International Journal of Innovative Research in Advanced Engineering (IJIRAE) ISSN: 2349-2163
Volume 1 Issue 10 (November 2014) www.ijirae.com

Brain Emotional Learning Control System Design for Nonlinear Systems

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Abstract*—Brain emotional learning controller is constructed based on the physical meaning of human's brain; this controller uses neural network to imitate the judgment and emotion factors of brain. This paper proposes a brain emotional learning intelligent algorithm; beside the learning algorithm like neural network, it also included the calculation algorithm of emotion factor. Beside self-adjust the weight trough learning, this algorithm can self-judge the emotion factor and includes it into the calculation algorithm so as to achieve more intelligent algorithm. An example, the three-tank system, is demonstrated to illustrate the effectiveness of the proposed control method. Simulation results show that the proposed controller can achieve satisfactory control performance for the liquid level control of the three tank system.

***Keywords*—Brain emotional learning controller, nonlinear systems, three-tank system.**

I. INTRODUCTION

Many control theories have successfully solved most problems of the control systems, but right now control systems have become extremely complex and non-linear. So many researchers began to deal with this kind of problem using some intelligent control algorithms. A lot of neural networks have been proposed for control problems; however, in these algorithms emotion factor is always ignored.

Brain emotional learning controller (BELC) is a mathematical model that approximates judgment and emotion of a brain. The BELC has an orbitofrontal cortex and an amygdala; the former is a sensory neural network and the latter is an emotional neural network allows fast learning for the BELC [1, 2]. Many works studied the form of the amygdala to determine the usefulness for a neural network control system. An emotional neural network undergoes stimulation by external factors and has an indirect impact on the sensory neural network. These two networks affect each other, and the output of brain emotional learning controller (BELC) contains two networks. The controller has neural network and emotional system; neural network can effectively reduce the tracking error, and the emotional system can adjusts the learning error quickly. In the past, emotion has been ignored for intelligent control; however, in recent years, BELC has been used for control systems in several literatures [3-7].

In this study, by incorporating the parameter updating system into a BELC, the proposed control system is applied to nonlinear systems. Finally a tank control system is simulated to illustrate the effectiveness of the proposed BELC.

II. PROBLEM FORMULATION

A class of *n*-th order multi-input multi-output nonlinear systems is described by the following equation:

$$\boldsymbol{x}^{(n)}(t) = \boldsymbol{f}(\underline{\boldsymbol{x}}(t)) + \boldsymbol{G}(\underline{\boldsymbol{x}}(t))\boldsymbol{u}(t) + \boldsymbol{d}(t) \tag{1}$$

where $\boldsymbol{u}(t) = [u_1(t), u_2(t), \cdots, u_m(t)]^T \in \Re^m$ and $\boldsymbol{x}(t) = [x_1(t), x_2(t), \cdots, x_m(t)]^T \in \Re^m$. The former is a control input and the latter represents the state vectors of the system. $\boldsymbol{d}(t) = [d_1(t), d_2(t), \cdots, d_m(t)]^T \in \Re^m$ denotes the unknown bounded external disturbance and m is the number of system inputs and outputs. $\underline{\boldsymbol{x}}(t) = [\boldsymbol{x}^T(t), \dot{\boldsymbol{x}}^T(t), \cdots, \boldsymbol{x}^{(n-1)T}(t)]^T \in \Re^{mn}$ is defined as the system state vector and it is assumed to be measureable. It is also true that $\boldsymbol{f}(\underline{\boldsymbol{x}}(t)) \in \Re^m$ and $\boldsymbol{G}(\underline{\boldsymbol{x}}(t)) \in \Re^{m\times m}$. They are smooth nonlinear uncertain functions, which are assumed to be bounded, but not exactly known.

