

## EMOTIONAL LEARNING TO CONTROL LARGE-SCALE SYSTEMS

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**Abstract:** In this paper, with a new look at emotional controller and modifying its structure; a novel approach to hierarchical control of large-scale systems is introduced. Design of controller is founded on emotional learning and the control system consists of neuro-fuzzy controller, whose weights are updated according to emotional signals. This signal is produced in a block called critic, whose job is to evaluate system behaviour. Simulation results demonstrate that the proposed learning scheme, which is applied to a nonlinear three-tank system, provides better control reliability and robustness than classic robust schemes. *Copyright © 2005 IFAC*

**Keywords:** Neuro-Fuzzy Controller, Emotional Learning, Intelligent System, Large-Scale System, Hierarchical Control, Multi-agent Systems.

### 1. INTRODUCTION

A centralized compensator is often considered not feasible for systems with high dimension; in turn hierarchical control is much more acceptable. Hierarchical strategy decomposes the large-scale system into a number of subsystems and then coordinates the resulting subsystem's solutions until feasibility and optimality of the overall system are achieved. (Jamshidi 1997)

Multi agent systems have been used extensively in robotic and AI applications. In (Fatourehchi *et al.*, 2003) an approach to use agent based concept to control dynamic systems is introduced. In proposed method, each agent consists of a controller and a critic. The task of critic is to evaluate systems behaviour and to provide an emotional signal, which demonstrates the system situation, according to its goal. The neuro-fuzzy controller uses this signal and emotional signals from other agents, to tune its parameters. But in this approach, the number of interconnections between agents equals  $n(n-1)$  where  $n$  is the number of agents or subsystems, which becomes so large as the as the number of agents increases. In this paper, the idea of hierarchical

structure and agent-based control are combined to reduce the number of interconnections of system to  $2n$ .

This paper is organized as follows: In section 2, emotional learning and how it can be applied in control schemes is introduced. A brief review of agent concepts is brought up in section 3. The structure of the proposed controller, its adaptation law and the proposed modification are developed in section 4. In section 5, an illustrative example is carried out to show the effectiveness of the proposed methodology; and finally, concluding remarks are made in section 6.

### 2. EMOTIONAL LEARNING

Usually emotions are considered as a negative factor in decision-making process, which should be suppressed in order to arrive to a proper, logical decision. But in order to make an entirely rational decision, a complete knowledge about system is required which is not available in many cases. Besides, computational burden is a sever problem for such decision-making (Simon, 1987). So, in recent

years, the positive and important role of emotions has been emphasized not only in psychology, but also in AI and robotics (Balkenius and Moren, 2000; El-Nasr *et al.*, 1999; Velasquez, 1998). Briefly, emotional cues can provide an approximate method for selecting good actions when uncertainties and limitations of computational resources render fully rational decision-making based on Bellman- Jacobi recursions impractical (Fatourechi *et al.*, 2003). In (Fatourechi *et al.*, 2001 a, b, c; Lucas and Jazbi, 1998; Lucas *et al.*, 2000), a very simple cognitive/emotional state designated as stress has been successfully utilized in various control applications.

This approach is actually a special case of the popular intelligent control technique, i.e. reinforcement learning. However, in this case the assessment of the present situation in terms of overall success or failure is continual. So, modification and adaptation learning, the designation of emotional learning seems more appropriate (Fatourechi *et al.*, 2003).

### 3. AGENT CONCEPT AND MULTI-AGENT SYSTEM

In this section, some characteristics of agents are reviewed. Agent is a system, which has the ability to accomplish the tasks that the user has defined. Agents usually have the following characteristics (Wooldridge and Jennings, 1995):

- Autonomy
- Deliberative
- Reactive
- Social ability
- Reasoning
- Planning
- Learning
- Adaptability

Multi-agent systems (MASs) are systems where there is no central control: the agents receive their inputs from the system (and possibly from other agents as well) and use these inputs to apply the appropriate actions. The global behaviour of MAS depends on the local behaviour of each agent and the interactions between them (Wooldridge, 1999). The most important reason to use MAS when designing a system is that some domains require it. Other aspects include:

- Parallelism
- Robustness
- Scalability
- Simple Design

### 4. EMOTIONAL BASED APPROACH IN CONTROL DYNAMIC SYSTEMS

In emotional control of dynamic systems, learning is based on existence of emotional signals such as

stress. Stress cue, is the output of a block called critic, whose task is to assess the present situation in the terms of satisfactory achievement of the control goals. The controller should modify its characteristics so that the critic's stress is decreased.

