

DEVELOPMENT OF A BRAIN EMOTIONAL LEARNING BASED CONTROLLER FOR APPLICATION TO VIBRATION CONTROL OF A BUILDING STRUCTURE UNDER SEISMIC EXCITATION

M. Braz-César^{1,4}, J. Gonçalves^{1,2,3}, J. Coelho^{1,2,3} and R. Barros⁴

¹ Polytechnic Institute of Bragança, Portugal
{brazcesar, gonalves, jpcoelho}@ipb.pt

² INESC-TEC, Portugal

³ Research Center in Digitalization and Intelligent Robotics

⁴ CONSTRUCT R&D Unit, FEUP, Portugal
rcb@fe.up.pt

Abstract. *In this paper, a numerical simulation of a semi-active neuroemotional based control system for vibration reduction of a 3-story framed building structure under seismic excitation is presented. The Brain Emotional Learning Based Intelligent Controller (BELBIC) is used to design a closed-loop control system that determines the required control action (emotional response) based on the desired and actual system response (sensory input). In this case, the control signal is used to adjust in real time the damping force of a MagnetoRheological (MR) damper to reduce the system response. The results obtained from the numerical simulation validate the effectiveness of the brain emotional learning semi-active controller in improving the overall response of the structural system.*

Keywords: BEL Controller, Vibration Control, Structural Dynamics

1 Introduction

The Brain Emotional Learning Based Intelligent Controller (BELBIC) is a neuroemotional computational model that aims to trigger a system response based on artificial emotions. This controller is based on the limbic system of mammalian brain composed by a set of interconnected brain structures involving the amygdala, orbitofrontal cortex, sensory cortex and thalamus [1]. The emotional learning process modeled by the BELBIC algorithm has been successfully implemented on a wide-range of control engineering applications [2, 3, 4]. The BEL controller presents interesting features that can be exploited to design structural control systems for civil engineering applications. Thus, the presented semi-active control system was developed based on this bio-inspired controller.

In this paper, a numerical simulation of a semi-active neuroemotional based control system for vibration reduction of a 3-story framed building structure under seismic excitation is presented. Previously to this work, this controller was applied to control a single degree of freedom system, being the obtained results presented in [5]. The BELBIC is used to design a closed-loop control system that determines the required control action (emotional response) based on the desired and actual system response (sensory input). In this case, the control signal is used to adjust in real time the damping force of a MagnetoRheological (MR) damper to reduce the system response.

2 BELBIC Controller

The Brain Emotional Learning (BEL) controller is a novel bio-inspired control model based on the emotional learning mechanism of the brain limbic system which has been employed to develop feedback controllers for complex control problems [6, 7, 8].

Essentially the BEL controller comprises four main components, i.e., the amygdala (Am), the orbitofrontal cortex (OC), the sensory cortex (SC) and the thalamus (Th). The amygdala and the orbitofrontal cortex are used to process the emotional signal (SE) while the sensory cortex and the thalamus receive and processes sensory inputs (SI). The Simulink model of the BEL controller is shown in Figure 1.

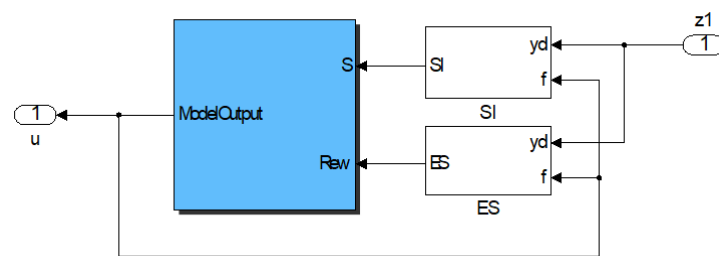


Figure 1: Simulink model of the BEL controller for the three DOFs system.

Sensory inputs (SI) are processed in the thalamus initiating the process of response to stimuli and passing those signals to the amygdala and the sensory cortex. Then, the sensory cortex operates by distributing the incoming signals properly between the amygdala and the orbitofrontal cortex. In this controller, the learning procedure is mainly processed in the orbitofrontal cortex and is based on the difference between an expected punishment or reward and the received punishment or reward (Rew). The perceived punishment/reward (ES) is processed in the brain using learning mechanisms while the received punishment/reward represents an external input.

