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DESIGN OF BRAIN EMOTIONAL LEARNING BASED ON CEREBELLAR ARCHITECTURE FOR INVERTED PENDULUM CONTROL

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ABSTRACT

A bio-inspired controller called Brain Emotional Learning (BEL) was developed through research on the limbic system of the mammalian brain. Based on BEL structure design of intelligent and cognitive controllers with different tuning algorithms has attracted more attention. In contrast to the traditional formulation of BEL, the paper analyzes and designs certain functions used in Brain Emotional Learning to improve the system's performance. It focuses on the critical parameters that influence the dynamics of BEL and based on Cerebellar Architecture emotional cues are formed. The controller mimics the emotional behavior of the brain and ensures improved dynamic control performance. Stability analysis of the system is described using Jacobian formulation. The method is used for the inverted pendulum model as the benchmark case study and is applicable to the design of system controllers in general. Hardware-in-Loop simulations show the effects of parameter variations within a specific range and the dynamic control performance is compared with PID formulations.

Keywords: BEL, Stability Analysis, Cart Pendulum, Emotional Cue, Cerebellar Model

1 INTRODUCTION

The design of Intelligent controllers based on biological and natural phenomena is leading to class of controllers with high cognition and decision making. Recent research has shown that researchers can solve complex nonlinear problems based on the architecture of the mammalian brain with particular features using knowledge derived from psychologically motivated behavior. In intelligent engineering applications, numerous bio-inspired models have been put forth and effectively used. [1-4]. The amygdala and orbitofrontal cortex are two major limbic system components that work together to accurately and quickly process emotional stimuli, according to LeDoux's findings [5]. The learning process in mammalian brain consists of long term and short term transforming phases. Emotion plays a crucial role in the transformation of long and short term memory. The behavioral transformation in the mammalian brain takes a very less reactionary time, therefore the responses are primarily affected by the reaction to emotions. [1, 6-9]. Moren and Balkenius arrived at the first neurological-inspired computational system known as Brain Emotional

Learning based Intelligent Controller (BELBIC)[10]. Caro Lucas used BELBIC, as an effective controller, BELBIC has high performance functional due to its structure [4]. According to Jafari et al [11], Pasrapoor M [7] and others, the controller is widely used in classification, clustering and system control applications. The reward factor for emotions in the amygdala-orbitofrontal model is crucial for modifying the weights of the orbitofrontal cortex and amygdala. Different reward signal formulations have been proposed by numerous researchers [10, 4]. Sharma [12] and Yuntao [13] explicitly determined the reward signal as PID formulization. Abdi [14] defined the reward signal as the multiplication of a related weight and used a BEL model to predict short-term traffic flow. Lotfi al. [6, 12] presented a novel BEL-based pattern identifier that updated the orbitofrontal cortex and amygdala weights using a pattern-target approach rather than reward-based reinforcement learning.

Despite the fact that this approach is model-free, there is a correlation between the accuracy of classification and the precision of the learning process. These parameters are chosen with consideration for both transient dynamics and steady state stability. This paper addresses the effects of the BEL parameters on system performance and presents the methodology for choosing the parameters based on cerebellar architecture. The emotion cues for BEL training obtained from Cerebellar algorithm shows better performance as compared with PID based generation for Emotion. The improved performance is demonstrated on an inverted pendulum, which is frequently used as a benchmark problem for control applications like space booster rocket, satellite attitude control, aircraft automatic landing, stabilization systems, ship roll control etc [15 & 16].

Section 2 presents the mathematical modelling of Inverted Pendulum, Section 3 presents development of BELBIC and its control parameters, the system stability analysis is in Section 4, Cerebellar Model based Emotion Cue is simulated in Hardware-in-loop platform and it is delineated in section 5 and the conclusion are presented in section 6.

2 MATHEMATICAL MODELLING OF CART INVERTED PENDULUM

The pendulum system has two degrees of freedom and its dynamics are in terms of rotational displacement, θ and the cart's horizontal displacement, x . A force is applied to the base which controls these two variables. A normal pendulum is always stable at the equilibrium points when hanging downwards, but inverted pendulum is inherently unstable, and must be continuously balanced to remain in upright position [17]. The insights of the dynamics acting on the cart pendulum are presented subsequently.

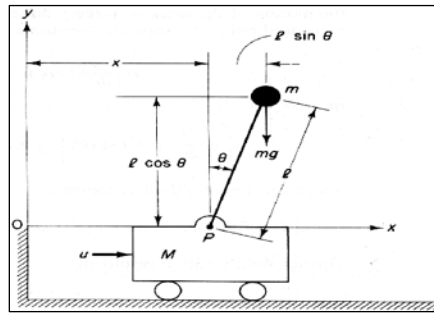


Figure 1: Cart Inverted Pendulum System along with the forces acting

2.1 Generalized Forces

The non-conservative work can be used to derive the models based on generalized forces. For the inverted pendulum as shown in Fig. 1, the input force and system damping produce the non-conservative forces.

$$\delta W_{nc} = f(t)\delta x - c\dot{x}\delta x - b\dot{\theta}\delta\theta \quad (1)$$

δW_{nc} is the change in the non-conservative force.

δx is the change in the displacement.

$\delta\theta$ is the change in the rotational angle.

c is translatory friction coefficient.

b is rotational friction coefficient.

The total kinetic energy is obtained by using Lagrangian multiplier [18].

$$L = \frac{1}{2} M \dot{x}^2 + \frac{1}{2} m (\dot{x}^2 - 2\dot{x}l \cos \theta \dot{\theta} + l^2 \dot{\theta}^2) + \frac{1}{2} I \dot{\theta}^2 + mgl \cos \theta \quad (2)$$

Where M is the mass of the cart.

m is the mass of pendulum.