In this section, structure of emotional controller based on (Fatourechi *et al.*, 2003) is reviewed. Fig. 1 shows the agent's components and their relation with each other, based on the idea presented in (Russel and Norwig, 1995). The agent is composed of four components. It perceives the states of the system through its sensors and also receives some information provided by other agents, then influences the system by providing a control signal through its actuator. The critics assess the behaviour of the control system (i.e. criticize it) and provide the emotional signals for the controller. According to these emotional signals, the controller produces the control signal with the help of the Learning element, which is adaptive emotional learning. Inputs of this learning element are the emotional signals provided by both the agent's critics and other critics and also some knowledge provided by the controller.

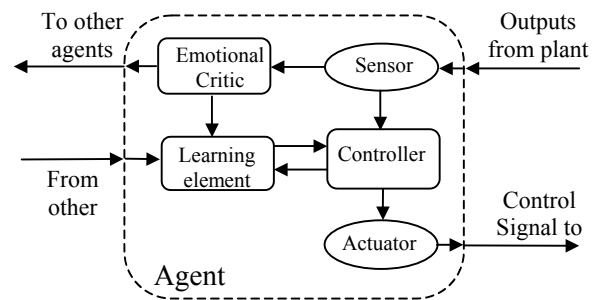


Fig. 1. Structure of an agent

The number of the agents assigned here is determined based on the number of the inputs of the system. The number of the outputs of the system is effective in determining the number/structure of the system's critics, which their role is to assess the status of the outputs. Fig.2 demonstrates the schematic of this approach when applied to a four-input – four-output control system. As it can be seen, the number of interconnection between agents is:

$$N_c = 2 \frac{n(n-1)}{2} = n(n-1)$$

where  $n$  is the number of agents.

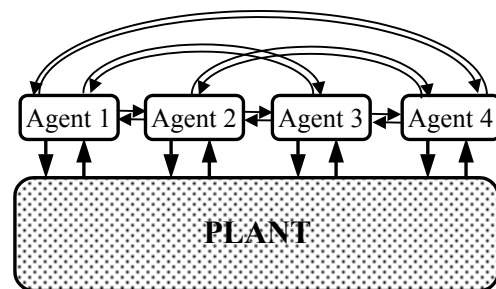


Fig 2. Schematic of multi-agent based approach to multivariable control

Now the structure of controller for the multivariable systems, in general is reviewed.

#### 4.1 Structure of neuro-fuzzy Controller

In the general case of multivariable systems, each agent consists of a neurofuzzy controller, which has an identical structure to other controllers, i.e. four layers for each one. The first layer's task is the assignment of inputs' scaling factors in order to map them to the range of [-1, +1] (the inputs are chosen as the error and the change of the error in the response of the corresponding output). In the Second layer, the fuzzification is performed for each input assigning five labels {NL,NS,Ze,PS,PL} for each one. For decision-making, max-product law is used in layer 3. Finally, in the last layer, the crisp output is calculated using Takagi- Sugeno formula (Takagi and Sugeno, 1983),

$$u_i = \frac{\sum_{l=1}^p w_{il}(a_{il}e_i + b_{il}\dot{e}_i + c_{il})}{\sum_{l=1}^p w_{il}} \quad (i=1,2,\dots,n) \quad (1)$$

where  $e_i$  and  $\dot{e}_i$ , are the error and its derivative of the corresponding output,  $i$ ,  $n$ ,  $w_{il}$ ,  $p$ , and  $y_i$  are the index of the controller, number of controllers,  $l$ th input of the last layer, number of rules in the third layer and output of the controller, respectively and  $a_{il}$ 's,  $b_{il}$ 's and  $c_{il}$ 's are parameters to be determined via learning.

