h_i(\bar{\boldsymbol{x}}_i)(s_i^2 - \frac{\left|\tilde{\boldsymbol{W}}_i^T\right|\left|S_i(\bar{\boldsymbol{x}}_i)\right|\left|s_i\right| + \left|\tilde{\delta}_i\right|\left|s_i\right|}{h_i(\bar{\boldsymbol{x}}_i)}\} \\ &\le -\frac{1}{\varepsilon}\sum_{i=1}^{N}\{(s_i^2 - \frac{2M_{W_i}\left|S_i(\bar{\boldsymbol{x}}_i)\right|\ \left|s_i\right| + 2M_{\delta_i}\left|s_i\right|}{\frac{1}{\varepsilon}\sqrt{1 + M_{W_i}^2\left|S_i(\bar{\boldsymbol{x}}_i)\right|^2 + M_{\delta_i}^2}}\} \\ &\le -\frac{1}{\varepsilon}\sum_{i=1}^{N}(s_i^2 - 2\varepsilon^2 - \frac{s_i^2}{2}) \\ &\le -\frac{1}{\varepsilon}(V_1 - 2N\varepsilon^2)\end{aligned} \tag{9}$$

From expression (9), when

$$t \ge T_1 = \max(0, \varepsilon \ln \frac{\sum_{i=1}^{N} s_i^2(0) + 4N\varepsilon^2}{4N^2\varepsilon^2 - 4N\varepsilon^2})\ (\varepsilon > 1),$$

$\sum_{i=1}^{N} s_i^2(t) \le 4N^2\varepsilon^2$ that is $\left|s_i(t)\right| \le 2N\varepsilon$.

According to the lemma 1, when

$t \ge T_1 + \frac{n_i - 1}{\lambda_i}, \left|e_{i,j}\right| \le 2^j N\lambda_i^{j-n_i}\varepsilon\ (j = 1, \cdots n_i)$, $\boldsymbol{x}_i \in \Omega_{x_i} = \left\{\left|x_{i,j}\right| \le 2^j N\lambda_i^{j-n_i}\varepsilon + Y_i\right\}$, $u_i \in \Omega_{u_i} = \{\left|u_i\right| \le u_{i\max}\}$, where $u_{i\max} = 2N\varepsilon(\frac{\sqrt{1 + 4M_{\theta_i}^2 + 4M_{\hat{\varepsilon}_i}^2}}{\varepsilon} + 1) + M_{\hat{W}_i} + M_{\hat{\delta}_i}\}$.

Thus the closed-loop system has global stability.

Use $V = V_1 + \sum_{i=1}^{N}(\frac{1}{\gamma_i}\tilde{\boldsymbol{W}}_i^T\tilde{\boldsymbol{W}}_i + \frac{1}{\eta_i}\tilde{\delta}_i^2)$ then

$$\dot{V} = -\sum_{i=1}^{N} h_i(\bar{\boldsymbol{x}}_i)s_i^2 \le 0$$

According to the lemma of barbalat, $s_i \to 0$, integrating lemma 1 can reach: $e_{i,1}(t) \to 0$,the demonstration is complete.

4. CONTROL EFFECTS SIMULATION

Large scale system with relevance of input saturation is as the following expression (10)

$$P_1: \begin{cases} \dot{x}_{1,1} = x_{1,2} \\ \dot{x}_{1,2} = -x_{1,1}^3 - x_{1,2} + (1 + 0.5\sin x_{1,1}) \times \\ \qquad p_1(u_1) + d_1(\boldsymbol{X}, t) \end{cases}$$

$$P_2: \begin{cases} \dot{x}_{2,1} = x_{2,2} \\ \dot{x}_{2,2} = x_{2,1} - x_{2,1}^2 + (1 + e^{-x_{2,1}}) \times \\ \qquad p_2(u_2) + d_2(\boldsymbol{X}, t) \end{cases} \tag{10}$$

Among, $d_1(\boldsymbol{X}, t) = 0.012\cos t + 2x_{2,1}\sin(3t) + x_{2,2}\cos(10t) + 0.5x_{1,2}\sin(0.5t)$, $d_2(\boldsymbol{X}, t) = 0.01\sin(5t) + 2x_{1,1}\sin(x_{2,1}) + x_{2,2}\cos(0.2t)$.