If these signals are not identical, the orbitofrontal cortex inhibits and restrains the emotional response for further learning. Otherwise, the controller generates an output response [1, 7].

In this case the sensory input (SI) and the emotional signal (ES) can be related with the system response y_d (inter-story drifts in this case) and the BEL model output u , which are determined using the following equations:

$$SI = \omega_1 y_d + \omega_2 u \quad (1)$$

$$ES = \omega_3 y_d + \omega_4 \int u dt \quad (2)$$

where ω_i are weight factors that define the relative importance given to the drift response ($z_1=y_d$) and the output of the BEL controller ($f = u$). The sensory and emotional outputs are forwarded as the stimuli and the reward/punishment for the BEL controller, respectively. Finally, the BEL control block uses this information to construct a response (model output) that represents the control action.

The BEL algorithm can be also combined with a PID controller to improve the performance of the control system. The PID controller is integrated in the BEL controller as part of the emotional signal, i.e.,

$$ES = K_P y_d + K_I \int y_d dt + K_D \frac{d}{dt} y_d + \omega_4 \int u dt \quad (3)$$

where K_P , K_I , and K_D are weight factors of the PID controller that must be carefully selected to obtain the desired performance [8]. The learning system of both amygdala (AM) and orbitofrontal cortex (OC) are based on internal weight adjusting rules defined by

$$\frac{dG_{Am,i}}{dt} = \alpha SI_i \max(0, ES - \sum A_{m,i}) \quad (4)$$

$$\frac{dG_{OC,i}}{dt} = \beta SI_i \max(MO - ES) \quad (5)$$

where α is the learning rate of the amygdala, β is the learning rate of the orbitofrontal cortex, ES and MO are the emotional signal and the model output, respectively. These learning rates represent model parameters that must be adjusted in accordance with the input variables (i.e., structural responses) to achieve the required control action.

3 Numerical simulation

In this section, a numerical simulation of a semi-active neuroemotional based control system for vibration reduction of a 3-story framed building structure under seismic excitation is presented. The Brain Emotional Learning Based Intelligent Controller is used to design a closed-loop control system that determines the required control action (emotional response) based on the desired and actual system response (sensory input). In this case study, the MR damper (reference RD-1005-3) is located between the ground and the first floor as shown in Figure 2.

The equation of motion describing the response of the system is defined as:

$$M\ddot{X}(t) + C\dot{X}(t) + KX(t) = \Gamma f_{c1}(t) - M\lambda\ddot{x}_g(t) \quad (6)$$

where $X(t)$ defines the displacement response, $f_{c1}(t)$ the control force, $\ddot{x}_g(t)$ the ground acceleration, $M_{(3 \times 3)}$, $C_{(3 \times 3)}$ and $K_{(3 \times 3)}$ are the mass, damping and stiffness matrices, respectively, given by:

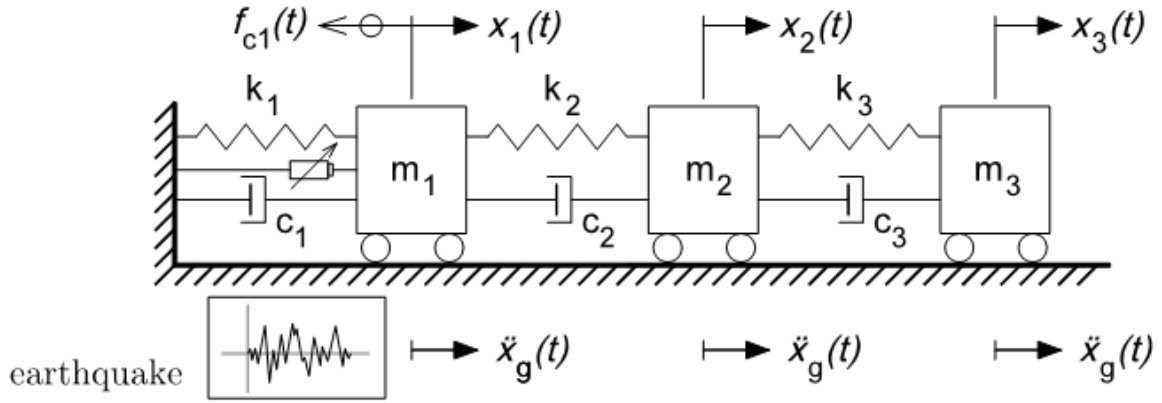


Figure 2: Schematic representation of a 3DOF control system under seismic loading.