#### 4.2 Structure of emotional critic

For each output, a critic is assigned whose task is to assess the control situation of the output and to provide the appropriate emotional signal. The role of these critics is very crucial here because the eliminating of the unwanted cross-coupled effects of the multivariable control systems is very much dependent on the correct operation of these critics. Here, all the critics have the same structure as a PD fuzzy controller with five input labels, {NL,NS,Ze,PS,PL} and seven output labels, {NL,NM,NS,Ze,PS,PM,PL}. Inputs of the critic are error and its derivative and its output is the corresponding emotional signal. Deduction is performed by max-product law, and for defuzzification, the centroid law is used. Table 1 shows fuzzy rules, used for critic.

Table 1 fuzzy rules for critic

$\dot{e} \backslash e$	NL	NS	Ze	PS	PL
NL	NL	NL	NM	NS	Ze
NS	NL	NM	NS	Ze	PS
Ze	NM	NS	Ze	PS	PM
PS	NS	Ze	PS	PM	PL
PL	Ze	PS	PM	PL	PL

The emotional signals provided by these critics contribute collaboratively for updating output layer's parameters of each controller. With this definition, an emotional signal is produced based on system's behaviour. For example when error is positive and its derivative is negative, it means that the system is in a good condition and the error becomes zero, so, it is not necessary to change controller's parameters. Therefore, the stress signal should equal 0.

#### 4.3 Learning rules of emotional learning controller

The aim of the control system is the minimization of the sum of squared emotional signals. Accordingly, first the error function  $E$  is described as follows,

$$E = \sum_{j=1}^m K_j (1/2 r_j^2) \quad (2)$$

where  $r_j$  is the output signal of  $j$ 's critic,  $K_j$  is the corresponding output weights and  $m$  is the total number of outputs (for the special case of SISO systems,  $K_j=1$  and  $m=1$ )

For the adjustment of weights of controller, the steepest descent method is used ( $\omega_i$  stands for controller's parameters  $a_i, b_i, c_i$ )

$$\Delta \omega_i = -\eta_i \frac{\partial E}{\partial \omega_i} \quad (3)$$

where  $\eta_i$  is the learning rate of the corresponding neuro-fuzzy controller and  $n$  is the total number of controllers.

In order to calculate the RHS of (3), the chain rule is used,

$$\frac{\partial E}{\partial \omega_i} = \sum_{j=1}^m \frac{\partial E}{\partial r_j} \cdot \frac{\partial r_j}{\partial y_j} \cdot \frac{\partial y_j}{\partial u_i} \cdot \frac{\partial u_i}{\partial \omega_i} \quad (4)$$

From (2),

$$\frac{\partial E}{\partial r_j} = K_j \cdot r_j \quad (5)$$

also,

$$\frac{\partial y_j}{\partial u_i} = J_{ji} \quad (6)$$

where  $J_{ji}$  is the element located at the  $i$ th column and  $j$ th row of the Jacobian matrix. To compute  $J$ , gradient of  $y_j$  with respect to  $u_i$  must be calculated. Considering difficulties in this calculation, just its sign is used, which can be found by trial and error procedure.

Taking

$$e_i = y_{refi} - y_i \quad (7)$$

where  $e_j$  is the error produced in the tracking of  $j^{\text{th}}$  output and  $y_{\text{ref}j}$  is the reference input (in case number of outputs is greater than the number of inputs, some of  $y_{\text{ref}j}$ 's are taken as zero), it is concluded that:

$$\frac{\partial r_j}{\partial y_j} = -\frac{\partial r_j}{\partial e_j} \quad (8)$$

Since with the incrimination of error,  $r$  will also be incremented and on the other hand, on-line calculation of  $\frac{\partial r_j}{\partial e_j}$  is accompanied with measurement

errors, which results in producing unreliable results, only the sign of it (+1) is used in calculations.

