Emotional Learning based Intelligent Robust Adaptive Controller for Stable Uncertain Nonlinear Systems

Ali Reza Mehrabian, and Caro Lucas

Abstract—In this paper a new control strategy based on Brain Emotional Learning (BEL) model has been introduced. A modified BEL model has been proposed to increase the degree of freedom, controlling capability, reliability and robustness, which can be implemented in real engineering systems.

The performance of the proposed BEL controller has been illustrated by applying it on different nonlinear uncertain systems, showing very good adaptability and robustness, while maintaining stability.

Keywords—Learning control systems, emotional decision making, nonlinear systems, adaptive control.

I. INTRODUCTION

BIOLOGICALY motivated intelligent controllers have been widely used for controlling uncertain dynamical systems in recent years [1]-[5]. Fuzzy logic and neural networks are among the most popular tools for control applications in complex nonlinear settings.

In Fuzzy system approach, control laws are being designed based on some prior knowledge or through learning and automatic rule induction schemes. In addition, an appropriate Fuzzy logic controller can overcome the environmental variation during operation process [2], [5]-[7].

Neuro-controllers have also been widely used in recent years. Motivated by the fact that human control actions are regulated by the brain, artificial neural networks have been designed as (over)simplified models of human neural structures. The ability to act as universal approximator is a significant characteristics of these nets which has made them useful for modeling nonlinear systems; this is of primary importance in the synthesis of nonlinear controllers. A neuro-controller in general, performs a specific form of adaptive control, with the controller in the form of a multilayer neural

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network and the adaptable parameters being defined as the adjustable weights. Generally, the massively parallel distributed processing character of the neural nets makes them ideal for VLSI and optical implementations in cases where very rapid response is required [8].

To get the advantage of both the types of Fuzzy and neural controllers it is interesting to use the combined scheme, which leads us to Fuzzy-Neural controllers [2], [8]. Neuro-Fuzzy control, genetically optimized fuzzy control, back-propagation through plant and reinforcement learning have shown successful implementation [16]-[19].

For human, as a biological intelligence system emotion and cognition are two major aspects of his mental life [9], [10]. Thus, over the last couple of years there has been an increasing interest in the development of computational models for emotion. The models have been integrated into different architectures for the development and control of several agents in a variety of embodiments and environments [10]-[15].

Based on these studies many efforts has been made to develop models for decision making and find a control strategy for effective control of dynamic systems. Methodologies called emotional control or merely an analog version of reinforcement learning with critic (evaluative control) are increasingly being utilized by control engineers, robotic designers and decision support systems developers and yielding excellent results [20]-[23]. Although, for a long time, emotion was considered as a negative factor hindering the rational decision making process, the important role of emotions in human cognitive activities is progressively being documented by psychologists [24], [25]. It has now become clear that far from being a negative trait in biology, emotions are important positive forces crucial for intelligent behavior in natural as well as artificial systems [20], [26].

Interesting model of brain emotional learning has been presented in [11] 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. Successful implementation of this model for decision making and controlling of simple linear systems in [27] as well as more complex nonlinear systems in [28], [29], [30], made us to further study of this scheme and develop a more reliable and

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effective algorithm which has more similarity to its parent model in [11]. Proposed modified model has better adaptability and robustness, since is able to receive more than one sensory input. In this study, ability of this modified version of emotional learning based intelligent controller (BELBIC) in facing nonlinear uncertain systems has been investigated.

In the remainder of this paper emotional learning methodology is introduced in details in Section II. In Section III control problems and obtained results have been presented. And finally, in Section IV, conclusions have been made.