In the case that the modelling uncertainties and external disturbance are neglected, the nominal system of (1) is:

$$\boldsymbol{x}^{(n)}(t) = \boldsymbol{f}_0(\underline{\boldsymbol{x}}(t)) + \boldsymbol{G}_0\,\boldsymbol{u}(t) \tag{2}$$

where $f_0(\underline{x}(t)) \in \Re^m$ and the constant matrix, $G_0 = diag(g_{01}, g_{02}, \cdots, g_{0m}) \in \Re^{m \times m}$, are the nominal parts of $f(\underline{x}(t))$ and $G(\underline{x}(t))$, respectively. Without loss of generality, it is assumed that $g_{0i} \geq 0$ for $i = 1, \cdots, m$. It is also assumed that the nonlinear system of (2) is controllable and that G_0^{-1} exists. If there are modelling uncertainties and external disturbances, the nonlinear system (1) can be reformulated as

$$x^{(n)}(t) = f_0(\underline{x}(t)) + G_0\, u(t) + l(\underline{x}(t), t) \tag{3}$$

where $l(\underline{x}(t), t)$ is referred to as the lumped uncertainty, which includes the system uncertainties and the external disturbances.
The control problem is the design of a proper control system wherein the system output, $x(t)$, can track a desired trajectory vector, $x_r(t) = [x_{r1}(t), x_{r2}(t), \cdots, x_{rm}(t)]^T \in \Re^m$.
The tracking error is defined as

$$e(t) \triangleq x_r(t) - x(t) \in \Re^m \tag{4}$$

and the system tracking error vector is defined as

$$\underline{e}(t) \triangleq [e^T(t), \dot{e}^T(t), \cdots, e^{(n-1)T}(t)]^T \in \Re^{mn} \tag{5}$$

In the case that the nominal functions, $f_0(\underline{x}(t))$, G_0 and the lumped uncertainty, $l(\underline{x}(t), t)$, are exactly known, an ideal controller can be designed as

$$u_I = G_0^{-1}[x_r^{(n)} - f_0(\underline{x}) - l(\underline{x}, t) + \underline{K}^T \underline{e}] \tag{6}$$

where $\underline{K} = [K_n, \cdots, K_2, K_1]^T \in \Re^{mn \times m}$ is the feedback gain matrix, which contains the real numbers, and $K_i = diag(k_{i1}, k_{i2}, ...k_{im}) \in \Re^{m \times m}$ is a nonzero positive constant diagonal matrix.
Substituting the ideal controller (6) into (3) gives the error dynamic equation:

$$e^{(n)} + \underline{K}^T \underline{e} = \mathbf{0} \tag{7}$$

In (7), if $\underline{K}$ is chosen to correspond to the coefficients of a Hurwitz polynomial, it implies that $\lim_{t \to \infty} \|\underline{e}\| = 0$. However, the lumped uncertainty, $l(\underline{x}(t), t)$, is generally unknown for practical applications, so u_I in (6) is unobtainable. Thus, a BELC will be proposed in the next section to mimic the ideal controller.

III. Brain Emotion Learning Control System Design

The BELC can be classified as a supervised network. A brain emotional learning controller is designed with the following form:

$$u_{BELC} = a - o = \sum_i \sum_j s_{ij} v_{ij} - \sum_i \sum_j s_{ij} w_{ij}, i = 1, 2, \cdots, m, \ j = 1, 2, \cdots, n \tag{8}$$

$$s_{ij} = I_i \times \lambda_{ij} \tag{9}$$

where s_{ij} is the prefrontal system input and amygdala system input for the sensory cortex output, I_i is controller input and λ_{ij} is the gains. The brain emotional learning controller is proposed as shown in Fig. 1

