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INTELLIGENT ADAPTIVE CONTROL OF NON-LINEAR SYSTEMS BASED ON EMOTIONAL LEARNING APPROACH

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Drawing upon the past research on neuromorphic implementation of an emotionally intelligent control system, a developed version of the brain emotional learning based intelligent controller, BELBIC, is proposed in this paper. The modified system, which essentially realizes direct adaptive control scheme, deals very well for SISO plants, and does not need any pre-training. It is adaptive and robust with respect to changes in the environment since it learns to produce appropriate control actions on-line. An additional advantage of BELBIC is its simplicity as well as low computational load. The performance of the system is demonstrated via application on previously studied benchmarks involving optimization and adaptive control in nonlinear systems with MLP-backpropagation (BP) nets.

Keywords: Intelligent systems; emotional decision making; non-linear control; neural networks; direct adaptive control.

1. Introduction

The design of nonlinear control systems has been an active research area in recent years. Model free approaches have gained prominence because of the difficulty of finding accurate mathematical models for the systems. Intelligent control techniques that manipulate and implement heuristic knowledge[1] as well as various artificial intelligent algorithms and machine learning techniques are of the most popular approaches. Among these control techniques, there are control algorithms based on artificial neural networks,[2] fuzzy control,[3] and reinforcement learning control.[4]

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In Fuzzy system approach, control laws are being developed based on some prior knowledge or through learning and automatic rule induction schemes about the plant. In addition, an appropriate Fuzzy logic controller can overcome the environmental variation during operation process.[5-7] Direct and indirect adaptive fuzzy control (DAFC and IAFC) as well as fuzzy model predictive control (FMPC) scheme is applied for solving different control problems.[8] The ability of fuzzy systems in modeling of complex non-linear processes made them favorable for data-driven modeling and non-linear control.

With the aim of applying IAFC or FMPC, a model of the process must be available which can predict the process variables. For complex and non-linear or moderately known processes, deriving a mathematical model is often not practical, thereby impeding the application of IAFC or FMPC to many real world processes. Another drawback that retains the application of IAFC and, specially, FMPC to dynamically fast and non-linear systems is that a non-linear identification process (if the identification is performed on-line), in IAFC scheme, or a non-linear optimization problem, for FMPC scheme, must be solved for each sample time, which increases the computational load and complexity.

Similar to fuzzy systems, neural networks are recognized as universal approximators.[9] So, they are being used for different purposes like pattern recognition, identification and control of nonlinear systems as well as finding the solution of optimization problems.[10] Neural networks (NNs) have been employed for optimal predictive control (NMPC) and indirect adaptive neural-control approach (IANC, or model reference adaptive control) extensively in recent researches.[11-13] This is due to neural nets capacity in approximating the dynamics of the different systems including those with high non-linearities or dead-time. In order to estimate non-linear processes, NNs must be trained until the optimal values of the weight vectors are found (which is called pre-training process). For the purpose of identification, feedforward and dynamic NNs are of the most widely used structures. While training of feedforward NNs is less complicated than dynamic NNs, in return, dynamic NNs have smaller size and shorter training time. It should be noted that the abovementioned difficulties for IAFC and FMPC are valid for IANC and NMPC approaches too, although recently studies have been conducted to reduce the computational load. [8, 14, 15]

For human, as a biological intelligent system, emotion and cognition are two major aspects of his mental life.[16] Whenever we contact another person we are in contact with their emotional self; it is inevitable. When we touch someone's flesh, we enter their mind, and we are in contact with the wellsprings of their personality. As life itself is inseparable from the great geochemical processes of the earth, so are our most intimate feelings inseparable from the most basic biological processes of our cellular life. Our noblest thoughts, our most inspired actions, the uniqueness of our personalities and our perceptions all arise from the organic processes of our cellular life. Therefore, over the last couple of years there has been an increasing interest in development of computational models for emotional behavior of the mankind. The models have been integrated into different architectures for the development and control of several agents in a variety of embodiments and environments.[16, 17]

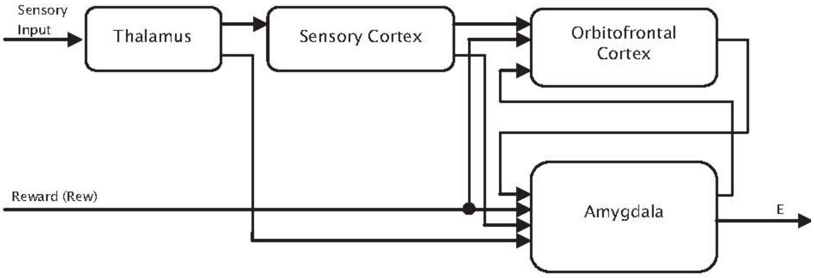

Fig. 1. Brain emotional learning architecture.

