Brain emotional learning based intelligent controller applied to neurofuzzy model of micro-heat exchanger

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Abstract

In this paper, an intelligent controller is applied to govern the dynamics of electrically heated micro-heat exchanger plant. First, the dynamics of the micro-heat exchanger, which acts as a nonlinear plant, is identified using a neurofuzzy network. To build the neurofuzzy model, a locally linear learning algorithm, namely, locally linear mode tree (LoLiMoT) is used. Then, an intelligent controller based on brain emotional learning algorithm is applied to the identified model. The intelligent controller is based on a computational model of limbic system in the mammalian brain. The brain emotional learning based intelligent controller (BELBIC) based on PID control is adopted for the micro-heat exchanger plant. The contribution of BELBIC in improving the control system performance is shown by comparison with results obtained from classic PID controller without BELBIC. The results demonstrate excellent improvements of control action, without any considerable increase in control effort for PID + BELBIC.

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1. Introduction

Although industrial processes usually contain complex nonlinearities, most of the conventional control algorithms are based on a linearized model of the process. Linear models can be identified in a straightforward manner from process test data; e.g. via step or impulse response. However, if the process is highly nonlinear and subject to large frequent disturbances, a nonlinear model will be necessary to describe the behavior of the process. For such systems nonlinear identification methods should be used to describe the dynamic behavior of the system, which can be achieved by means of neural networks. An alternative approach is to design a nonlinear model consisting of several linear functions. The major output function is derived from a combination of linear models. Many training algorithms and structures are suggested for the mentioned networks such as locally linear model tree (LoLiMoT), adaptive network based fuzzy inference system (ANFIS), Takagi-Sugeno (TS) and piecewise linear networks (PLN) (Eppler & Beck, 1999; Jang, 1993; Nelles, 1997; Sugeno & Kang, 1988). In this work we will make use of LoLiMoT for training...
algorithm of the neurofuzzy network because of its rapid and accurate operation in control applications.

We will use brain emotional based learning intelligent controller (BELBIC) (Lucas, Abbaspour, Gholipour, Nadjar Araabi, & Fatourechi, 2003; Lucas, Shahmirzadi, & Sheikholeslami, 2004), our recently developed neuromorphic controller based on emotional learning model elaborated in (Balkenius & Moren, 2000; Moren, 2002), to produce the control action. Model-based approaches to decision making are being replaced by data-driven and rule-based approaches in recent years (Miyazaki et al., 1998; Savinov, 1999). New approaches where intelligence is not given to the system from outside, but is acquired by the system through learning, have proven much more successful (Fatourechi, Lucas, & Khaki Sedigh, 2003). A more cognitively based version of reinforcement learning has also been developed in which a critic constantly assesses the consequences of actuating the plant with the selected control action in any given stage in terms of the overall objectives or performance measures and produces an analog reinforcement cue which in turn directs the learning in the controller block (Fatourechi et al., 2003). This cognitive version of the reinforcement signal has been denoted as an emotional cue, for it is indeed the function of emotions like stress, concern, fear, satisfaction, happiness, etc. to assess the environmental conditions with respect to goals and utilities and to provide cues regulating action selection mechanisms (Fatourechi et al., 2003; Inoue, Kawabata, & Kobayashi, 1996). Whether called emotional control or merely an analog version of reinforcement learning with critic (evaluative control), the method is increasingly being utilized by control engineers, robotic designers and decision support systems developers and yielding excellent results (Balkenius & Moren, 2000; Fatourechi, Lucas, & Khaki Sedigh, 2001a; Fatourechi, Lucas, & Khaki Sedigh, 2001b; Fatourechi et al., 2003; Inoue et al., 1996; Lucas et al., 2003; Lucas et al., 2004; Moren, 2002; Neese, 1998).