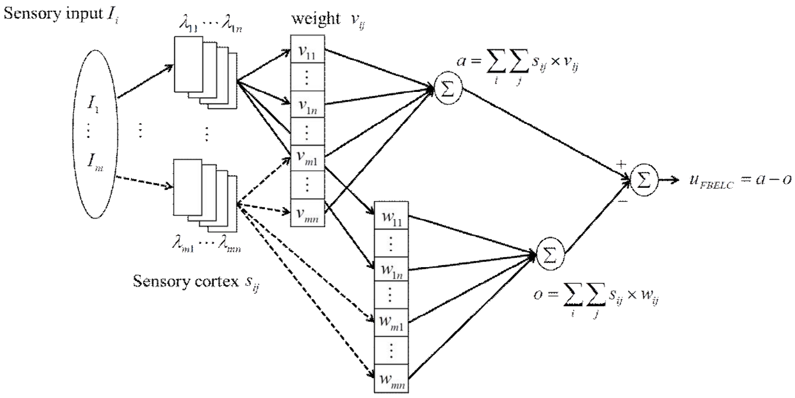

Fig. 1 Brain emotional learning controller

The update weights, Δv_{ij} and Δw_{ij} , are given by

$$\Delta v_{ij} = \alpha[s_{ij} \times (\max[0, d_i - a])] \tag{13}$$

$$\Delta w_{ij} = \beta \times [s_{ij} \times (u_{BELC} - d_i)] \tag{14}$$

where α and β are the learning rates. In (13) and (14), d_i is the parameter adjustment given by

$$d_i = b_i \times I_i + c \times u_{BELC} \tag{15}$$

where the weights, b_i and c are the gains.

The proposed intelligent tracking control system is shown in Fig. 2.

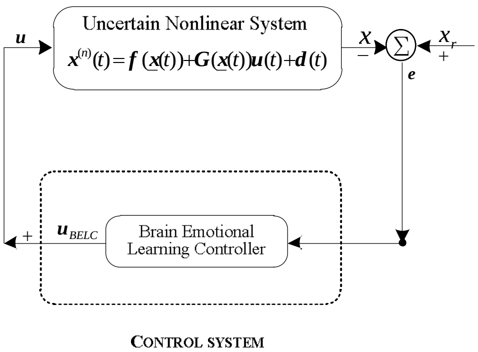

Fig. 2 An intelligent control system for uncertain nonlinear systems

IV. SIMULATION RESULTS

A three tank system is shown in Fig. 3 which is studied in order to illustrate the effectiveness of the proposed design method.

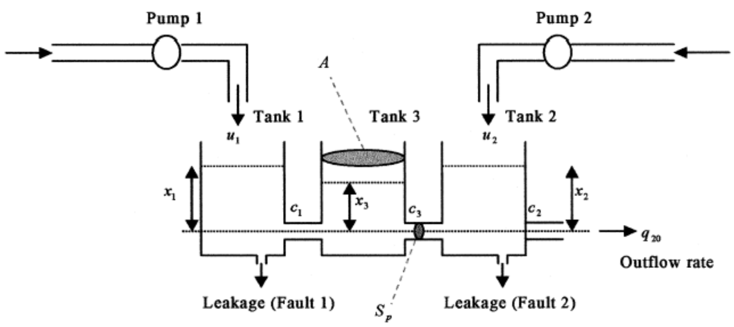

Fig. 3 Three tanks system

Consider a three-tank compression system as shown in Fig. 3, it's dynamic function is given as [8]

$$\dot{x}_1 = \frac{(-z_1 S_p \operatorname{sgn}(x_1 - x_3)\sqrt{2g|x_1 - x_3|} + u_1)}{A} + \eta_1(x,u) \tag{16}$$

$$\dot{x}_2 = \frac{(-z_3 S_p \operatorname{sgn}(x_2 - x_3)\sqrt{2g|x_2 - x_3|} - z_2 S_p \sqrt{2gx_2} + u_2)}{A} - q_{20} + \eta_2(x,u) \tag{17}$$

$$\dot{x}_3 = \frac{(-z_1 S_p \operatorname{sgn}(x_1 - x_3)\sqrt{2g|x_1 - x_3|} - z_3 S_p \operatorname{sgn}(x_3 - x_2)\sqrt{2g|x_3 - x_2|})}{A}) + \eta_3(x,u) \tag{18}$$