II. BRAIN EMOTIONAL LEANING 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 emotional computations 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 and the then controller parameters are adjusted based on these estimates. The first scheme is used in this paper.
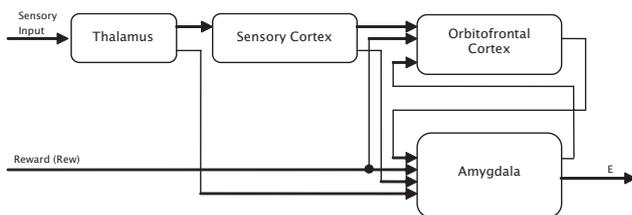
Fig. 1 Scheme of BEL structure

BELBIC is divided into two parts (see Fig. 1), very roughly corresponding to the Amygdala and the Orbitofrontal cortex, respectively. The Amygdaloid part receives inputs from the thalamus and from cortical areas, while the orbital part receives inputs from the cortical areas and the amygdale only. The system also receives reinforcing (REW) 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.

$$E = \sum_i A_i - \sum_i O_i \qquad (including \ A_{th})$$
$$E' = \sum_i A_i - \sum_i O_i \qquad (not \ including \ A_{th}) \qquad (1)$$

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

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

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:

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

where α_a is learning rate in Amygdala, REW is 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

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

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

The nodes values are then calculated as

$$A_i = S_i V_i$$
$$O_i = S_i W_i \qquad (5)$$

Note that this system works at two levels: the Amygdaloid part learns to predict and react to a given reinforcer. The Orbitofrontal system tracks mismatches between the base systems predictions and the actual received reinforcer and learns to inhibit the system output in proportion to the mismatch.

The reinforcing signal REW comes as a function of others signal which can be supposed as a cost function validation i.e. award and punishment are applied based pervious defined cost function.

$$REW = J \left(S_i, e, y_p \right) \qquad (6)$$

where y_p is plant output, and e is error signal.

Similarly the sensory inputs must be a function of plant outputs and controller outputs as follow

$$S_i = f \left(u, e, y_p, y_r \right) \qquad (7)$$

Architecture of BEL controller is shown in Fig. 2. As it is illustrated in (6, 7), sensory input and reward signal can be arbitrary function of reference output, y_r , controller output, u , error (e) signal, and the plant output y_p . It is all up to the designer to find a proper function for control.
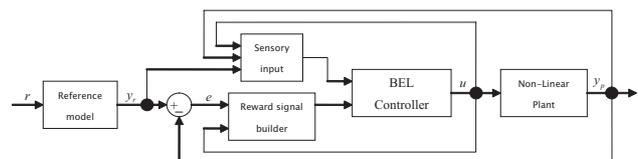
Fig. 2 BEL controller architecture

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III. SIMULATION STUDIES

A. Example 1: The Van Der Pol Oscillator

A question of particular interest in nonlinear systems is whether they exhibit closed trajectories; as such trajectories imply periodic motion. Closed trajectories can occur also in nonconservative nonlinear systems, provided the net energy change at the completion of a full cycle is zero. This implies that the systems dissipates energy over some parts of the cycle and acquires energy over the balance of the cycle.

Closed trajectories exhibiting this type of characteristics are referred to as limit cycles. A classical example of a system known to possess a limit cycle is the van der Pol oscillator, described by differential equation

$$\ddot{x} + \mu\left(x^2 - 1\right)\dot{x} + x = 0, \quad \mu > 0 \tag{8}$$

It can be regarded as an oscillator with variable damping, as the term $\mu\left(x^2 - 1\right)$ represents an amplitude-dependent damping coefficient; such a system is both non conservative and nonlinear [31].

It must be pointed out that the van der Pol oscillator is a very good example of a nonlinear system for which linearization about a trivial equilibrium is totally inadequate. It must be also noted that the shape of the limit cycle depends on the parameter alone, so that the initial condition have no effect on the amplitude of motion after the system has reached the limit cycle.

Now consider the van der Pol forced oscillator described as

$$\ddot{x} = \left(\mu \times d\right)\left(1 - x^2\right)\dot{x} - x + F, \quad \mu > 0 \tag{9}$$

where F is the control input, and d is the external disturbance and assumed as a random number between 0.5 and 1.5, with sampling time of 5 sec.