Control objective: status $\boldsymbol{x}_i = (x_{i,1}, x_{i,2})^T$ trace $\boldsymbol{Y}_{di} = (0.05\sin t, 0.05\cos t)^T$, $i = 1,2$.

Use $\boldsymbol{x}_1 = (2.5, 2.5)^T$, $\boldsymbol{x}_2 = (2.5, 2.5)^T$, $\varepsilon = 2$, $\delta_1 = \delta_2 = 0.05$, $k_{1,1} = k_{2,1} = 2$, $r_1 = r_2 = 0.8$, $\eta_1 = \eta_2 = 0.9$. Use sampling time of 0.02 second, simulation for 20 seconds, obtain simulation results as expressed in figure 1-8:

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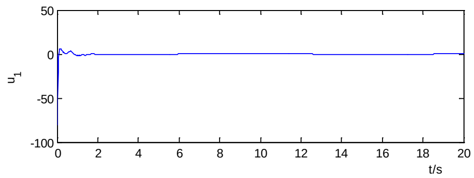

Figure1: Control Input u_1

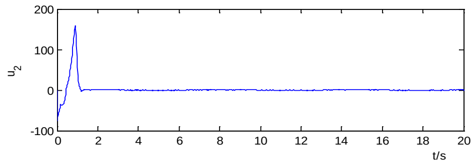

Figure2: Control Input u_2

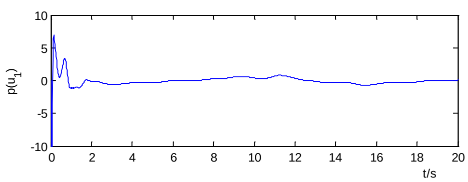

Figure 3:Control Input $p(u_1)$

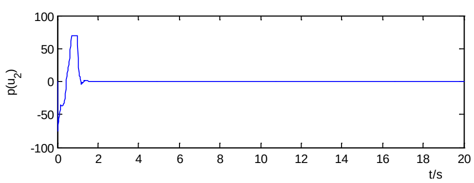

Figure 4:Control Input $p(u_2)$

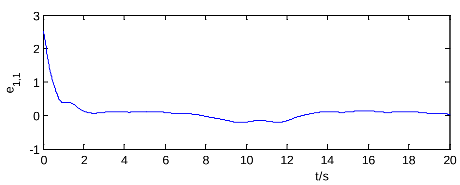

Figure 5: Tracking Error $e_{1,1}$

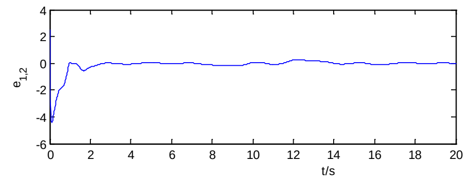

Figure 6: Tracking Error $e_{1,2}$

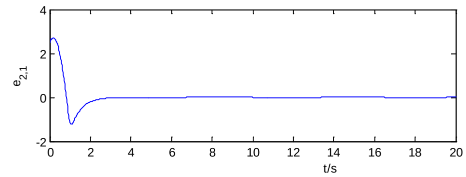

Figure 7: Tracking Error $e_{2,1}$

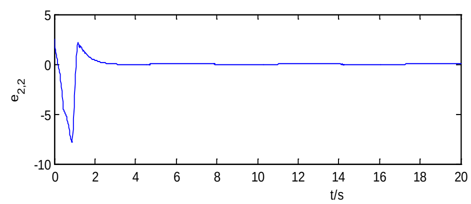

Figure 8: Tracking Error $e_{2,2}$

5. CONCLUSION

The article focuses on one category of relevant large scale system with saturation input and unknown gain symbol, and design a new method of neural network decentralized control.This method not only cancel the assumption condition that relevant item has qualified function of one or high order, but cancel premise assumption that unknown function and controlled gain of the system has bound, theoretical analysis concludes that the design method can guarantee overall situation stability of the system.

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