Recently, a computational model of emotional learning in mammalians' brain has been developed in Ref. 18. The introduced model has been successfully employed for decision making and control of simple linear systems[19], control of power system[20] and speed control of magnet synchronous motor.[21] In this paper, the control method developed in Ref. 19, which is based on the computational model of emotional learning in mammalians' brain introduced in Ref. 18, has been modified to be able to control SIMO non-linear systems. The proposed modified control algorithm is successfully used for adaptive control of nonlinear systems. The proposed method is a direct adaptive control scheme with low on-line computation load, while it does not require any off-line training process. One of its abilities is on-line optimization of a performance index through time. This feature is being studied in this paper to compare its optimization and adaptation ability with neural-control schemes presented in Ref. 11.

The rest of this paper is organized as follows. The computational model of the emotional leaning based intelligent controller (BELBIC) is presented in Section 2. In Section 3, BELBIC is employed for near-optimal control of magnet levitation system; and the obtained results are compared with a neural-predictive controller. Another application of BELBIC for direct adaptive control of a nonlinear system is described in Section 4. Finally, Section 5 presents the conclusions.

2. Brain Emotional Learning Based Intelligence Controller (BELBIC) Model

Generally speaking, direct and indirect adaptive control schemes represent two distinct methods for the design of adaptive controllers. To use intelligent systems to design adaptive controllers, we will easily end up with *Direct Adaptive Control* (DAC) and *Indirect Adaptive Control* (IAC) schemes. In the DAC the parameters of the controller are directly adjusted to minimize the tracking error, while in the IAC scheme, parameters of the plant under study are estimated on-line, then, parameters of the controller are adjusted based on the estimated plant parameters. The first scheme is used in this paper.

The emotional learning mechanism in the brain (see Fig. 1) is divided into two parts, very roughly corresponding to the Amygdala and the Orbitofrontal cortex, respectively. The Amygdala part receives inputs from the thalamus and from cortical areas, while the orbital part receives inputs from the cortical areas and the Amygdala only. The system also receives a reinforcing signal. There is one A node for every stimulus S (including one for the thalamic stimulus). There is also one O node for each of the stimuli (except for the thalamic node). There is one output node in common for all outputs of the model, called E. The E node simply sums the outputs from the A nodes, and then subtracts the inhibitory outputs from the O nodes. The result is the output from the model. The E' node sums the outputs from A except A_{th} and then subtracts from inhibitory outputs from the O nodes:

$$\begin{aligned} E &= \sum_i A_i - \sum_i O_i \qquad (\textit{including } A_{th}) \\ E' &= \sum_i A_i - \sum_i O_i \qquad (\textit{not including } A_{th}) \end{aligned} \tag{1}$$

The thalamic connection is calculated as the maximum over all stimuli S and becomes another input to the Amygdala part:

$$A_{th} = \max(S_i) \tag{2}$$

Unlike other inputs to the Amygdala the thalamic input is not projected into the Orbitofrontal part and cannot be inhabited. The emotional learning occurs mainly in Amygdala. The learning rule of Amygdala is given as follow:

$$\Delta V_i = \alpha_a \left(S_i \max\left(0, REW - \sum_i A_i \right) \right) \tag{3}$$

where α_a is learning rate in Amygdala, REW is the reinforcing signal and V_i is weight of the plastic connection in Amygdala.

Similarly, the learning rule in Orbitofrontal cortex is calculated as the difference between the E' and the reinforcing signal REW:

$$\Delta W_i = \alpha_o \left(S_i \left(E' - REW \right) \right) \tag{4}$$

where W_i is the weight of Orbitofrontal connection and α_o is Orbitofrontal learning rate. The Orbitofrontal learning is very similar to the Amygdala. The only difference is that the Orbitofrontal connection weight can both increase and decrease as needed to track the required inhibition.