The objective of the control system is to make the system to track the reference model

$$\frac{d^2 y_r}{dt^2} = -k_0 \ y_r - 6\frac{dy_r}{dt} + 9r$$
$$k_0 = \begin{cases} 5 & t < 50 \quad \text{sec} \\ 9 & t \geq 50 \quad \text{sec} \end{cases} \tag{10}$$

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

System initial condition was set equal to $x_0 = 2$ and $\dot{x}_0 = 0$. For BEL controller, sensory input was selected as

$$S = \begin{bmatrix} 2 \ y_p & 3 \ y_r \end{bmatrix}^T \tag{11}$$

and the reward signal was chosen to be

$$REW = 650 \ e + 50\int e \tag{12}$$

The learning rate in Amygdala and Orbitofrontal was set equal to $\alpha_a = 1e - 6$ and $\alpha_o = 2e - 3$, respectively.

The upper diagram of Fig. 3 shows the reference signal and the system response using the BEL controller. The lower diagram gives the control action commanded by BEL controller.
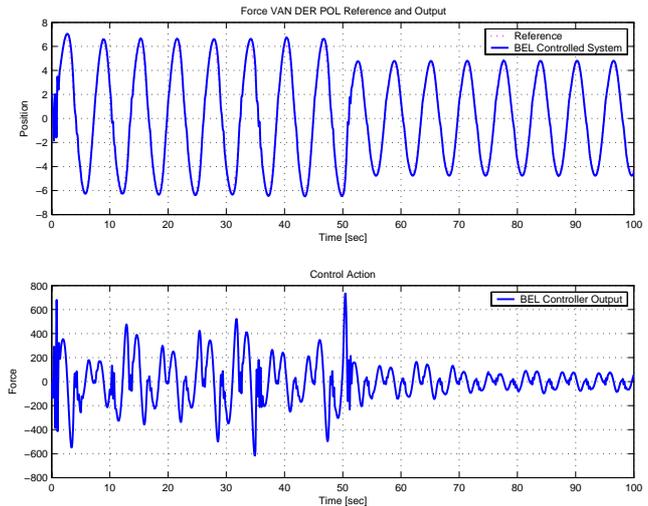
Fig. 3 Van der Pol oscillator response and control action for the BEL Controller in example A
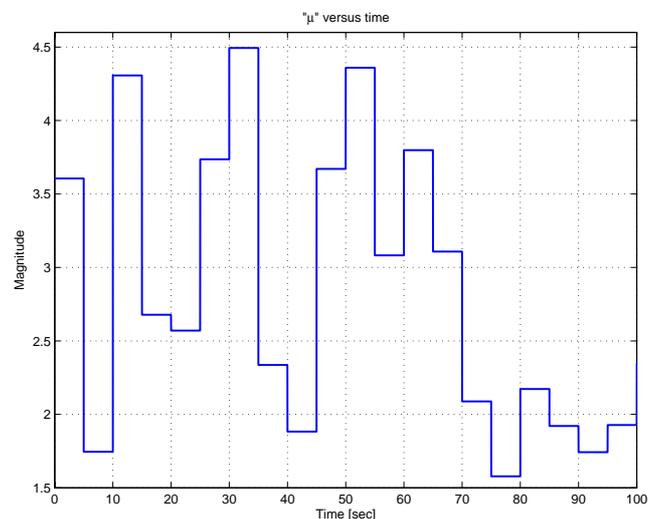
Fig. 4 Damping coefficient $\left(\mu \times d\right)$, versus time

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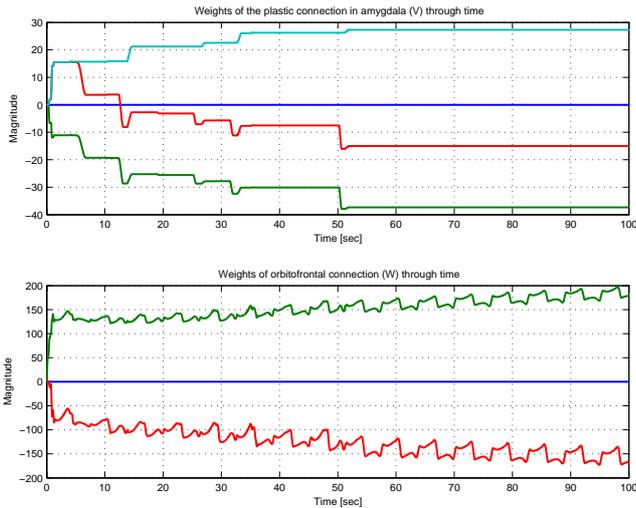
Fig. 5 Weights of the BEL controller through time,
for van der Pol oscillator example