where $\boldsymbol{x} = [x_1, x_2, x_3]^T$, $\boldsymbol{u} = [u_1, u_2]^T$, g is the gravity acceleration, η_i, for $i = 1,2,3$ represent the modelling uncertainty due to the inaccuracy on the cross section of connection pipes. $q_{20} = z_1 S_P \sqrt{2gx_2}$ is the outflow rate from the tank 2. The cross section $A = 0.0154\text{m}^2$ and the cross section of the connection pipes is $S_p = 5\times10^{-5}\text{m}^2$. The $z_1 = 1$, $z_2 = 0.8$ and $z_3 = 1$ denote the no dimensional outflow coefficients. Initial conditions are set to be the liquid levels $x_1(0) = x_2(0) = x_3(0) = 0.15\text{m}$, and the control objective is to keep all the liquid levels at 0.2m (i.e. $x_{1_r}(k) = x_{2_r}(k) = x_{3_r}(k) = 0.2m$).

The simulation results are shown in Figs 4-6. Figure 4 denotes the liquid levels of the three tanks systems ; Figure 5 denotes the tracking errors of this system ; and Figure 6 denotes the control output of this system. The simulation results show that the proposed BELC can effectively achieve the liquid level control of the three tank system.

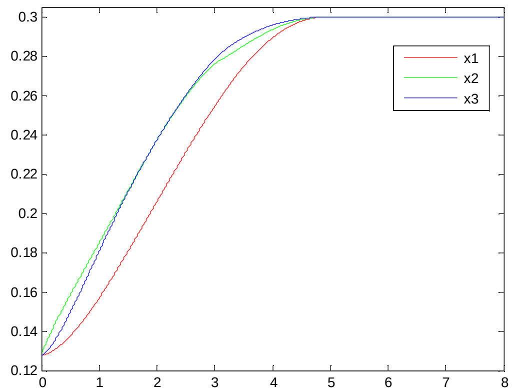

Fig. 4 The liquid level of three tank system

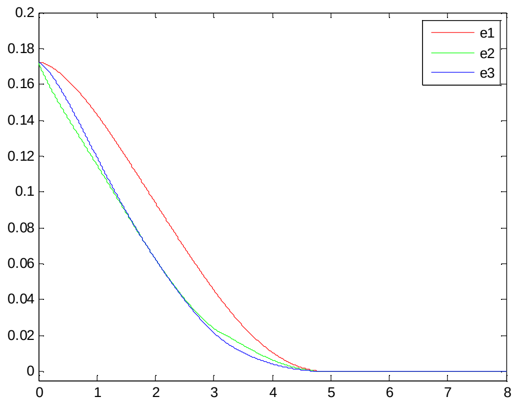

Fig. 5 The tracking error of three tank system

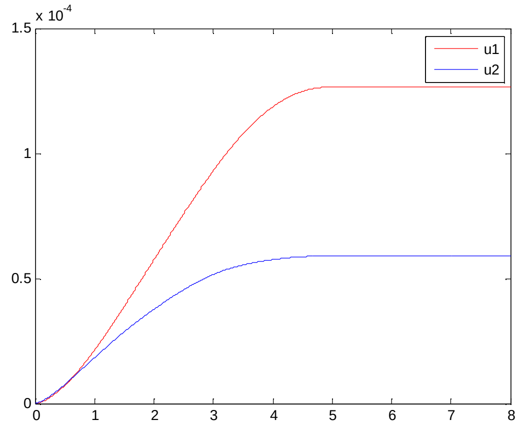

Fig. 6 The controller output of three tank system

V. CONCLUSION

This study has successfully proposed a BELC for nonlinear systems. The proposed BELC can effectively reduce the tracking error and effectively adjusts the learning error quickly. Then, the developed BELC is applied to a three-tank system to demonstrate the effectiveness of the proposed control method. Simulation results show that the proposed controller can effectively control the liquid level of the three tank system.

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