The node values are then calculated as:

$$\begin{aligned} A_i &= S_i V_i \\ O_i &= S_i W_i \end{aligned} \tag{5}$$

Note that this system works at two levels: the Amygdala part learns to predict and react to a given reinforcing signal. The Orbitofrontal system tracks mismatches between the base system’s predictions and the actual received reinforcing signal and learns to inhibit the system output in proportion to the mismatch. In order to illustrate the emotional learning mechanism and connections/relations between signals in Amygdala and Orbitofrontal system a graphical description of adaptation/learning mechanism is presented in Fig. 2, which clearly shows connections between signals of Amygdala, Orbitofrontal, Sensory Cortex and Thalamus.

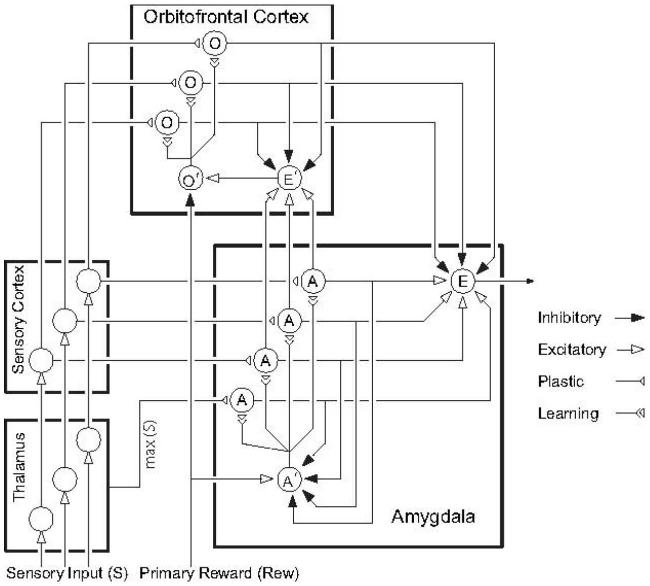

Fig. 2. A graphical depiction of the model of emotional learning mechanism. At the top is the Orbitofrontal part (here without an external context), at the bottom right is the Amygdaloid part and at left are the thalamic and sensory-cortical modules.[18]

The reinforcing signal REW, comes as a function of other signals which can be supposed as a cost function validation, i.e. award and punishment that are applied based on a previously defined cost function:

$$REW = J\left(u, e, y_p\right) \tag{6}$$

Likewise, sensory signals can be functions of plant's output y_p, controller's output (command or signal) u, tracking error e, and reference model output y_r, as follows:

$$S_i = f\left(u, e, y_p, y_r\right) \tag{7}$$

Architecture of BELBIC is shown in Fig. 3. As it is illustrated in Eq. (6) and Eq. (7), sensory input and reward signal can be arbitrary functions of the reference signal, the

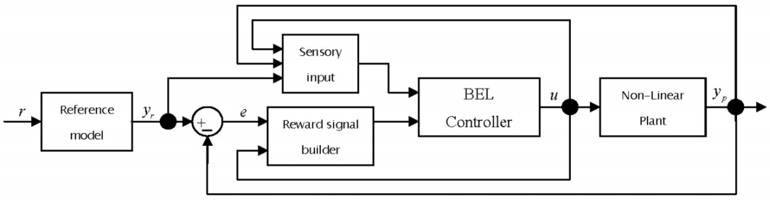

Fig. 3. The architecture of the brain emotional learning (BEL) based feedback-controller.

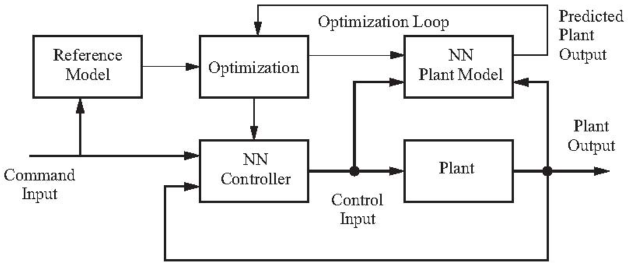

Fig. 4. Neural network predictive control scheme.[22]

controller's output (signal), the plant's output and the error signal. It is the skill of the designer to find a proper function for control. Note that the u signal, which is the controller's command, is the E signal generated by the model of emotional learning mechanism.