From Fig. 3, it can be seen that the BEL controller has converged very fast and has controlled the nonlinear system very well. Fig. 4, shows coefficient $(\mu \times d)$ versus time and in Fig. 5 weights of the BEL controller is given. Obviously Orbitofrontal weights are changing very fast, to compensate mismatches between the base systems predictions and the actual received reinforcer and learns to inhibit the system output in proportion to the mismatch.

B. Example 2: Duffing forced oscillator

A classical example of a nonlinear conservative system known to possess periodic solutions consists of a mass m attached to a stiffing, or hardening spring. We consider a spring with a restoring force in the form of the sum of two terms, one proportional to the elongation and the other varying as the third power of the elongation. We are concerned with the case in which the cubic term is appreciably smaller than the linear term, so that is nearly linear. In the case in which the system described is viscously damped, the equation of motion has the form

$$\ddot{x} + \omega^2 x = \varepsilon \left[-2\,\varsigma\,\omega\,\dot{x} - \omega^2 \left(\alpha\,x + \beta\,x^3 \right) + F \right], \quad \varepsilon << 1$$

where ς is damping ratio, ω is natural frequency of the harmonic system when $\varepsilon = 0$, and α, β are coefficients of the dynamic system. The control signal was shown as F. Equation (13) is the well-known viscously damped Duffing's equation.

It was shown in that the period of oscillation of nonlinear conservative systems, like (13), depends on the initial conditions, as well as on the system parameters, in contrast with the period of linear conservative systems, which is not effected by the initial conditions [31].

The object of the controller is to generate command such that the system track the reference signal given in (10). To do so, sensory inputs to the BEL controller was set to

$$S = \begin{bmatrix} 2\,y_p & 5\,y_r \end{bmatrix}^T \tag{13}$$

and the reward signal was selected as

$$REW = \left(100\,e + 20\,\frac{d}{dt}\,e \right) \tag{14}$$

Also, the learning rate in Amygdala and Orbitofrontal was set equal to $\alpha_a = 1e-10$ and $\alpha_o = 3e-2$, respectively.

Note that the system with numerical data for simulation is taken from [2]

$$\ddot{x} = -0.1\dot{x} - x^3 + 12\cos(t) + F + d_d \tag{15}$$

where F is the control input the coefficient d_d is the external disturbance and is assumed to be a square wave with the amplitude ± 1 and the period 2π.

Response of BEL controlled system, with control command, $F(t)$, is shown in Fig. 6. It can be seen that the BEL controller is able to control system very gently.
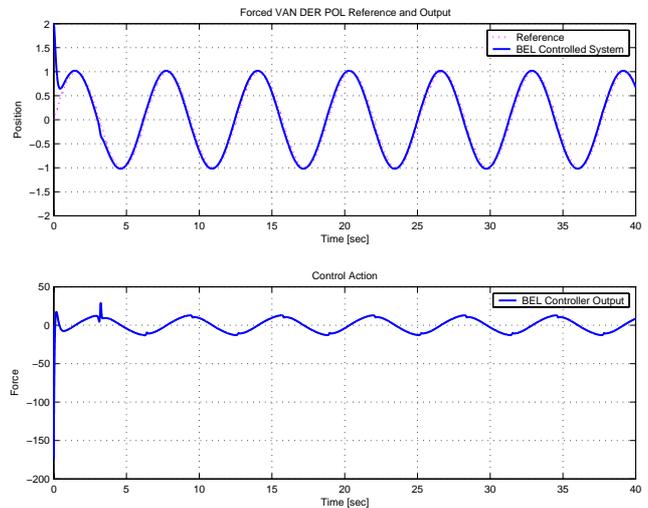
Fig. 6 Duffing's oscillator response and control action for the
BEL Controller in example B

Weights of the BEL controller are given in Fig. 7 with respect of time.