In this paper, an intelligent controller will be applied to output temperature tracking problem in an electrically heated micro-heat exchanger plant. First, the nonlinear behavior of the process is identified using a neurofuzzy network based on locally linear model tree (LoLiMoT) learning algorithm and then brain emotional learning based intelligent controller (BELBIC), which has a PID type structure, is applied to the plant. Using the proposed strategy, the tracking problem of the temperature profile will be tackled. The performance of the proposed controller is compared with that of a classical PID controller, which simulation results show better match for BELBIC. Aforementioned comparison seems to be more reasonable when the structure of BELBIC in this work is based on PID controller and the contribution of brain emotional learning will be improvement of performance of PID controller on a nonlinear plant.

This paper is organized as follows: Section 2 present the electrically heated micro-heat exchanger plant with characteristics and advantages. The procedure of the nonlinear system identification using neurofuzzy models with LoLiMoT learning algorithm will be discussed briefly in Section 3. Section 4 includes the structure of the proposed intelligent controller. The paper is followed by some simulation results in Sections 5 and 6 concludes the paper with some brief remarks.

2. Electrically heated micro-heat exchanger

Electrically heated micro-heat exchangers have been developed to accelerate the fluid and gas heating in a reduced space (Brandner et al., 2005; Henning, Brandner, & Schubert, 2004). This system consists of a diffusion bonded metal foil stack with many grooves, the heating element are placed between the foils (Fig. 1). In a small volume, powers to 15 kW can be converted. The advantages of this heat exchanger are:

- Fluids and gas heated by electrical power and not by additional flow cycle
- Efficient transformation of electrical energy in thermal energy
- Fast temperature change of the media and temperature good fit for sensitive media
- Compact construction due to micro-system technology

Also, the results of that are:

- Production of 45 °C warm water by an electric power of 14 kW and a flow of about 6 l/min
- Complete evaporation of water with a flow of 5 l/h
- Heating of an air stream in only 1 ms from 25 °C to 850 °C with an electrical power of 400 W and a flow of 2000 l/h

Its characteristics are listed in below:

- Heat transmission coefficient: 17500 (W m⁻² k⁻¹) (for water)

Fig. 1. Electrically heated micro-heat exchanger (http://hikwww4.fzk.de/imvt/englisch/micro_el.htm).
• Yield an efficiency higher than 90%
• Ultimate electric power: 15 kW
• Pressure drop: 100 mbar for 5 l/h water-flow
• Dimensions: 95 mm * 30 mm * 35 mm

For the identification of the plant, the input–output data obtained from experimental results is used. For this plant, the input temperature and voltage are the system inputs and the output temperature is the output while only the voltage is used as output of controller.

3. Locally linear model tree identification of nonlinear systems

In the following, the modeling of nonlinear dynamic processes and nonlinear function approximation using LoLiMoT algorithm is briefly described. The network structure of a local linear neurofuzzy model (Fink, Fischer, Nelles, & Isermann, 2000; Fink, Topfer, & Isermann, 2003; Hafner, Schukler, Nelles, & Isermann, 2001; Nelles, 2001) is depicted in Fig. 2. Each neuron realizes a local linear model (LLM) and an associated validity function that determines the region of validity of the LLM. The validity functions form a partition of unity, i.e. they are normalized such that

\[ \sum_{i=1}^{M} \phi_i(z) = 1 \]  

(1)

for any model input \( z \).

The output of the model is calculated as follows (Nelles, 2001):

\[ \hat{y} = \sum_{i=1}^{M} \left( w_{i0} + w_{i1}x_1 + \cdots + w_{in}x_n \right) \phi_i(z) \]  

(2)

where the local linear models depend on \( x = [x_1, \ldots, x_n]^T \) and the validity functions depend on \( z = [z_1, \ldots, z_n]^T \).