3. Near-Optimal Control

Neural networks are employed to develop optimal predictive controllers frequently in recent years. The objective of predictive control strategy using neural predictors is twofold: (1) to estimate the future output of the plant, and (2) to minimize a cost function based on the error between output of the processes and the reference trajectory (see Fig. 4). One of the recent studies on this subject is carried out by Hagan *et. al.*[11], where the following cost function for optimization is employed:

$$J = \sum_{j=N_1}^{N_2} \left(y_r(k+j) - y_m(k+j)\right)^2 + \rho \sum_{j=1}^{N_u} \left(u'(k+j-1) - u'(k+j-2)\right)^2 \tag{8}$$

where N_1, N_2 and N_u define the horizons over which the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, y_r is the reference response and y_m is the network model response. The ρ value determines the contribution that the sum of the squares of the control increments has on the performance index.

One disadvantage of the predictive optimal control strategies is its high volume on-line computational load. In addition, when the scheme is provided with a pre-trained NN as a model for the process, the sensitivity of the algorithm to changes in the characteristics of the plant increases, which is the main drawback of the predictive optimal control scheme. While the identification process is not perfect itself, dynamics of the non-linear system may change due to aging, wear and tear, etc. Furthermore, there are various noises and disturbances present in the system. Thus, the control algorithm drifts from optimal solution in time. To solve this problem on-line identification can be employed, which, in turn, increases the computational load and complexity of the algorithm.

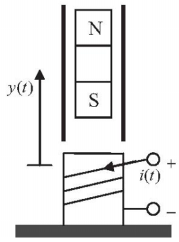

Fig. 5. Magnet levitation system.

To solve mentioned difficulties, it will be easier to use near-optimal schemes, which have lower computational complexity. One of proper algorithms for implementing this idea is BELBIC. It is illustrated in Eq. (6) that if the components and weights of the reward signal are being selected adeptly, BELBIC will be able to find a near-optimal solution.

3.1. *Benchmark Application 1: Magnetic Levitation System*

In this example, abilities of BELBIC in control of a magnet levitation system are demonstrated, and the results are compared with a well-known neuro-predictive control method proposed in Ref. 11. In this problem, the objective is to control the position of a magnet above an electro magnet, where the magnet is considered so that it can only move in the vertical direction, as shown in Fig. 5.

The equation of motion of the magnet is:[11]

$$\frac{d^2}{dt^2}y(t) = -g + \frac{\alpha}{M}\frac{i^2(t)\operatorname{sgn}\left[i(t)\right]}{y(t)} - \frac{\beta}{M}\frac{d}{dt}y(t) \tag{9}$$

where $y(t)$ is the distance of the magnet above the electromagnet, $i(t)$ is the current flowing in the electromagnet, M is the mass of the magnet, and g is the gravitational constant. The parameter β is a viscous friction coefficient that is determined by the material in which the magnet moves, and α is a field strength constant that is determined by the number of turns of wire on the electromagnet and the strength of the magnet. For our simulations, the current is allowed to range from 0 to 4 amps. The parameter values are set to $\beta = 12$, $\alpha = 15$, $g = 9.8$ and $M = 3$.

The neuro-predictive controller consists of a neural network plant model and an optimization block as shown Fig. 4. The optimization block determines the value of u' that minimizes J, and then optimal value for u that is the input to the plant.

Training process of the neural identifier is being discussed with details in Ref. 11 where controller parameters are set to $N_2 = 3$, $N_u = 3$, $\rho = 0.01$, with sampling interval of 0.01 second.

As it was mentioned in the previous section, BELBIC needs sensory inputs and a reward signal for making proper decision. In this example, BELBIC has the reference model's output $\left(y_r\right)$ and the plant's output $\left(y_p\right)$ as sensory inputs:

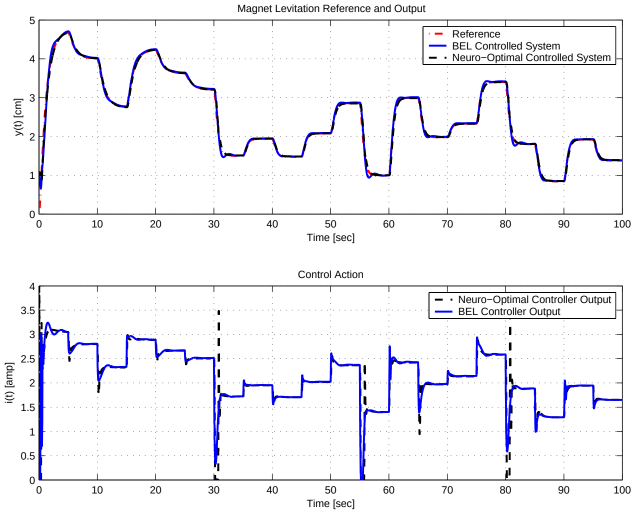

Fig. 6. Magnet levitation time response and control action for BELBIC and the neural-predictive controller.