From (2) to (8),  $\Delta\omega_i$  will be calculated as follows

$$\Delta\omega_i = \eta_i \sum_{j=1}^m K_j \cdot r_j \cdot J_{ji} \cdot \frac{\partial u_i}{\partial \omega_i} \quad (9)$$

Equation (9) is used for updating the learning parameters  $a_{il}$ 's,  $b_{il}$ 's and  $c_{il}$ 's in (1). Above equations are the formulation introduced in (Fatourechi *et al.*, 2003). In the following lines, it is shown how a change in this formulation makes this approach suitable to hierarchical control of large-scale systems.

Since in equation (9),  $\frac{\partial u_i}{\partial \omega_i}$  is independent of index  $j$ ,

it can be rewritten as:

$$\Delta\omega_i = \eta_i \cdot \frac{\partial u_i}{\partial \omega_i} \cdot \sum_{j=1}^m K_j \cdot r_j \cdot J_{ji} = \eta_i \cdot \frac{\partial u_i}{\partial \omega_i} \cdot co_i \quad (10)$$

where,

$$co_i = \sum_{j=1}^m K_j \cdot r_j \cdot J_{ji} \quad (11)$$

Using this update rule, parameters of neuro-fuzzy controller can be calculated as:

$$\begin{aligned} a_{il\_new} &= a_{il\_old} + \eta_i co_i e_i \frac{w_{il}}{\sum_{l=1}^p w_{il}} \\ b_{il\_new} &= b_{il\_old} + \eta_i co_i \dot{e}_i \frac{w_{il}}{\sum_{l=1}^p w_{il}} \\ c_{il\_new} &= c_{il\_old} + \eta_i co_i \frac{w_{il}}{\sum_{l=1}^p w_{il}} \end{aligned} \quad (12)$$

$co_i$  can be considered as the output of a coordinator unit, whose inputs are emotional signals of each agent. The task of this unit is to coordinate among different agents.

With this modification, structure of the controller will change to Fig. 3.

which has a structure of hierarchical controller. (Jamshidi 1997)

Number of interconnections between agents in this structure equals:

$$N_c = 2n$$

which is much less than the previous structure, especially in large scale systems.

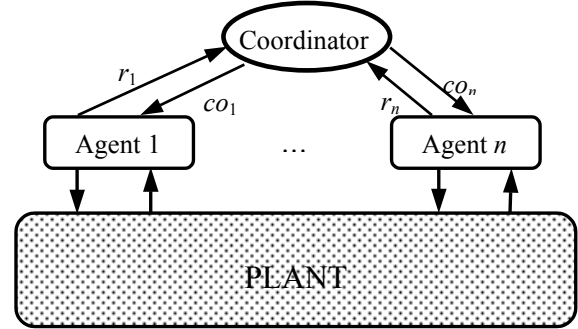


Fig 3. Schematic of modified multi-agent based approach to multivariable control

It should be noted that, if there isn't any disturbance in the system, it is sufficient to learn parameters of controller once during training phase, and it is not necessary to update them after that. In fact, can controller can be considered as a hierarchical controller during training phase, and then after, disconnect the interconnections and consider it as a decentralized controller. So, if in any system, the time of entering a disturbance to the system or changing the parameters of the system is known, (i.e. with fault detection techniques) this approach gives good results.

## 5. SIMULATION RESULTS

Three-tank (Labibi, 2001) system is chosen as a nonlinear plant to be controlled by the proposed approach.