Fig. 7 Weights of the BEL controller through time,
for example B

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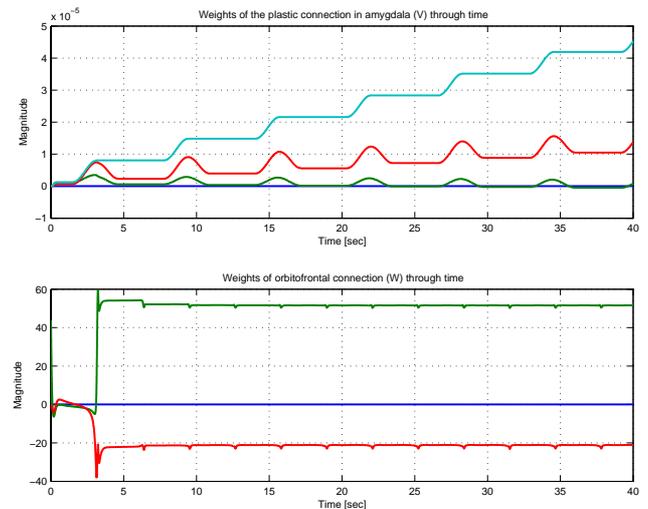
It can be seen in Fig. 7 that weights of the controller reach to steady-state condition very soon and the effect of disturbance is being eliminated through time due learning ability of BEL controller.

The proposed controller has been capable of achieving both better output performance and more reasonable control efforts than the one suggested in [2]. Furthermore, it has better adaptability, requires less initial tuning, and has lower computational complexity.

C. Example 3: Automatic self balancing scale [32]

An automatic self balancing scale in which the weighting operation is controlled by an electrical motor is shown in Fig. 8.
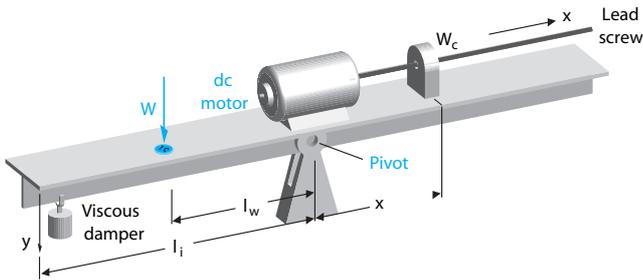
Fig. 8 An automatic self balancing scale

The balance is shown in the equilibrium condition, and x is the travel of counter weight W_c from an unloaded equilibrium condition. The constant weight W is applied $30\,cm$ from the pivot, and the length of the beam to the viscous damper, l_i, is $1\,m$. Inertia of the beam is equal to $0.05\,kg-m^2$ was chosen. We will utilize a lead screw of $20\,turns/cm$ and the viscous damper with damping constant of $f = 10\sqrt{3}\,kg/m/s$ was selected. Finally, a counterweight W_C is chosen so that the expected range of desired equilibrium angles can be obtained. Therefore, in summery, the parameters of the system are selected as listed in Table I.

The transfer function of the dc motor is

$$\frac{x(s)}{V_m(s)} = K_s \frac{10}{s} \qquad (16)$$

It is desired the controller generate a proper voltage to make the system track the commanded equilibrium angle.

Governing nonlinear equation of motion of the self balancing system shown above is

$$I\,\ddot{\theta} = \cos\theta\left(W\,l_w - W_c\,x - f\,l_i^2\,\dot{\theta}\cos\theta\right) \qquad (17)$$

Since the counter weight has rotation around pivot, thus W_C is obtained as

$$W_C = m\left(x\,\ddot{\theta} + 2\,\dot{x}\,\dot{\theta} + g\,\cos\theta\right) \qquad (18)$$

Full equation of motion of the system is obtained by solving

Symbol	Quantity	Magnitude
I	moment of Inertia	$0.05\,kg-m^2$
l_w	constant weight position	$30\,cm$
l_i	viscous damper distance	$1\,m$
f	damping constant	$10\sqrt{3}\,kg/m/s$
m	mass of balancing weight	$1\,kg$
W	constant exerted weight	$1.5\,kg$
K_s	lead screw gain	$\dfrac{1}{4000\pi}\,m/rad$

equation (17) and (18) simultaneously.