$$S = \begin{bmatrix} 2\,y_p & 3\,y_r \end{bmatrix}^T \tag{10}$$

In addition, the reward signal is selected as:

$$REW = 5\,e + 15\int e + 2\frac{d}{dt}e + 0.1\int u \tag{11}$$

The term $\int u$ intends the BELBIC to minimize the energy consumption (control effort). The learning rate in Amygdala and Orbitofrontal is set equal to $\alpha_a = 1e-4$ and $\alpha_o = 7e-4$, respectively.

Simulation results for both controllers are presented in Fig. 6, where the reference signal and the system's output are given in the upper diagram, and the controller's command is given in the lower diagram. For better deduction on the performance of the two controllers, the time integral of squared errors and the time integral of the squared control efforts are given for both control approaches in Eq. (12):

$$\begin{gathered} \int u^2_{BELBIC}\,dt = 482.8, \quad \int u^2_{Neuro-predictive}\,dt = 481.8 \\ \int e^2_{BELBIC}\,dt = 0.433, \quad \int e^2_{Neuro-predictive}\,dt = 0.5389 \end{gathered} \tag{12}$$

It can be seen that energy consumption of BELBIC is almost the same as energy consumption of the neuro-predictive controller, whilst BELBIC has 19.56% lesser squared tracking error in 100 seconds. The oscillatory response of the neuro-predictive controller in some regions is due to poor training of neuro-identifier and/or neural-controller, which can be eliminated if more training data is provided. Note that BELBIC does not have this problem, since it learns the dynamics of the plant on-line through time. Also, please remember that the computational load of BELBIC is much lower than

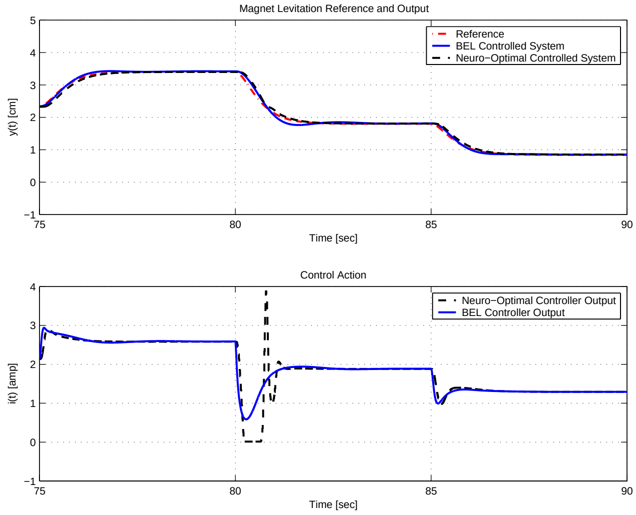

Fig. 7. Magnet levitation time response and the controller's command for BELBIC and the neural-predictive controller for $75 < t < 90$.

NMPC. Fig. 7 presents the time response of the system as well as the control effort for 75 to 90 seconds.

4. Adaptive Control

The neural model reference adaptive control (NMRAC) is a well-known indirect control scheme, while BELBIC is a direct adaptive control scheme. A NMRAC method that is presented in Ref. 11 is supplied with a NN to model (identify) the plant (called 'the neural network plant model'), where the neural-identifier is trained off-line. In the next benchmark application, it is desired to demonstrate the usefulness of BELBIC, and its leaning and adaptation ability.

4.1. *Benchmark Application 2: Robot Arm Control*

The performance of the NMRAC method, which is introduced in Ref. 11, and BELBIC for the control of a simple, single-link, robot arm, shown in Fig. 8, is studied in this section.

The equation of motion for the robot arm is:[11]

$$\frac{d^2\phi}{dt^2} = -10\sin\phi - c_0\frac{d\phi}{dt} + u$$
$$c_0 = \begin{cases} 2 & t < 1000 \quad \text{sec} \\ 5 & t \geq 1000 \quad \text{sec} \end{cases} \tag{13}$$

where ϕ is the angle of the arm, and u is a torque supplied by the DC motor.

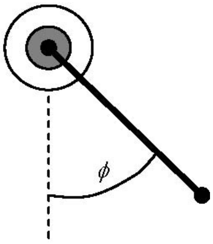

Fig. 8. Single-link robot arm.