I is moment of Inertia of Inverted pendulum.

l is the length of the pendulum.

State equations are generated using Lagrange's Equation:

$$\frac{d}{dt} \left(\frac{\partial L}{\partial \dot{X}_j} \right) - \frac{\partial L}{\partial X_j} = F_j \quad (3)$$

Considering the variable x, the equation is:

$$\frac{d}{dt} \left(\frac{\partial L}{\partial \dot{x}} \right) - \frac{\partial L}{\partial x} = F_x \quad (4)$$

The following equation results from evaluating the partial derivatives.

$$\frac{d}{dt} (M\dot{x} + m\dot{x} - ml \cos \theta \dot{\theta}) - 0 = f(t) - c\dot{x} \quad (5)$$

which reduces to

$$(M + m)\ddot{x} - ml \cos \theta \ddot{\theta} + ml \sin \theta \dot{\theta}^2 = f(t) - c\dot{x} \quad (6)$$

Considering the variable θ , the equation for (3) is:

$$\frac{d}{dt} \left(\frac{\partial L}{\partial \dot{\theta}} \right) - \frac{\partial L}{\partial \theta} = F_{\theta} \quad (7)$$

The partial derivatives yields are evaluated.

$$\frac{d}{dt} (-m\dot{x} \cos \theta + ml^2 \dot{\theta} + I\dot{\theta}) - (ml\dot{x} \sin \theta \dot{\theta} - mgl \sin \theta) = -b\dot{\theta} \quad (8)$$

$$(ml^2 + I)\ddot{\theta} - m\ddot{x} \cos \theta + m\dot{x} \sin \theta \dot{\theta} - m\dot{x} \sin \theta \dot{\theta} - mgl \sin \theta = -b\dot{\theta} \quad (9)$$

The system state equations are simplified and rearranged.

$$(M + m)\ddot{x} + c\dot{x} - ml \cos \theta \ddot{\theta} + ml \sin \theta \dot{\theta}^2 = f(t) \quad (10)$$

$$-m\ddot{x} \cos \theta + (ml^2 + I)\ddot{\theta} + b\dot{\theta} + mgl \sin \theta = 0 \quad (11)$$

Substituting into the system state equations of (10 & 11) and after linearization results into the following transfer functions.

$$\frac{X(s)}{F(s)} = \frac{ml^2 s^2 + bs + mgl}{Mml^2 s^4 + [(M+m)b + ml^2 c]s^3 + [(M+m)mgl + bc]s^2 + mglcs} \quad (12)$$

$$\frac{\theta(s)}{F(s)} = \frac{mls}{Mml^2 s^3 + [(M+m)b + ml^2 c]s^2 + [(M+m)mgl + bc]s + mglc} \quad (13)$$

$\theta(s)$ is to be controlled by applying appropriate Force $F(s)$ to the cart. The above model as given by equation (13) is used for demonstrating the control aspects of the proposed method.

3 BRAIN EMOTIONAL LAERNING

A computational model based on amygdala, orbitofrontal cortex, thalamus, sensory input cortex, connectivities and neuro signal process was created by Moren and Balkenius [8]. Further this model was applied for system control applications by Lucas [4]. Figure 2 displays Lucas C.'s computational model of emotional learning. The orbitofrontal cortex and the amygdala are the two components of the model. The Thalamus and cortical regions provide inputs to the Amygdala portion, whereas the Orbitofrontal receives inputs from both the Amygdala and the cortical regions

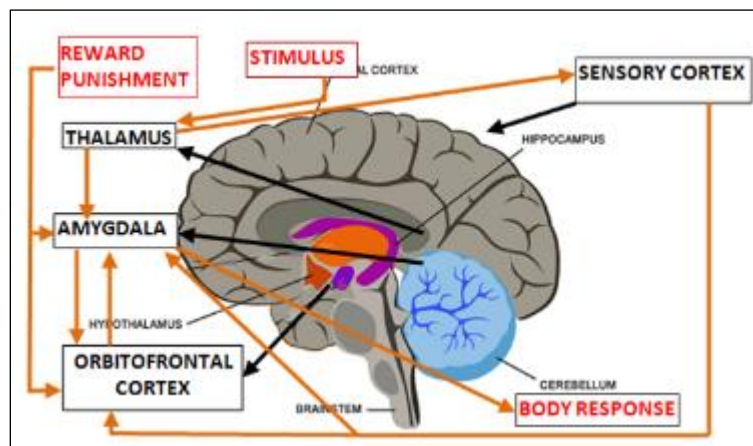


Figure 2: Amygdala based brain emotional model Structure

The system's input stimuli are displayed by the vector "S.". For every stimulus "S," there is one "A" node. As seen in Figure 3, Each A node has a connection weight V. Each node's output is produced by multiplying corresponding input by the weight V. The V_i is modified in proportion to the difference between the reinforcement signal EC and the activation of the A nodes. The α term is a constant used to adjust the learning speed. Mathematically, the node transformations are given by:

$$A_i = S_i V_i \quad (14)$$

$$O_i = S_i W_i \quad (15)$$

$$E = \sum A_i - \sum O_i \quad (16)$$

$$\Delta V_i = \alpha (S_i \max(0, EC - \sum A_j)) \quad (17)$$

There can be no decrease in the weights V. This design decision is justified by the fact that once an emotional response is learned, it should be irreversible. When this response is inappropriate, the orbitofrontal region's job is to suppress it. Although the Orbitofrontal connection weight can fluctuate, the Orbitofrontal learning rule and the Amygdala rule are extremely similar. Similar behavior is exhibited by the "O" node, which generates an output by applying a connection weight W to the input signal. Another learning rate constant connected to the orbitofrontal cortex is β . ΔW_i is computed as follows.

$$\Delta W_i = \beta (S_i \max(E - EC)) \quad (18)$$

The "E" node merely subtracts the inhibitory outputs from the O nodes after adding up the outputs from the A nodes. The model's output is the outcome. The O nodes suppress the output of E when needed, while the A nodes provide

outputs in proportion to their role in anticipating the Emotional Cue. The Emotional Cue acts like a reward factor in the channel, and therefore it is also known as Reward (Rew). The E node subtracts the inhibitory outputs from the O nodes from the sum of the outputs from A.