For BEL controller the sensory input was selected

$$S = \begin{bmatrix} 10\,x & 1000\,e & 500\,\theta_c \end{bmatrix}^T \qquad (19)$$

where the error signal is

$$e = \theta - \theta_c$$

Also, the reward signal is

$$REW = 1000 \times \left(4\,e + 2\int e + 5\frac{d}{dt}e\right) \qquad (20)$$

The learning rate in Amygdala and Orbitofrontal was set equal to $\alpha_a = 1e-5$ and $\alpha_o = 7e-6$, respectively.

The response of BEL controlled self balancing system is shown in upper diagram of Fig. 10 and the BEL command is given in lower diagram, while in middle diagram of Fig. 9, position of the counter weight is shown.
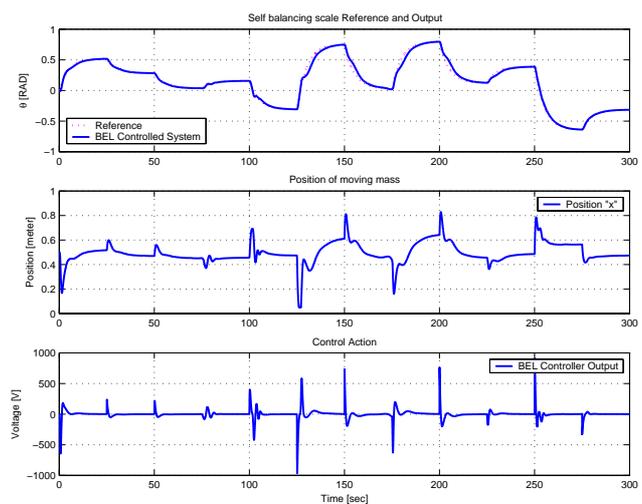
Figure 9 Auto-balancing scale response and control action for the BEL Controller in example C.

In Figure 10, weights of the BEL controller are given.
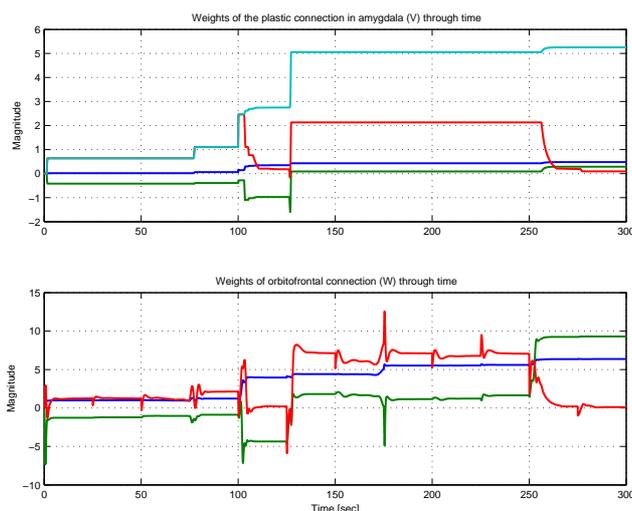
Figure 10 Weights of the BEL controller through time,
for example C

IV. CONCLUSIONS

In this paper, we applied a biologically inspired intelligent controller, BELBIC, for adaptive control of nonlinear uncertain systems. The results have shown that the proposed BELBIC have very satisfactory control performance. Especially, it is very powerful in stabilizing and has very fast convergence to appropriate control signal. This is due to learning ability that BELBIC have.

The proposed algorithm must be provided with some sensory signals and an emotional cue signal, to be able to generate the proper action regarding the emotional situation of the system. So the art of the designer is to cope with appropriately choosing the system's emotional condition and tune the learning rates of the system itself, to obtain the desired goal.

REFERENCES

[1] K. S. Narendra, K. Parthasarathy, "Identification and Control of Dynamical Systems Using Neural Networks," *IEEE Transactions on Neural Networks*, vol. 1, no. 1, March 1990.