Thus, the network output is calculated as a weighted sum of the outputs of the local linear models where the \( \phi_i \) are interpreted as the operating point dependent weighting factors. The network interpolates between different locally linear models (LLMs) with the validity functions. The weights \( w_{ij} \) are linear network parameters. The validity functions are typically chosen as normalized Gaussians. If these Gaussians are furthermore axis-orthogonal, the validity functions are

\[ \phi_i(z) = \frac{\mu_i(z)}{\sum_{j=1}^{M} \mu_j(z)} \]  

(3)

with

\[ \mu_i(z) = \exp \left( -\frac{1}{2} \frac{(z_1 - c_{i1})^2}{\sigma_{i1}^2} + \cdots + \frac{(z_n - c_{in})^2}{\sigma_{in}^2} \right) \]  

(4)

The centers and standard deviations are nonlinear network’s parameters. In the fuzzy system interpretation each neuron represents one rule. The validity functions represent the rule premise and the LLMs represent the rule consequents. One-dimensional Gaussian membership functions (Nelles, 2001):

\[ \mu_{ij}(z_i) = \exp \left( -\frac{1}{2} \frac{(z_i - c_{ij})^2}{\sigma_{ij}^2} \right) \]  

(5)

can be combined by a \( t \)-norm (conjunction) realized with the product operator to form the multidimensional membership functions in Eq. (2). One of the major strengths of local linear neurofuzzy models is that premises and consequents do not have to depend on identical variables, i.e. \( z \) and \( x \) can be chosen independently.

The LoLiMoT algorithm consists of an outer loop in which the rule premise structure is determined and a nested inner loop in which the rule consequent parameters are optimized by local estimation. This loop can be summarized as follows:

1. Start with an initial model
2. Find worst LLM
3. Check all divisions
4. Find best division
5. Test for convergence

For the termination criterion various options exist, e.g. a maximal model complexity, that is a maximal number of LLMs, statistical validation tests, or information criteria. Note that the effective number of parameters must be inserted in these termination criteria.

The training algorithm LoLiMoT is found out to be rapid, precise, self tuned and more user friendly than other conventional methods for training of neurofuzzy networks which makes it more acceptable in online control applications. The model based on this training algorithm is used in the following process control.
4. Brain emotional based learning intelligent controller

Motivated by the success in functional modeling of emotions in control engineering applications (Balkenius & Moren, 2000; Fatourechi et al., 2001a; Fatourechi et al., 2001b; Fatourechi et al., 2003; Moren, 2002), the main purpose of this research is to use a structural model based on the limbic system of mammalian brain for decision making and control engineering applications. A network model have been adopted which is developed by Balkenius and Moren (Balkenius & Moren, 2000; Moren, 2002), as a computational model that mimics amygdala, orbitofrontal cortex, thalamus, sensory input cortex and generally, those parts of the brain thought responsible for processing emotions. There are two approaches for intelligent and cognitive control: direct and indirect. In the indirect approach, the intelligent system is used for tuning the parameters of the controller while in the direct approach the intelligent system itself functions as the controller. While in our past utilizations of BELBIC the direct approach was taken (Lucas et al., 2004), here we have used BELBIC for tuning an existing controller, i.e. a PID controller. As a result, the basic performance of the system is determined by our choice of the controller block in ideal situation, and BELBIC is responsible for tuning the parameters of the controller and, generally, to improve its performance. Excellent performance at the expense of more reasonable levels of control effort has thus been achieved.

The model is illustrated in Fig. 3. BELBIC is essentially an action generation mechanism based on sensory inputs and emotional cues. In general, these can be vector valued, although in the benchmark discussed in this paper public for the sake of illustration, one sensory input and one emotional signal (stress) have been considered (Lucas et al., 2004). The emotional learning occurs mainly in amygdala. The learning rule of amygdala is given in formula (6):

\[ \Delta G_\alpha = k_1 \cdot \max(0, EC - A) \]  

where \( G_\alpha \) is the gain in amygdala connection, \( k_1 \) is the learning rate in amygdale. EC and \( A \) are the values of emotional cue function and amygdala output at each time. The term \( \max \) in the formula (6) is for making the learning changes monotonic, implying that the amygdala gain can never be decreased as it is modeled to occur in biological process in amygdala (Balkenius & Moren, 2000; Moren, 2002). This rule is for modeling the incapability of unlearning the emotion signal (and consequently, emotional action), previously learned in the amygdala (Balkenius & Moren, 2000; Moren, 2002). Similarly, the learning rule in orbitofrontal cortex is shown as