$$M = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix} \quad (7)$$

$$C = \begin{bmatrix} c_1 + c_2 & -c_2 & 0 \\ -c_2 & c_2 + c_3 & -c_3 \\ 0 & -c_3 & c_3 \end{bmatrix} \quad (8)$$

$$K = \begin{bmatrix} k_1 + k_2 & -k_2 & 0 \\ -k_2 & k_2 + k_3 & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix} \quad (9)$$

and finally Γ and λ are location vectors of the control forces and the earthquake excitation, respectively and given by:

$$\Gamma = [-1, 0, 0]^T ; \lambda = [1, 1, 1]^T \quad (10)$$

The mass, damping and stiffness are defined as: $m_1 = m_2 = m_3 = 100$ kg; $c_1 = 175$ Ns/m, $c_2 = c_3 = 50$ Ns/m and $k_1 = k_2 = k_3 = 6 \times 10^5$ N/m.

The seismic acceleration time history of the 1940 NS component of the El-Centro earthquake is used as the ground motion (see Figure 3). A time-scaled seismic record (1:5) was used to ensure a ground motion compatible with the scale of the structural model.

The Simulink model of the semi-active control system based on the BEL controller is displayed in Figure 4.

In this type of smart damping devices, the viscosity of the MR fluid within the damper can be controlled depending on a prescribed input voltage/current. There are several numerical models to represent the hysteretic behavior of MR dampers. A common approach is to use the modified Bouc-Wen model shown in Figure 5 [9].

The numerical formulation of this parametric and the corresponding model parameters are described by the following equations:

$$F(t) = c \dot{y} + K_1(x - x_0) \quad (11)$$

$$\dot{y} = \frac{1}{c_0 + c_1} (\alpha z + c_0 \dot{x} + K_0(x - y)) \quad (12)$$

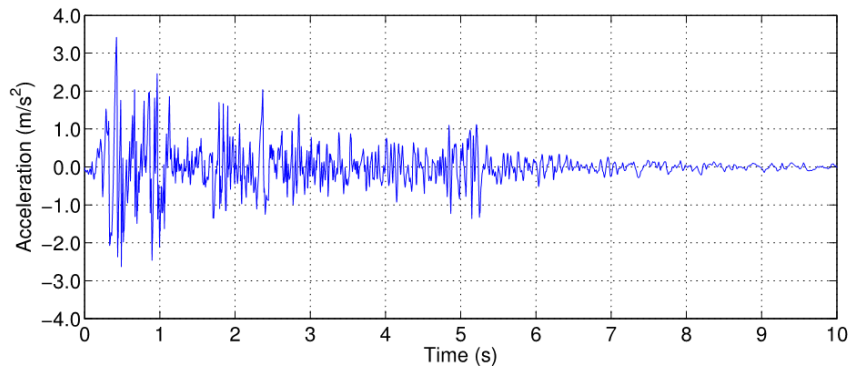


Figure 3: N-S El-Centro earthquake ground motion (time scale 0.2t).