[2] Y. G. Leu, W. Y. Wang, T. T. Lee, "Robust adaptive Fuzzy-Neural Controllers for Uncertain Nonlinear Systems*," IEEE Transactions on Robotics and Automation*, vol. 15, no. 5, October 1999.

[3] Hofmeyr, S., S. Forrest, "Architecture for an Artificial Immune System," *Evolutionary Computation Journal*, vol. 8, no. 4, pp. 443 – 473, winter 2000.

[4] J. Chen, E. Antipov, B. Lemieux, W. Cedeno, D. H. Wood, "DNA Computing Implementing Genetic Algorithms," *Preliminary Proceedings DIMACS Workshop on Evolution As Computation*, pp. 39-49, DIMACS, Piscataway NJ, January 1999.

[5] D. G. Schwartz, G. J. Klir, H. W. Lewis, Y. Ezawa, "Application of Fuzzy Sets and Approximate Reasoning," *IEEE Transactions on System*, vol. 82, no. 4, April 1994.

[6] C. Locus, A. Abbaspour, A. Gholipour, B. N. Araabi, M. Fatourechi, "Enhancing the Performance of Neuro-Fuzzy Predictors by Emotional Leaning Algorithm," *International Journal of Informatica*, vol. 27, no. 2, pp. 165-174, June 2003.

[7] B. N. Araabi, N. Kehtarnavaz, C. Locus, "Restrictions Imposed by Fuzzy Extension Relations and Functions," *International Journal of Fuzzy and Intelligent Systems*, vol. 11, no. 2, pp.9-22, November 2001.

[8] P. K. Dash, S. K. Panda, T. H. Lee, J. X. Xu, A. Routray, "Fuzzy and Neural Controllers for Dynamic Systems: An Overview," *IEEE Proceedings of International Conference on Power Electronics and Drive Systems*, vol. 2, pp. 810-816, May 1997.

[9] P. Ekman, & R. J. Davidson, *The Nature of Emotion: Fundamental Questions*, Oxford University Press: New York, 1994.

[10] Jeremy R. Gray, Todd S. Braver, and Marcus E. Raichle, "Integration of emotion and cognition in the lateral prefrontal cortex," *PNAS*, vol. 99, no. 6, pp. 4115-4120, March 2002.

[11] J. Moren, C. Balkenius, "A Computational Model of Emotional Learning in The Amygdala," *From animals to animals 6: Proceedings of the 6th International conference on the simulation of adaptive behavior*, Cambridge, Mass., 2000. The MIT Press.

[12] Miha Černetič, "Investigating the role of appraisal processes in emotion: benefits from the pyramid approach to cognitive neuroscience," *multiconferenceproceedings*, Cognitiveneuroscience, Information society 2001, Ljubljana.

[13] Hiroshi Yamasaki, Kevin S. LaBar, and Gregory McCarthy, "Dissociable prefrontal brain systems for attention and emotion," *PNAS*, vol. 99, no. 17, pp. 11447–11451, August 2002.

[14] Hirohide Ushida, Yuji Hirayama, Hiroshi Nakajima, "Emotion Model for Life-like Agent and Its Evaluation,", American Association for Artificial Intelligence,1998 (www.aaai.org).

[15] Mario Beauregard, Johanne Levesque, Pierre Bourgouin1, "Neural Correlates of Conscious Self-Regulation of Emotion," *The Journal of Neuroscience*, 2001, Vol. 21 RC165, pp. 1-6.

[16] C. Lucas, S. A. Jazbi, M. Fatourechi, M. Farshad, "Cognitive Action Selection with Neurocontrollers," *Third Irano-Armenian Workshop on Neural Networks*, August 2000, Yerevan, Armenia.

[17] Voigt, M. H., "Fuzzy evolutionary algorithms," June 1992, Technical Report 92-038, *International Computer Science Institute (ICSI)*, 1947 Center Street, Suite 600, Berkeley, CA, 94704.

[18] Bergman, A., W. Burgard, A. Hemker, "Adjusting parameters of genetic algorithms by fuzzy control rules," *New Computer Techniques in Physics Research III*, World Scientific Press, 1994, pp. 235-240.