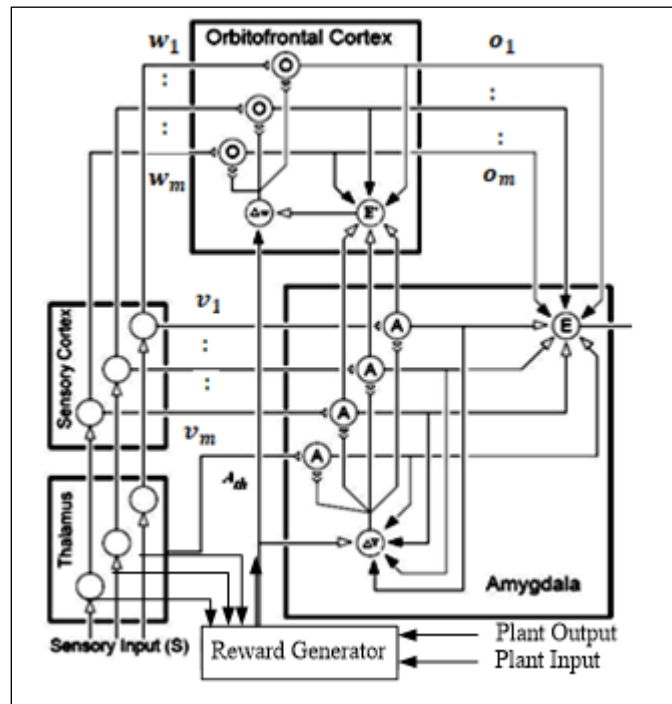


Figure 3: Graphical depiction of the Modified Brain Emotional Learning

The achieved Control Objectives with respect to this particular methodology for BEL design are as follows:

To determine (1) Emotional Cue (2) Amygdala learning factor, α (3) Orbitofrontal cortex learning factor, β , so that all the signals in the overall closed-loop system are bounded and to minimize the Performance Index specified by:

$$J(e) = \int_0^\infty e^2(t) dt. \quad (19)$$

4 STABILITY ANALYSIS FOR THE COMPOSITE SYSTEM

The weight updation of the i^{th} Amygdala channel and i^{th} Orbitofrontal Cortex channel is given by

$$\frac{dV_i}{dt} = \alpha S_i \max(0, EC - S_i V_i) \quad (20)$$

$$\frac{dW_i}{dt} = \beta S_i (S_i V_i - S_i W_i - EC) \quad (21)$$

When $EC < S_i V_i$, results in $\frac{dV_i}{dt} = 0$. This indicates that the system is stable in steady state, therefore the stability is tested by the condition: $EC > S_i V_i$, which results in

$$\frac{dV_i}{dt} = \alpha S_i (EC - S_i V_i) \quad (22)$$

$$\frac{dV_i}{dt} = -\alpha(S_i)^2 V_i + \alpha S_i EC \quad (23)$$

For the inverted pendulum operated with a DC motor, the transfer function for position control is of the form,

$$\frac{\theta(s)}{F(s)} = \frac{m l s}{M m l^2 s^3 + [(M+m)b + m l^2 c] s^2 + [(M+m) m g l + b c] s + m g l c} \quad (24)$$

Converting transfer function into state space model

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -a_3 & -a_2 & -a_1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u \quad (25)$$

$$\text{Where } a_3 = \frac{g c}{M l}, a_2 = \frac{(M+m) m g l + b c}{M m l^2}, a_1 = \frac{(M+m) b + m l^2 c}{M m l^2}$$

$$y = \begin{bmatrix} 0 & m l & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

The parameters used for cart inverted pendulum are tabulated as follows:

Table 1: Parameters of the Cart Inverted Pendulum

Parameters	Values
Mass of Pendulum (m)	0.15 Kg
Mass of Cart (M)	1.3 Kg
Lenth of Pendulum	0.314 m
Rotational Friction Coefficient (b)	20
Linear Friction Coefficient (c)	1

Changing equation 22 and 23 in terms of 'e' using the relation $e(t) = S_i = r(t) - y(t)$.

$$\frac{dV_1}{dt} = -\alpha e^2(t) V_1 + \alpha e(t) E C = f_1 \quad (26)$$

$$\frac{dW_1}{dt} = \beta e^2(t) V_1 - \beta e^2(t) W_1 - \beta e(t) E C = f_2 \quad (27)$$

By evaluating Jacobian Matrix J based on the state vector is defined by $[X] = [V_1, W_1, x_1, x_2, x_3]$.