For training the neural-controller, the system is sampled at intervals of 0.05 seconds. To identify the system, input pulses with intervals between 0.1 and 2 seconds, and amplitudes between -15 and +15 N-m for $c_0 = 2$ is used. The neural network plant model uses two delayed values of torque ($m = 2$) and two delayed values of the arm position ($n = 2$) as the input to the network; furthermore, 10 neurons are used in the hidden layer (a 5-10-1 network).

The objective of the control system is to have the arm to track the reference model:

$$\frac{d^2 y_r}{dt^2} = -k_0\, y_r - 6\frac{dy_r}{dt} + 9r \qquad k_0 = \begin{cases} 5 & t < 500 \quad \text{sec} \\ 9 & t \geq 500 \quad \text{sec} \end{cases} \tag{14}$$

where y_r is the output of the reference model, and r is the input reference signal.

The neural-controller has five inputs and 13 neurons in its hidden layer (a 5-13-1 network). The inputs to the controller consist of two delayed reference inputs, two delayed plant outputs, and one delayed controller output. The controller is trained using a BFGS quasi-Newton algorithm, with dynamic backpropagation used to calculate the gradients.[11]

For BELBIC, the vector of sensory inputs is selected as:

$$S = \left[0.1u \quad y_p \quad 3\, y_r \right]^T \tag{15}$$

while the reward signal is chosen to be:

$$REW = 10\, e + 8\int e + 4\frac{d}{dt}e \tag{16}$$

The learning rate in Amygdala and Orbitofrontal is set equal to $\alpha_a = 1e-2$ and $\alpha_o = 7e-2$, respectively. The upper graph in Fig.s 9 to 12 shows the reference signal and the arm positions using BELBIC and the NMRAC for 1500 seconds, while the lower diagram shows the commanded control actions for both controllers.

As it was mentioned earlier, neural-controller is trained off-line, while BELBIC learns the dynamics through real-time simulation. This is the reason for poor tracking ability of BELBIC in the beginning of the simulation, while the command of the neural-controller (shown in the lower diagram) is smoother than BELBIC. As the time passes,

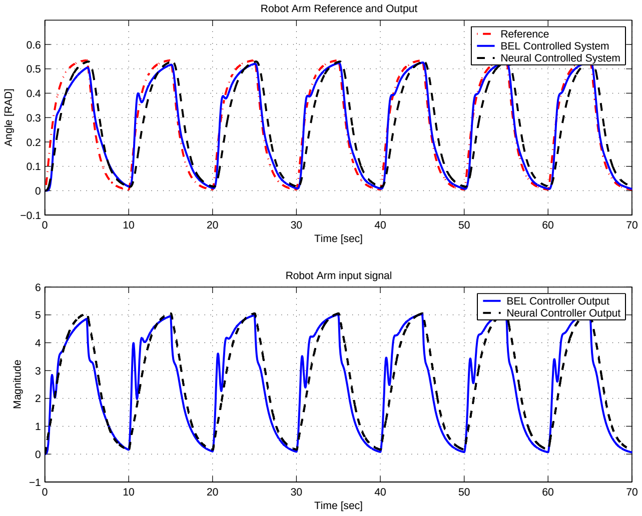

Fig. 9. Robot arm time response and control action for BELBIC and the neural-model reference controller for $0 < t < 70$.

BELBIC learns the dynamics of the plant. This fact is shown in Fig.s 9 and 10, where BELBIC has almost no tracking error or jumps in the control command after 400 seconds.

After 500 seconds, the reference command is changed as given in Eq. (14), but BELBIC adapts with the alteration in the reference signal, as shown in Fig. 10. Through time, BELBIC learns how to respond to the modified reference command. As shown in Fig. 11, after 900 seconds, BELBIC tracks the reference signal with very low error in comparison with the neural-controller.

After 1000 seconds, the dynamics of the system is altered according to Eq. (13), which causes a change in the control signal generated by BELBIC and the neural-controller. As illustrated in Fig. 11, BELBIC shows good robustness to the change in the dynamics of the system, where it has an acceptable overshoot and good tracking ability (compared with the neural-controller, which has very poor tracking ability). Time responses of the controlled systems as well as controllers' command at the end of the simulation are depicted in Fig. 12. It is clear that BELBIC is tracking the reference signal with a low tracking error and a smooth control command.