Three tank system:

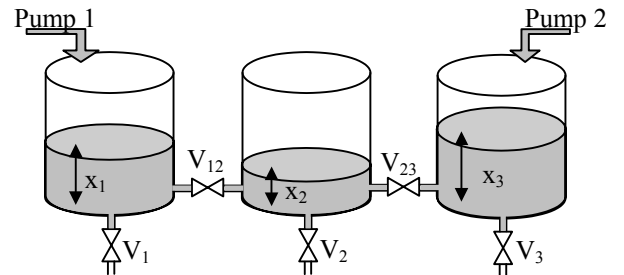


Fig 4. Three-tank system

Three-tank system consists of three tanks with equal diameter and height. Each of external tanks, (tank 1 and 3), is connected to the third tank via a controllable magnetic valve. Besides, each tank has

an output, which can be closed or open by its valve. Tanks 1 and 3 are filled by pumps 1 and 2 respectively; and tank 3, is filled by tanks 1 and 3. In each tank there is an analogue sensor to measure

$$\begin{aligned}\dot{x}_1 &= -V_1\sqrt{x_1+h_1} - \text{sign}(x_1-x_2)\left(-\frac{b_{12}}{2a_{12}} + \sqrt{\left(\frac{b_{12}}{2a_{12}}\right)^2 - \frac{g|x_1-x_2|}{a_{12}}}\right) + p_1u_1 \\ \dot{x}_2 &= -V_2\sqrt{x_2+h_2} + \text{sign}(x_1-x_2)\left(-\frac{b_{12}}{2a_{12}} + \sqrt{\left(\frac{b_{12}}{2a_{12}}\right)^2 - \frac{g|x_1-x_2|}{a_{12}}}\right) - \text{sign}(x_2-x_3)\left(-\frac{b_{23}}{2a_{23}} + \sqrt{\left(\frac{b_{23}}{2a_{23}}\right)^2 - \frac{g|x_2-x_3|}{a_{23}}}\right) \\ \dot{x}_3 &= -V_3\sqrt{x_3+h_3} + \text{sign}(x_2-x_3)\left(-\frac{b_{23}}{2a_{23}} + \sqrt{\left(\frac{b_{23}}{2a_{23}}\right)^2 - \frac{g|x_2-x_3|}{a_{23}}}\right) + p_2u_2\end{aligned}$$

Values of parameters are defined in appendix.

The results are compared with a decentralized robust controller introduced in (Labibi *et al.*, 2003). This method can be applied to linear systems, so the system is linearized at operating setpoint (dynamic equations of linearized system are brought up in appendix) and a robust controller for this system is designed. To compare results, both controllers are applied to nonlinear system. It should be noted that emotional controller needs an initial time (training phase) to learn its parameters, and also a robust decentralized controller, which is an output feedback controller, needs a time for observation and settling its states. So, this initial time is not included in results. Considering that it takes much more time for the neural networks' weights to adjust when the input of the system changes suddenly (and let's call it harsh input) with regards to the situation where a smoother input is applied, when applying a harsh input to a system, it was changed it to a smooth one by placing a pre-filter at the input of the system. It provides a smooth (filtered) input for the system instead of harsh (unfiltered) one. The specifications of the pre-filter are determined by the properties of the desired step responses (Fatourehchi *et al.*, 2003).

In this system, it is desired that both outputs have no overshoot and a rise time not more than 150 seconds. Accordingly, based on a rough measure the transfer functions of pre-filters are the same and are chosen as follows:

$$H(s) = \frac{1}{(20s+1)^2}$$

In the first simulation, system's response to different reference inputs and effect of interaction has been investigated. Initial states of the system are:  $x=[0.248 \ 0.2 \ 0.3]$ . The reference inputs are  $y_{ref}=[0.248 \ 0.3]$ ,  $y_{ref}=[0.248 \ 0.4]$ ,  $y_{ref}=[0.4 \ 0.4]$ ,  $y_{ref}=[0.4 \ 0.3]$ , respectively, which were applied to system at 600 seconds intervals. Fig. 5 shows results of this simulation. Response of the system with emotional learning controller and robust classic controller, are shown with solid and dash lines respectively. Both systems tracks input signal with the same speed, but interaction of the system is much smaller for

liquid level. The goal is to control liquid level in tanks 1 and 3. The normalized control signal can be changed in the range [0,100]. Dynamic equations of system are as follows:

emotional controller. Control signal is in allowed interval in both cases.