Taylor series expansion is used to linearize the state equation while ignoring higher order terms.

$$\dot{x}_i = f_i(X_0, u_0) + \sum_{j=1}^n \frac{\partial f_i(X, u)}{\partial x_j} \bigg|_{\substack{X=X_0 \\ u=u_0}} (x_j - x_{j0}) + \sum_{k=1}^m \frac{\partial f_i(X, u)}{\partial u_k} \bigg|_{\substack{X=X_0 \\ u=u_0}} (u_k - u_{k0}) \quad (28)$$

The Jacobian is formulated as

$$J = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_2}{\partial x_n} \\ \dots & \dots & \dots & \dots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \dots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} = \begin{bmatrix} -\alpha e^2 & 0 & 0 & 0 & 0 \\ \beta e^2 & -\beta e^2 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & -a_3 & -a_2 & -a_1 \end{bmatrix} \quad (29)$$

If the deviations of the composite state vector $\Delta[X] = [\Delta V_1, \Delta W_1, \Delta x_1, \Delta x_2, \Delta x_3]$ reduces with respect to time, it indicates a stable nature of the poles of the system.

Characteristic Equation of J is given $|\lambda I - J| = 0$, results in $(\lambda + \alpha e^2)(\lambda + \beta e^2)(\lambda^3 + a_1\lambda^2 + a_2\lambda + a_3) = 0$

Therefore, critical condition for convergence is $(\lambda + \alpha e^2) = 0$, $(\lambda + \beta e^2) = 0$ and $(\lambda^3 + a_1\lambda^2 + a_2\lambda + a_3) = 0$.

Whereas the conditions for absolute convergence are $\alpha e^2 > 0$, $\beta e^2 > 0$, and the poles of the system to be in the LHS of s plane. Substituting the parameters given in Table 1, the eigen values are obtained at -1.49, -0.0006, -0.00002. Since all the poles are on the LHS, the system guarantees absolute convergence.

5 HIL SIMULATION AND RESULTS

5.1 Hardware-in-loop Simulation

As seen in figure 4, a host computer uses the real-time simulator OP5600, which has a Spartan 3 FPGA processor with 2.4GHz and two core activation created by Opal-RT Technologies, to implement the suggested method for a real-time environment. The model of Inverted Pendulum and BEL Controller developed in the Simulink in the host PC with target computer (Intel® Quad CPU Optiplex 7040) for performing parallel computation, realized in Opal-RT Redhat OS. The inbuilt Xilinx Virtex-6 CX6VLX240T process computes floating-point models and for projects requiring large amount of on-board memory [7,10,11]. The controllers and plants are mathematically modeled and the models are developed in Simulink, and are embedded in one core of OP5600, where as the Inputs, Outputs and Plant Parameters are embedded in the others cores.

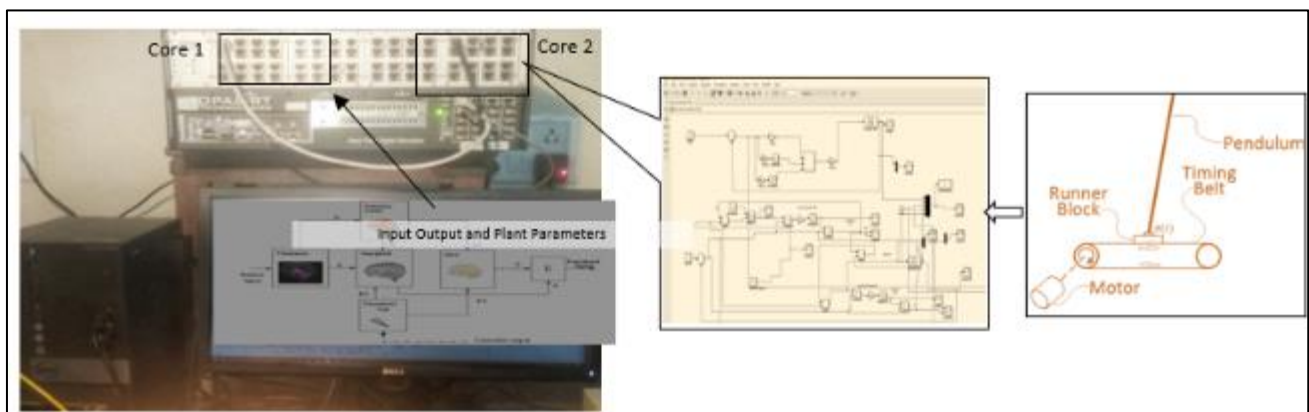


Figure 4: Hardware Set up for HIL Simulation for Inverted Pendulum

5.2 Selection of Parameters

In order to satisfy the stability criteria, the reward value is varied from lower to higher values, and the set of parameters taken into consideration for Amygdala learning and orbitofrontal cortex learning are in the $[0+10]$. It is clear from all the values in the $[10\ 800]$ range that the reward has a major impact on the output tracking performance. It is observed that the system is tracking very quickly and is very anticipatory with a quick settling time and steady state error when the Reward for Emotional Cue values are higher. However, the system tends to show high peak overshoot. The adaptation is slow and performs poorly in the short term for lower reward values (10 and 50). With the Reward =150, the system is having best performance as shown in Fig 5.