\[ \Delta G_o = k_2 \cdot (MO - EC) \]  

which is completely based on the original biological process. In the above formula, \( G_o \) is the gain in orbitofrontal connection, \( k_2 \) is the learning rate in orbitofrontal cortex and \( MO \) is the output of the whole model, where it can be calculated as formula (8)

\[ MO = A - O \]  

in which, \( O \) represents the output of orbitofrontal cortex. In fact, by receiving the sensory input SI, the model calculates the internal signals of amygdala and orbitofrontal cortex by the relations in (9) and (10) and eventually yields the output

\[ A = G_o \cdot SI \]  
\[ O = G_o \cdot SI \]  

Since amygdala does not have the capability to unlearn any emotional response that it ever learned, inhibition of any inappropriate response is the duty of orbitofrontal cortex. It should be noted that \( k_1 \) and \( k_2 \) may vary during the control process. As a logical improvement they can decrease gradually when the system performance approaches to its steady state situation. For instant, in this work \( k_1 \) and \( k_2 \) have been reduced by the factor of time sample square.

Controllers based on emotional learning have shown very good robustness and uncertainty handling properties (Fatourechi et al., 2001a; Fatourechi et al., 2001b; Lucas et al., 2003; Lucas et al., 2004), while being simple and easily implementable. To utilize our version of the Moren–Balkenius model as a controller, it should be noted that it essentially converts two sets of inputs (sensory input and emotional cue) into the decision signal as its output. A closed loop configuration using this block (termed BELBIC) in the feed forward loop of the total system in an appropriate manner have been implemented so that the input signals have the proper interpretations. The block implicitly implemented the critic, the learning algorithm and the action selection mechanism used in functional implementations of emotionally based (or generally reinforcement learning based) controllers, all at the same time. The structure of the control circuit we implemented in this study is illustrated in Fig. 4. The implemented functions in emotional cue and sensory input blocks are given in (11) and (12):
EC = |MO| \cdot (-W_1 \cdot \dot{e} \cdot e + W_2 \cdot |e|) \quad (11)

SI = W_3 \cdot e + W_4 \cdot \dot{e} + W_5 \cdot \int e dt \quad (12)

where EC, CO, SI and e are emotional cue, controller output, sensory input and output error and the \( W_1 \sim W_5 \) are the gains must tuned for designing a satisfactory controller. In the choice of these two signals (EC, SI) some principles are taken into consideration as following:

1. Sensory input is a kind of control signal which in BELBIC is reinforced or punished based on emotional cue, so it should be chosen as a function of error just like a PID controller. This choice has some advantages such as existence of a systematic way to tune the gains which was the dominant difficulty in previous works (Lucas et al., 2003; Lucas et al., 2004). In this way one can set the learning rates (\( k_1, k_2 \)) equal to zero at first, and then tune the gains of sensory input as a simple PID controller and then proceed to tune the gains of the other parts of BELBIC in the direction of improving the performance of primary sensory input signal. This method can solve the main problem of BELBIC which was the tuning of the gains. In addition to this point, the controller now has more reliability because of being based on a classic controller (PID). Also PID controller has some other advantages such as robustness to some extend which is very desirable especially in this work with possible uncertainties in estimated model including less than enough number of neurons. Besides, using this signal selection it does not need to concern on effect of noises on identification. So, an identification using less numbers of neurons can easily filter the noises while could be used in tuning of controller and it will accelerate the online control process certainly. It should be noted that PID gains have been tuned by means of trial and error. They might not be the best but BELBIC is expected to improve the corresponding PID controller’s performance.