In the second simulation, ability of the system to reject disturbance was tested. At  $t=200\text{sec}$ , the valve connected to the 3rd tank was opened to 33% of its nominal value, and it was closed at  $t=500\text{sec}$ . Results are plotted in Fig 6. Emotional controller has rejected disturbance faster and with a smaller overshoot, comparing with robust controller. It should be mentioned, that although the proposed approach, has much better performance, but the structure of the controller is not completely decentralized as it is in the robust classic controller.

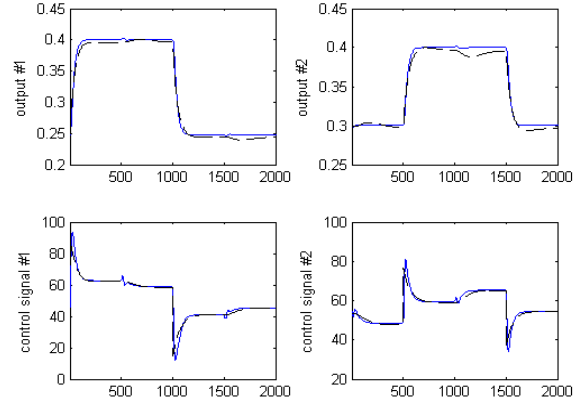


Fig 5. System response to different inputs (solid line: emotional control, dash line: robust control)

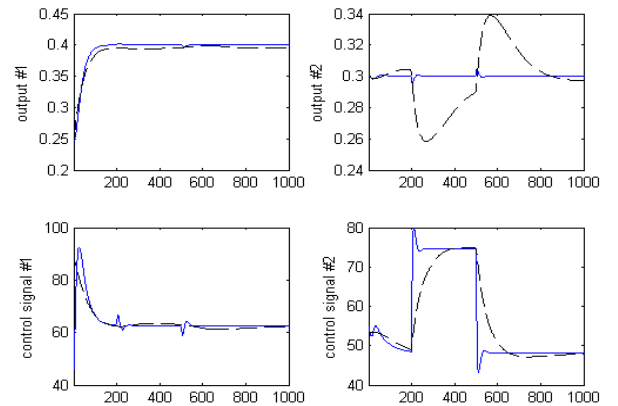


Fig 6. System response to disturbance (solid line: emotional control, dash line: robust control)

## 6. CONCLUSION

With rewriting equations of emotional controller, an equivalent hierarchical controller is designed. Both simulations show that with the proposed scheme, nonlinearities and disturbance rejection are handled easily. Besides, in order to design an emotional controller, equations of system are not needed and controller can tune and learn its parameters.

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## APPENDIX

Parameters of nonlinear systems:

$$\begin{aligned}
 V_1 &= 0.00466295555089 & V_2 &= 0.00470729612887 \\
 h_1 &= 0.04204892663654 & h_2 &= 0.04001797960217 \\
 a_{12} &= -4.8803401025576e5 & a_{23} &= -4.851840632836e5 \\
 b_{12} &= -0.00056467144213e5 & b_{23} &= -0.000366974464e5 \\
 V_3 &= 0.00468627163200 & h_3 &= 0.04159495274436 \\
 p_1 &= 0.007/(60*\pi*0.7^2) & p_2 &= 0.007/(60*\pi*0.7^2) \\
 g &= 9.81
 \end{aligned}$$

Parameters of linearized system around  $h_1=0.248m$ ,  $h_2=0.2m$ ,  $h_3=0.3m$

$$\begin{aligned}
 A &= \begin{bmatrix} -0.0146 & 0.0103 & 0 \\ 0.0103 & -0.0222 & 0.0071 \\ 0 & 0.0071 & -0.0111 \end{bmatrix} & B &= \begin{bmatrix} 0.7579e-4 & 0 \\ 0 & 0 \\ 0 & 0.7579e-4 \end{bmatrix} \\
 C &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} & D &= \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}
 \end{aligned}$$