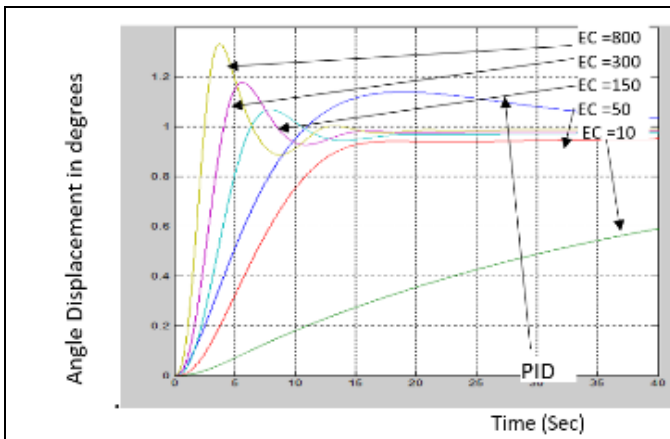


Figure 5: Dynamic Performance of Pendulum Angle with Reward Variation

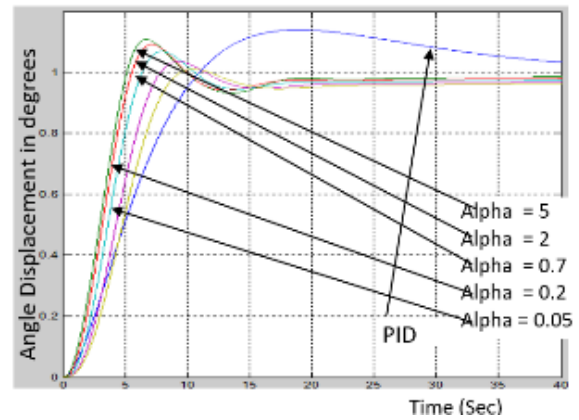


Figure 6: Dynamic Performance of Pendulum Angle with Amygdala Learning

Figures 6 and 7 illustrate how the amygdala and orbitofrontal cortex learning parameters impact learning and convergence speed. Lower learning rate values result in poor transient performance, but the system always becomes stable as the steady error gradually decreases. The system is simulated for values of $\alpha = 0.05, 0.2, 0.7, 2$ and 5 and $\beta = 0.05, 0.2, 0.4, 0.7, 1.5$ respectively. Inverted pendulum is having the best performance with Amygdala learning factor and OrbitoFrontal learning factor as 0.7 and 0.4 respectively as shown in Fig 8.

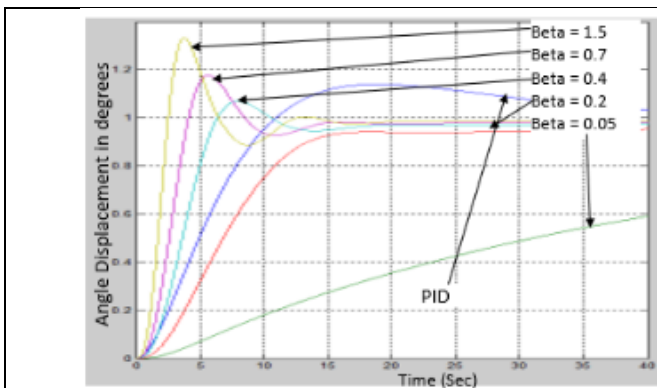


Figure 7: Dynamic Performance of Pendulum Angle with OFC Learning

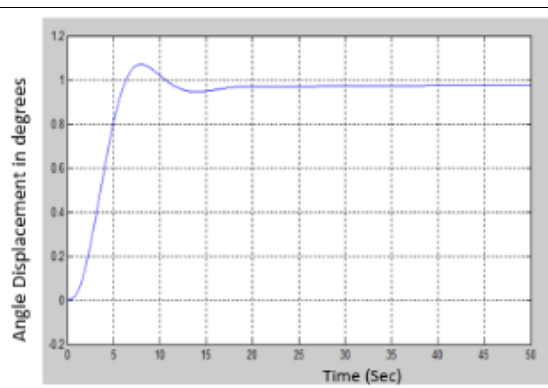


Figure 8: Dynamic Performance of the best BEL parameters Configuration

Also, it is observed that Emotional Cue has higher influence on the dynamic behavior, the formulation of the reward function for Emotional Cue is being investigated, as it is considered as an external factor influencing the signal transformations. It is suggested that the performance can be enhanced by making the reward function dependent on the observation of error conditions, plant inputs, and output [3]. Here, we are examining the system's performance by creating a reward function with variable parameters based on plant inputs and outputs, sensory signals, and Cerebellar architecture Liao, et al. [19].

5.3 Cerebellar Model

The Cerebellar Model Articulation Controller popularly known as CMAC is a neural network-based model for imitating certain properties associated with part of the brain known as the cerebellum. cerebellum stores and retrieves information for controlling human muscular system for producing organized temporal behavior, where in each muscle is driven by many signals which are functions of many variables such as position, velocity, and acceleration of the limb, muscular stretch, tendons tension and tactile sensations from skin pores.

The first computational model was introduced by Albus in 1989 [20]. Learning and anticipation are the key features of cerebellar computation. As a consequence, It exhibits many desirable properties for learning in biological creatures such as generalization, classification, learning interference, discrimination, memory storage and forgetfulness. The model for the control contains an anticipatory feed-forward with a complementary reactive feedback control [21 & 22]. The model as shown in Figure 9 consists of two subsequent mappings and an output computation with the following spaces: input space (I), association memory space (A), receptive-field space (R), weight memory space (W), and output

space (O). As illustrated in Figure 9, these functional mappings are Mapping $I:I \rightarrow A$, Mapping $A:A \rightarrow R$, and Mapping $R:R \rightarrow W$, where I and O are ni -dimension and no -dimension, respectively.