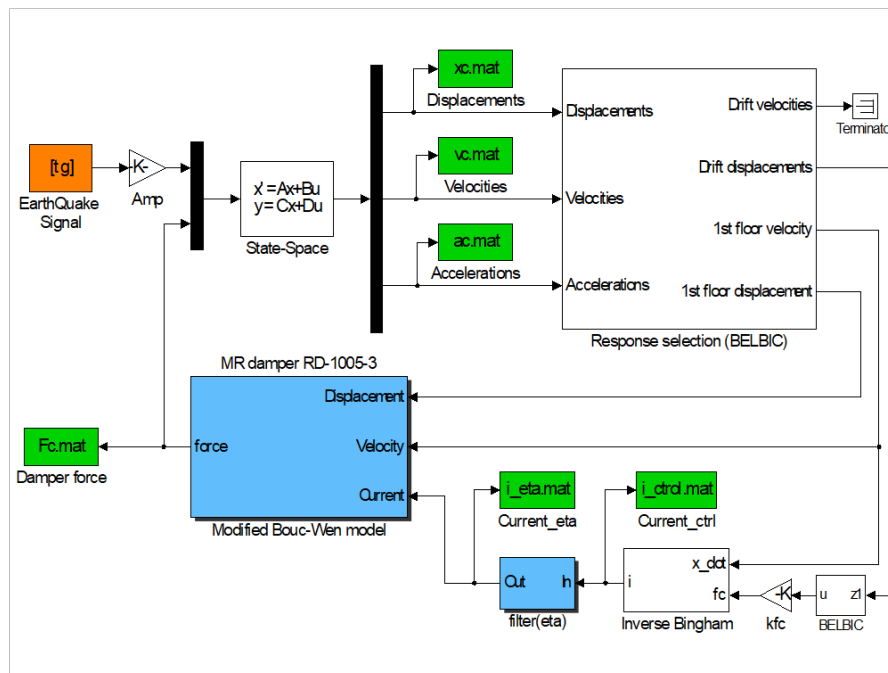


Figure 4: Simulink model of the BEL control system.

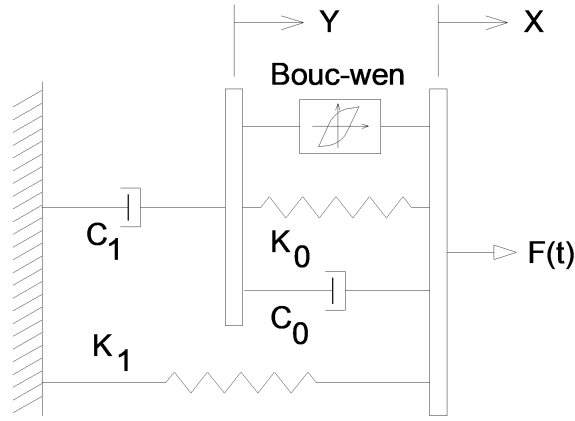


Figure 5: Modified Bouc-Wen model [9].

$$\dot{z}(t) = -\beta|\dot{x}(t)|z(t)|z(t)|^{n-1} - \gamma\dot{x}(t)|z(t)|^n + A\dot{x}(t) \quad (13)$$

The model parameters are defined based on experimental tests and some parameters are current (or voltage) independent, i.e., their values are not significantly affected by the magnetic field applied to the MR fluid. A commercial MR damper (RD-1005-3 by Lord Corp., USA) was experimentally tested to obtain the model parameters [10]. In this case, the current/voltage independent parameters are $A = 10.013$, $\beta = 3.044 \text{ mm}^{-1}$, $\gamma = 0.10 \text{ mm}^{-1}$, $K_0 = 1.121 \text{ N/m}$, $f_0 = 40 \text{ N}$ and $n = 2$. The remaining parameters are current dependent and can be defined by the following polynomial expressions:

$$\alpha(I) = -826.67 I^3 + 905.14 I^2 + 412.53 I + 38.24 \quad (14)$$

$$c_0(I) = -11.73 I^3 + 10.51 I^2 + 11.02 I + 0.59 \quad (15)$$

$$c_1(I) = -54.40 I^3 + 57.03 I^2 + 64.57 I - 4.73 \quad (16)$$

A first-order time lag involved in the current driver/electromagnet during a step command signal is also included in the numerical model of the device, which in this case is defined by a first order filter ($\eta = 130 \text{ sec}^{-1}$).

In this case, the inter-story drifts are used to determine the control action. The learning rates for the amygdala and orbitofrontal cortex were defined after a trial-and-error procedure and are computed to be $\alpha = 0.8$ and $\beta = 0.5$. Likewise, the sensory and the emotional outputs are determined by applying weight factors $\omega_1 = 2$, $\omega_2 = 0.56$, $\omega_3 = 2$ and $\omega_4 = 0.85$, which provide the best structural performance.

The structural responses obtained with the BEL control system along with the uncontrolled response of the third floor are displayed in Figure 6. The results demonstrate the effectiveness of the proposed controller in reducing the response of the three DOFs structure.