2. When the emotional cue is a positive number, the gain of amygdala connection will be increased and when the emotional cue is a negative number, the gain of orbitofrontal connection will be increased and the bigger emotional cue causes the bigger reinforcement or punishment, so the emotional cue should increase when the absolute value of error decreases. In order to avoid the offset error, the emotional cue should include error in addition to its derivative but with a very smaller coefficient. Finally, the emotional cue is compared with the control signal (MO) therefore it should have the same dimension with (MO). Therefore, one can define the emotional cue like (11). Nevertheless, according to the need of designer, one may choose another rational structure with the general structure of \( EC = F(e, \dot{e}, MO, \ldots) \). It may not be logical such as (11) but may work better for a certain case study.

5. Simulation results

In this section, the simulation results of the output temperature tracking problem using BELBIC with LoLiMoT

![Fig. 5. Input temperature for system identification.](image)

![Fig. 6. Output temperature for system identification.](image)
identifier will be presented. Output temperature is identified as a function of input temperature and voltage:

\[ T_{out}[t] = f(T_{out}[t-1], \ldots, T_{out}[t-4], \]
\[ T_{in}[t-1], T_{in}[t-2], V[t-1], V[t-2]) \] (13)

The input temperature, output temperature and input voltage profiles for identification of the plant are depicted in Figs. 5–7. Using LoLiMoT algorithm, the identified output temperature as well as the actual values are shown in Figs. 8 and 9. As it can be seen, the error is not considerable and the system is identified satisfactory. Now, one can apply BELBIC to the identified plant. The closed-loop system response using BELBIC is shown in Fig. 10. In order to investigate the performance of BELBIC, another simulation has been provided using conventional PID controller. Using trail and error algorithm, the best values for PID controller in which the closed-loop system is stable and has almost satisfactory performance is adopted. The closed-loop system response using PID controller is shown in Fig. 11. Comparing Fig. 10 with Fig. 11, one can see that the performance of the system using BELBIC is much better than that of PID controller. The system responses using BELBIC is rather faster with less overshoot and undershoot on this nonlinear, nonminimum phase system. Also BELBIC controller did not make a control effort no more than PID controller with less undershoots and overshoot in the response of plant (Figs. 12 and 13). In addition, using PID signal as sensory input

![Fig. 7. Input voltage for system identification.](image1)

![Fig. 8. The identified and actual normalized output temperature.](image2)

![Fig. 9. The error between identified and actual normalized output temperature.](image3)

![Fig. 10. Closed-loop system response using BELBIC with LoLiMoT identifier.](image4)

![Fig. 11. The error between identified and actual normalized output temperature.](image5)
which can be reinforced or punished by BELBIC can have some advantages of PID controller such as robustness. As it is shown in Fig. 14, while system is subjected with variation of input temperature as noise the performance of BELBIC is still much more admirable than PID (Figs. 15 and 16). Therefore, it can be claimed that BELBIC have enough robustness against noises and model uncertainties. In other word, BELBIC with this structure based on PID as sensory input can save many advantages of a conventional controller like PID and operates just like a brain emotional based learning tuned adaptive PID controller. Furthermore, the same architecture can be used in other applications, where the PID controller is replaced by some other control systems. In this application, this was not necessary because the persistent modifications introduced by BELBIC were enough to overcome the limitations of the PID controller due to the linear nature of the latter. Finally, it is notable that the proposed BELBIC works based on the same PID
as its sensory input. Therefore, the comparison is perfectly just between the performance of a PID controller and an online tuned version of the same one.

6. Conclusion

In this paper, a brain emotional based learning intelligent controller (BELBIC) was applied to electrically heated micro-heat exchanger, which was a nonlinear plant. To this end, the dynamics of the system was identified using locally linear model tree (LoLiMoT) algorithm. Then, BELBIC was applied to the system to tackle the output temperature tracking problem. The closed-loop system performance using BELBIC was compared with that of PID controller. It was shown that BELBIC could settle faster with less distortion while its control effort was not higher than PID controller’s. Also, selection of PID signal as sensory input of BELBIC besides making tuning easy could bring about some advantages such as robustness against noises and model uncertainties. Our use of BELBIC in this application also encompasses considerable improvement compared to our previous utilizations of this model, especially in terms of the required control efforts for achieving desired performance levels.

References