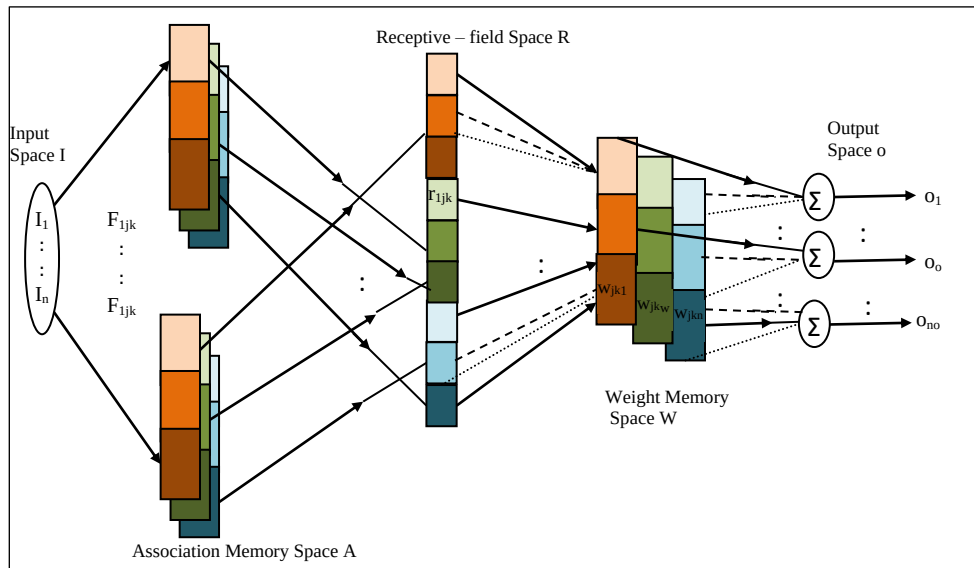


Figure 9: Cerebellar Model Articulation Controller Architecture

Input Space I is the signal receiving junction. For a given input $I(t) = [i_1(t) \dots i_i(t) \dots i_n(t)]^T \in R^n$, where each input variable I_i is assumed to be quantized into discrete regions called “elements”. The lowest value of the element can be termed as a resolution. Addresses for retrieving data from the corresponding state's memory are mapped to each discrete state. Rather than neuronal connectivity, the function is based on a series of memory and data mapping functions. A real, continuous input vector or matrix is transformed into a real, continuous output vector or matrix by the mapping.

The input partitioning scheme into discrete states is shown in Fig. 9. Every state and its associated variable are quantized into distinct areas known as blocks or hypercubes. N_e is the total number of elements in a block, and the decomposition splits into layers of hypercubes. The m th row and m th column define hypercubes in the m th layer. Each hypercube is linked to a physical memory element by the CMAC [22]. For transient control applications, the CMAC has many advantages over other algorithm types. It maintains the local generalization property with discrete state, which leads to quick learning convergence [17].

5.4 Emotion Cue Based on CMAC

To get a good response, the one partition of the input state space must be determined correctly. Figure 10 shows the Emotion Cue generated with PI controller which gives a proportional mapping with respect to the error and integral of error. This is linear mapping with respect to the variables. However, in real life experiences, the reward for emotional cues is seldom linear, it is a highly dynamic non-linear function with respect to the input variables. The value of the reward is to be progressively increased for reducing the performance index $J(e) = \int_0^\infty e^2(t)dt$. In the context CMAC architecture is used to generate the nonlinear function with respect to the variables. Figure 11 is the reward generation using CMAC considering error as the input variable.