As can be seen, the BEL controller achieves a good performance in reducing the structural responses using only floor displacements. Thus, the main advantage of the BEL based control system is that only inter-story drift responses of the structure are required to determine the control action. This means that the damping force generated during the control process does not needs to be monitored, as happens in other controllers. Obviously, the main drawback

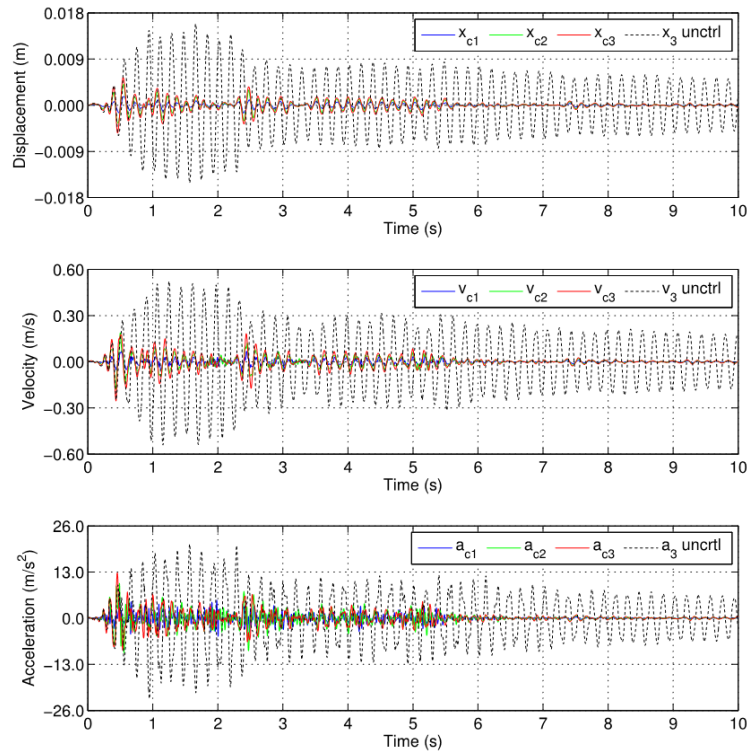


Figure 6: Structural responses obtained with the BEL controller.

regarding the implementation of the BEL based control system is related with the optimization of the controller parameters. It should be also noted that the combination of a BEL controller with other control techniques (e.g. PID control) has shown to be able to improve the overall performance of the resultant control system.

The damper force and the corresponding control signal are presented in Figure 7. As can be observed in the Simulink model depicted in Figure 4, the control system uses an inverse Bingham model to adjust the controller output to a continuous control signal (command current) compatible with the semi-active control operation of the MR damper. The resulting control action is similar to that obtained with other continuous controllers. The hysteretic behavior of the MR damper during the numerical simulation is portrayed in the force-displacement and force-velocity plots presented in Figure 8. The proposed control system is capable to explore the dissipative nature of this type of actuators. The shape and range of values of the hysteretic loops are comparable with those achieved with other semi-active controllers, whether they are based on a bi-state or a continuous operation of the actuator.

4 Conclusions and Future Work

Generally, the proposed BEL controller presents a remarkable overall performance being effective in reducing the peak responses and the control force compared with the passive modes, in particular the high damping state (passive on). This controller allows a consistent reduction in almost all structural responses (between 4 % and 13 %), but was unable to decrease the peak acceleration of the first floor that remained nearly the same as that of the best passive control mode. The maximum damping force generated during the simulation is also reduced which indicates that using large control input may not lead to a better control outcome. The main drawback of the BEL controller is related essentially with the appropriate definition of