In Fig. 13, BELBIC parameters are shown with respect to time. Obviously, the weights of the Amygdale, A_i, reach to a constant value, and do not reduce (upper diagram), while the weights of the Orbitofrontal part, O_i, change very fast (lower diagram) to compensate mismatches between the base systems predictions and the actual received reinforce signal, which means that it learns to inhibit the system's output in proportion to the mismatch.

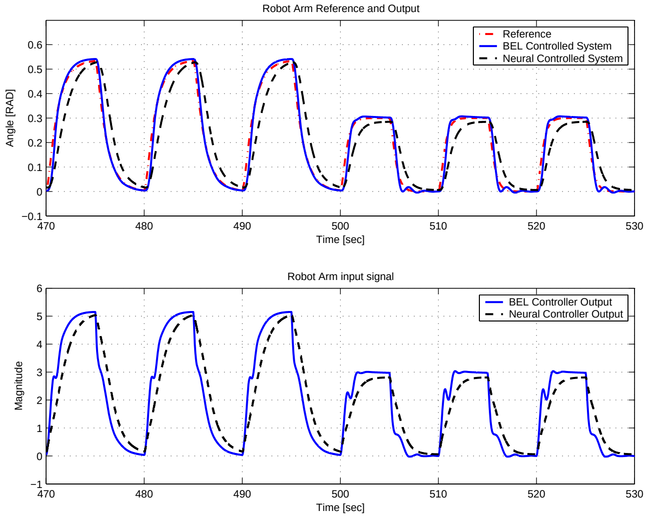

Fig. 10. Robot arm time response and control action for BELBIC and the neural-model reference controller for $470 < t < 530$.

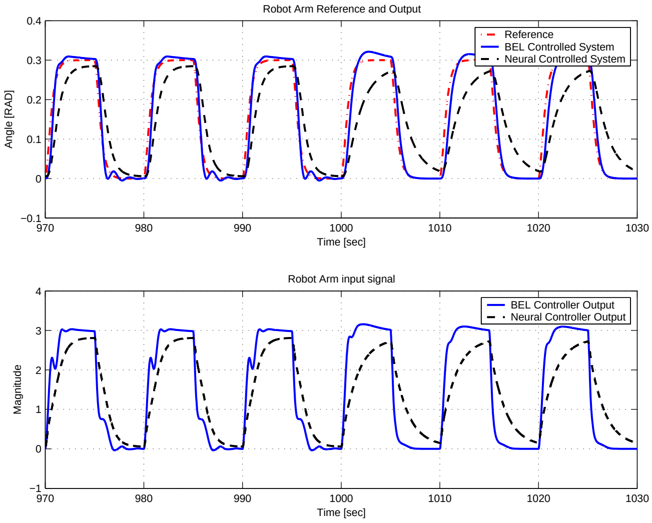

Fig. 11. Robot arm time response and control action for BELBIC and the neural-model reference controller for $970 < t < 1030$.

The performance of the two controllers is compared using two performance indices, which are the time integral of the squared error and the time integral of the squared control effort, given as follows:

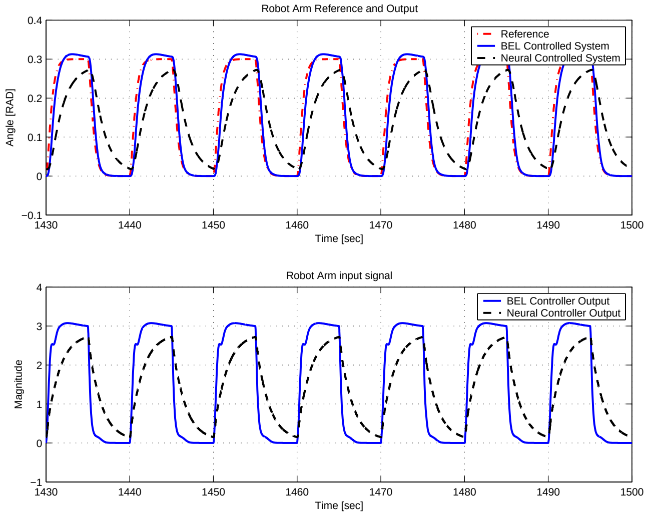

Fig. 12. Robot arm time response and control action for BELBIC and the neural-model reference controller for $1430 < t < 1500$.

$$\int_{t=0}^{t=1500} u_{BELBIC}^2 dt = 9.3812\text{e}3, \quad \int_{t=0}^{t=1500} u_{Neuro-controller}^2 dt = 8.0561\text{e}3$$
$$\int_{t=0}^{t=1500} e_{BELBIC}^2 dt = 1.1908, \quad \int_{t=0}^{t=1500} e_{Neuro-controller}^2 dt = 10.4467 \tag{17}$$

It can be concluded from Eq. (17) that the squared control effort of BELBIC is about 14.13% higher than NMRAC, while its squared tracking error is almost 88.6% lower.