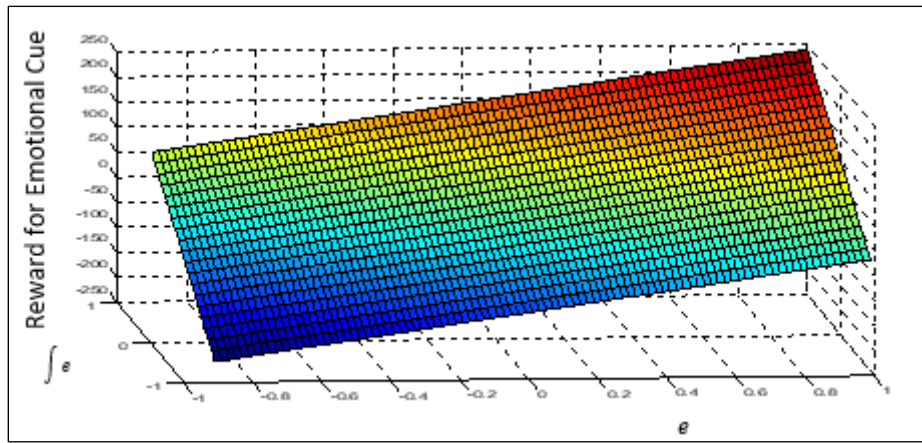


Figure 10: Emotional Cue output mapping for PI Controller

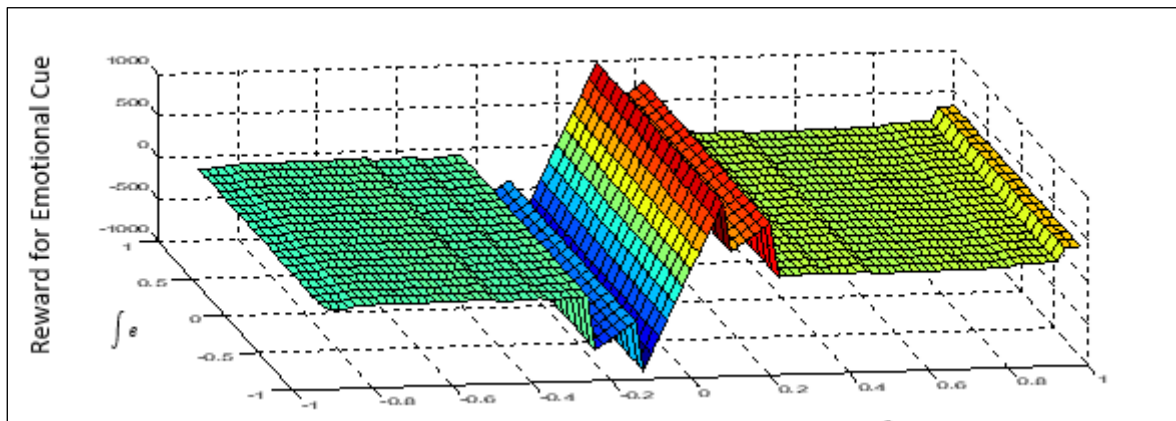


Figure 11: Emotional Cue output mapping for CMAC proportional to error

The controller is producing high value of Reward for lower values of error, the Reward is progressively decreased with higher values of error. The scheme is having desirable biological properties for Emotional Cue generation. However, for lower negative values of error, the Reward is tending to be negative, as shown in Figure 11. To avoid the negative region for reward, a gain scheduling approach is applied on the best configuration obtained with Reward = 150, Amygdala learning factor and OrbitoFrontal learning factor as 0.7 and 0.4 respectively. The Reward generation scheme with respect to the input variables is shown in Fig. 12, where in a high values of Reward, with 5 times to the generation shown in Fig 11 is obtained with all positive values bounded.

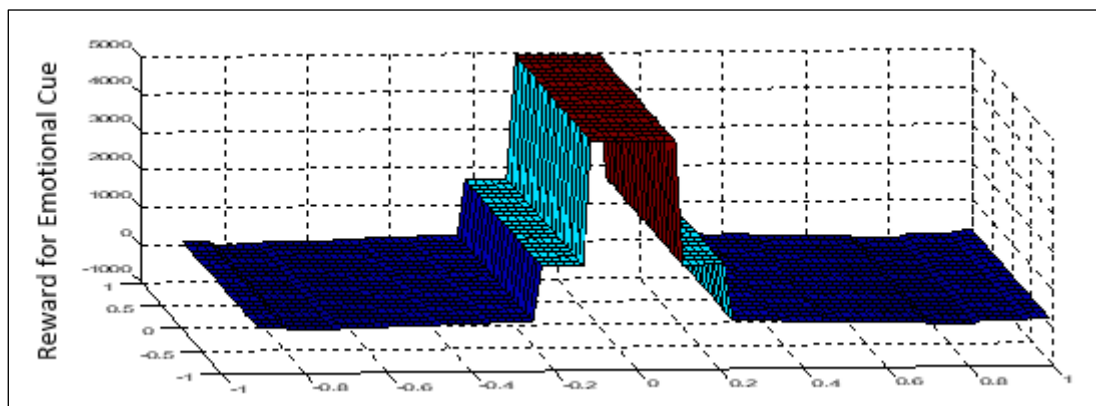


Figure 12: Emotional Cue output mapping for CMAC with Gain Scheduling Reward

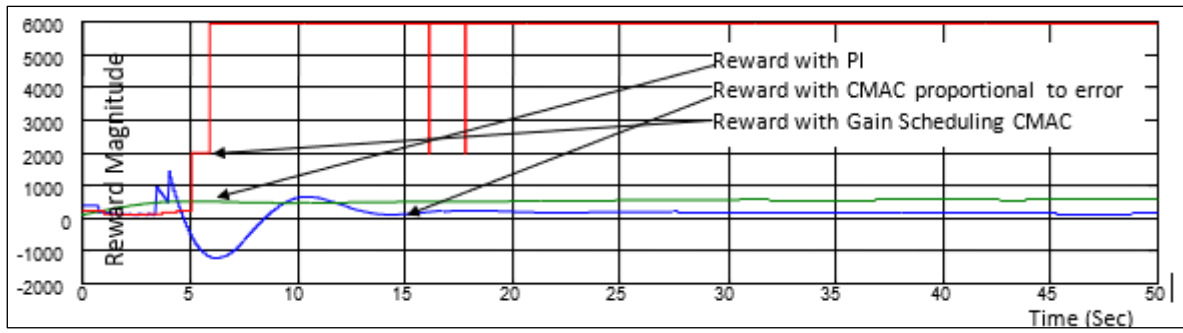


Figure 13: Reward Generation with various control schemes

The values of Reward, Amygdala learning factor, and Orbito Frontal learning factor are 150, 0.7, and 0.4, as can be inferred from the observation of Figures 5 to 8, are responding the most effectively. Figure 14 illustrates the comparison with a PID controller. The values of proportional controller $K_p = 68.8$, integral controller $K_i = 4.37$, and derivative controller $K_d = 0$ are obtained by tuning the PID controller using the Good Gain method. The derivative action is made zero due to the existence of zero at the origin in the system.