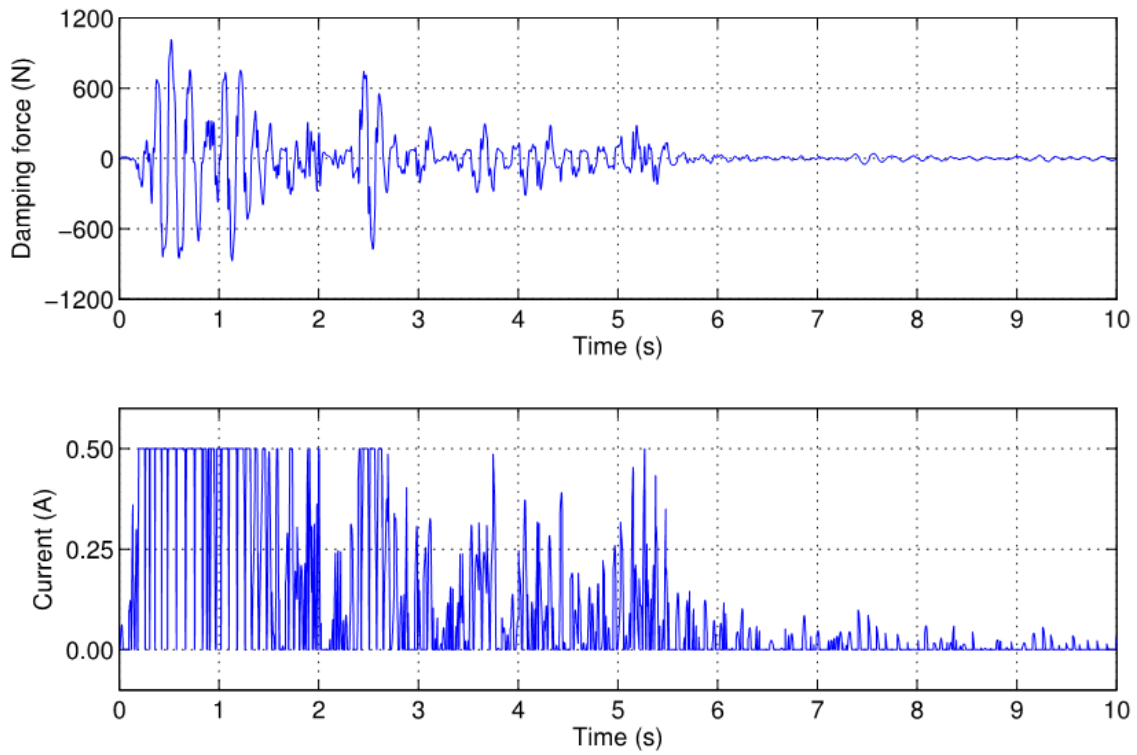


Figure 7: Damper force and corresponding operating current.

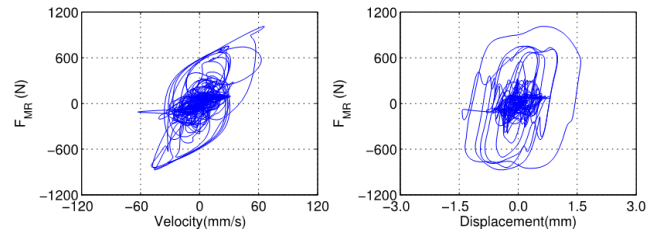


Figure 8: Three DOFs system - MR damper control force.

Control strategy		$\ddot{x}$ (cm)	$\dot{x}$ (cm/s)	$\ddot{x}$ (cm/s ²)	Drift (cm)	f (N)
Uncontrolled		0.695	27.09	1305	0.695	----
		1.251	45.78	1736	0.581	
		1.587	54.02	2272	0.371	
Passive OFF	Modified Bouc- Wen	0.518	20.02	999	0.518	166.4
		0.907	34.51	1358	0.443	
		1.191	42.79	1791	0.292	
Passive ON	Modified Bouc- Wen	0.171	7.77	613	0.171	1048.9
		0.423	19.36	1066	0.253	
		0.560	25.58	1366	0.208	
BELBIC		0.164	6.80	619	0.164 0.239 0.190	1014.4
		(-4%)	(-13%)	(1%)		
		0.403	17.88	964		
		(-5%)	(-8%)	(-10%)		
		0.525	24.19	1252		
		(-6%)	(-5%)	(-8%)		

Figure 9: Peak responses (time-scaled el-centro earthquake).

emotional and sensory signals that are able to represent with sufficient precision the system state and the control objective in order to maximize the performance of the control system.

There are numerous optimization methods available for tuning these parameters (e.g. genetic algorithms) although a common approach is to use a trial-and-error procedure. As future work the authors intend to use this controller applied to complexer systems and to optimize its performance applying soft computing techniques.

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