5. Conclusions

In this paper, Brain Emotional Learning Intelligent Controller (BELBIC) for the control of two benchmark nonlinear plants is applied, and the results are compared with the performance of two well-known neural-control techniques, which are neural-predictive and neural-model-reference adaptive control, to demonstrate the merits of BELBIC. It is revealed that the proposed method has lower computational load and complexity and shows very good robustness and adaptability in facing with unknown ever-changing non-linear plants due to its learning ability. It is also shown that BELBIC can serve like an optimal controller. Generally, there are two advantages in using BELBIC. The first advantage is the possibility of using bio-psychological inspiration for developing efficient or suitable control routines. Frequently, it is very hard to argue that the inspiration would be absolutely necessary in order to develop the needed control schema and that no other inspiration or motivation can do the same. The most that can definitely be claimed is that a very useful interpretation is there to guide us in developing a control routine which

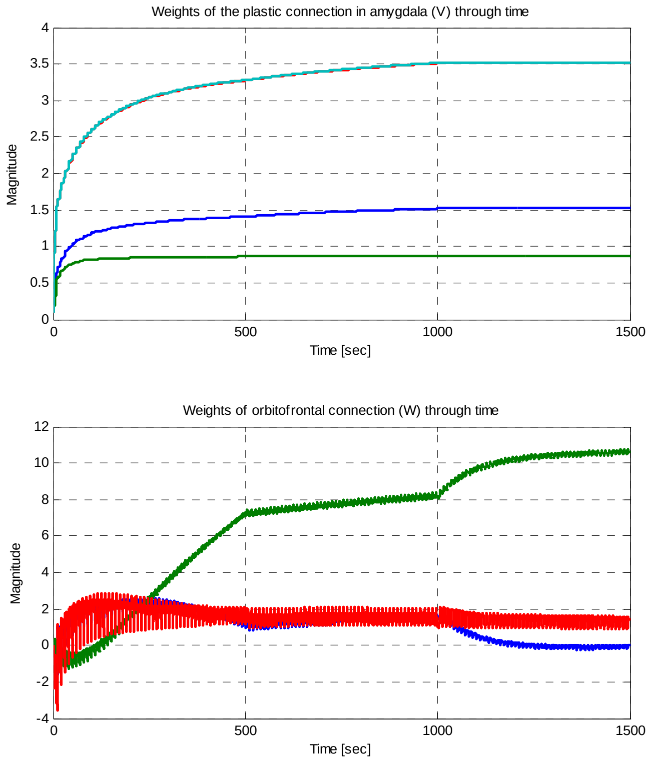

Fig. 13. Weights of BELBIC through time, for robot arm example.

otherwise would be more difficult, if not impossible, to develop. The second advantage, on a more practical and comparative level, is that the freedom to choose any reinforcing signal provides us with a much wider range of control possibilities. For example, one may be able to develop a control routine for tracking a set point via techniques like backpropagation through plant or pseudo-inverse plant construction that in many applications could be practically similar to the controller developed by emotional inspiration, but when other concerns like the magnitude of the control effort or its spent energy becomes also important then the second advantage of the proposed approach (and generally approaches based on ad-hoc rewarding) becomes apparent, since they can incorporate those new concerns without undue increase of the system complexity. A reward including the *integral of 'u'* term is selected in this study to show this advantage. Our use of BELBIC in this application also encompasses considerable improvement compared to our previous utilization of this model in Ref. 19, especially in terms of the required control efforts for achieving desired performance levels.

The use of BELBIC in control-theoretic decision problems requires combination of control engineering insights (in choosing the proper sensory input(s) and the reinforcement), bio-psychological inspiration, as well as experience in tuning of parameters. So, the art of the designer is appropriately choosing the system's emotional condition and tuning the learning rates of the system itself, to obtain the desired goal. This constitutes both the advantage (the adaptation of the control routine is accomplished implicitly through BELBIC) and the drawback (one still needs control engineering insights) of the proposed approach.

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