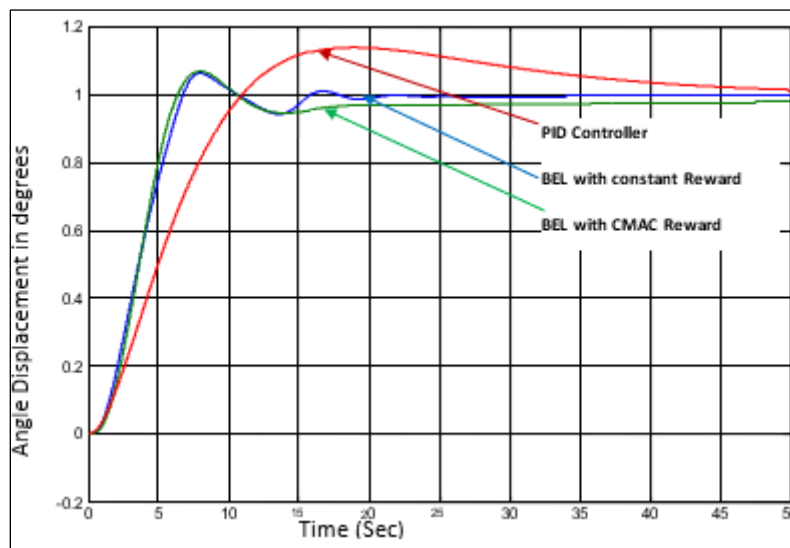


Figure 14: Comparison Performance of BEL with Reward Generated from CMAC

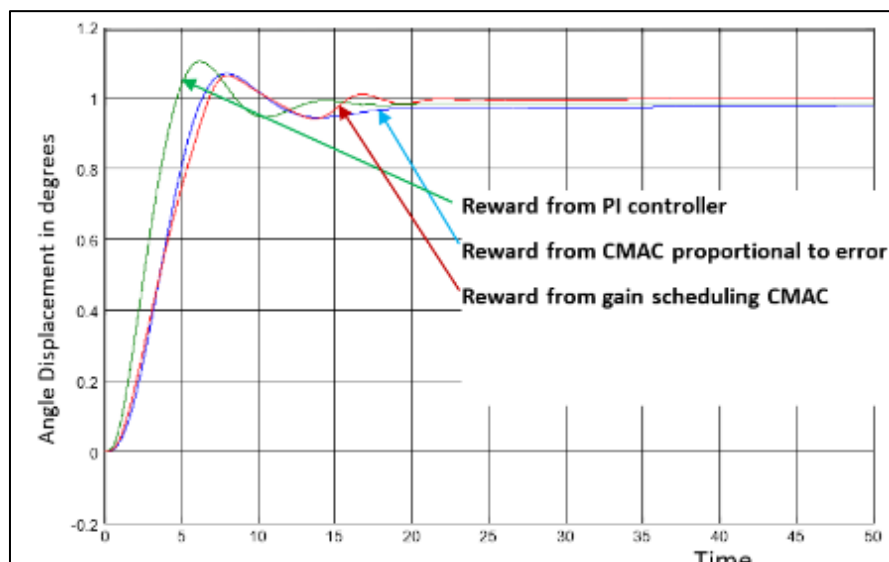


Figure 15: Comparison Performance CMAC Reward Generation

With the progressive increase in the Reward value according to CMAC architecture, the steady state performance is improved, the reward function formulation mapping is shown in the Figures 11 and 12. The performance for PID based Emotional Cue and CMAC based Emotional Cues are compared in Figure 15. It is observed that the Performance index is having lower values from time, $t = 5$ onwards as observed from Figure 16.

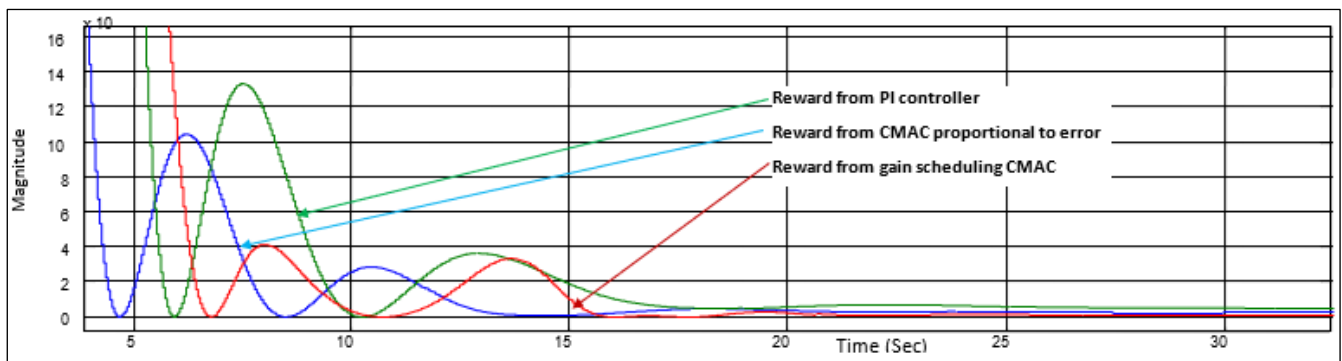


Figure 16: Steady State Performance Index Comparison for Reward Generation from Various Controllers

Therefore, it is desirable that the steady increase in the reward reduces the steady state error progressively and is achieved by CMAC. The system is having optimal performance in the steady state for Reward based on CMAC Gain Scheduling to reduce the specified performance index.

6 CONCLUSIONS

The effect of Brain Emotional Learning controller parameters are identified for the dynamic control performance improvement. The effects of these parameters are studied on the case study of inverted pendulum. It is observed that the Orbitofrontal and Amygdala learning factors effects the rate of learning and convergence. The selection of the parameters effects the output convergence. It is observed that of all the parameters, Reward for EC plays crucial role. Further, by making Reward function as dependent factor based on the observation of condition of error, plant inputs and output, the performance can be improved. Here a linear function for Reward is formulated and is further improved based on CMAC architecture. The approach is applicable to system controller design in general, and is applied for inverted pendulum model, as the benchmark case study in Hardware-in-Loop Simulation. The results prove remarkable in optimizing the control system performance indices as compared to P, PI PID formulations. Other nonlinear functions for BEL parameters can effectively be used for CMAC to improve the performance.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare no conflict of interest.

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