[19] Xu, X., H-G He, D. Hu, "Efficient Reinforcement Learning Using Recursive Least-Squares Methods," *Journal of Artificial Intelligence Research*, Vol. 16, 2002, pp. 259-292.

[20] K. Inoue, K. Kawabata, and H. Kobayashi, "On a Decision Making System with Emotion," *5th IEEE International Workshop on Robot and Human Communication*, 1996, pp. 461-465.

[21] J. S. Bay, "Behavior Learning in Large Homogeneous Populations of Robots," *IASTED International Conference on Artificial Intelligence and Soft Computing*, pp. 137-140, July 1997.

[22] K. Miyazaki, N. Araki, E. Mogi, T. Kobayashi, Y. Shigematsu, M. Ichikawa, G. Matsumoto, "Brain Learning Control Representation In Nucleus Accumbens," *1998 Second International Conference On Knowledge-Based Intelligent Electronic Systems*, pp. 21-23, April 1998, Australia.

[23] M. Fatourechi, C. Lucas, A. Khaki Sedigh, "Reducing Control Effort by means of Emotional Learning," *Proceedings of 9th Iranian Conference on Electrical Engineering (ICEE2001)*, pp. 41-1 to 41-8, May, 2001, Tehran, Iran.

[24] Neese, R,. "Emotional Disorders in Evolutionary Perspective," *British Journal of Medical Psychology* (1998), Vol. 71, pp. 397-415.

[25] Greene, J. D., R. B. Sommerville, L. E. Nystorm, J. M. Darley, J. D. Cohen, "An MRI Investigation of Emotional Engagement in Moral Judgment," *Science*, Vol. 293, 14 Sep. 2001, pp. 2105-2108.

[26] Toda, M., "The Urge Theory of Emotion and Cognition," *Emotion and urges, SCCS Technical Report*, No.93-1-01, 1993.

[27] C. Lucas, D. Shahmirzadi, N. Sheikholeslami, "Introducing BELBIC: Brain Emotional Learning Based Intelligent Controller," *International Journal of Intelligent Automation and Soft Computing*, Vol. 10, No.1, pp. 11-22, 2002.

[28] C. Lucas, R. Langari, and D. Shahmirzadi, "Stabilization of a Control System with Sensor Time Delays Using Brain Emotional Learning," Special Session on Emotional Learning and Decision Fusion in Satisficing Control and Information Processing, Minisymposium on Satisficing, Multiagent, and Cyberlearning Systems, 5th International Symposium on Intelligent Automation and Control, World Automation Congress, WAC 2004, Seville, Spain, June 28- July1, 2004.

[29] C. Lucas, F. Rashidi, and J. Abdi, "Transient Stability Improvement in Power Systems via Firing Angle Control of TSCS Using Context Based Emotional Controller," In M. Jamshidi, L. Foulloy, A. Elkamel, and J. S. Jamshidi (eds.), Intelligent Automations and Control- Trends, Principles,

World Academy of Science, Engineering and Technology
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and Applications. Albuquerque, NM, USA: TSI Press Series: Proceedings of WAC, 16, M. Jamshidi (series editor), 2004, pp. 37- 42.

[30] R. Mohammadi Milasi, C. Lucas, and B. N. Araabi, "Speed Control of an Interior Permanent Magnet Synchronous Motor Using BELBIC (Brain Emotional Learning Based Intelligent Controller)," In M. Jamshidi, L. Foulloy, A. Elkamel, and J. S. Jamshidi (eds.), Intelligent Automations and Control- Trends, Principles, and Applications. Albuquerque, NM, USA: TSI Press Series: Proceedings of WAC, 16, M. Jamshidi (series editor), 2004, pp. 280- 286.

[31] Leonard Meirovitch, *Fundamentals of Vibrations*, McGraw-Hill Book Co., 2001.

[32] Richard C. Dorf, Robert H. Bishop, *Modern Control Systems*, Addison-Wesley Pub., 1995.

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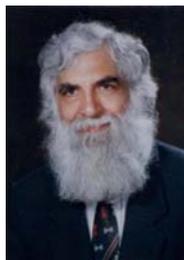
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