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Intelligent Auto pilot Design for a Nonlinear Model of an Autonomous Helicopter by Adaptive Emotional Approach

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There is a growing interest in the modeling and control of model helicopters using nonlinear dynamic models and nonlinear control. Application of a new intelligent control approach called Brain Emotional Learning Based Intelligent Controller (BELBIC) to design of autopilot for an autonomous helicopter is addressed in this paper. This controller is applied to a nonlinear model of a helicopter. This methodology has been previously proved to present robust characteristics against disturbances and uncertainties existing in the system. The simulation results of this controller arecompared with a PID controller. The policies for PID and BELBIC controller are the same. The controller design goal is that the helicopter tracks a special maneuver to reach the commanded height and heading. The performance of the controllers is also evaluated for robustness against perturbations with inserting a high frequency disturbance. Simulation results show a desirable performance in both tracking and improved control signal by using BELBIC controller.

***Keywords**: Model Helicopter, Nonlinear model, PID Controller, BELBIC.*

1 Introduction

Helicopter flight is a task that requires a great amount of experience and skills. This is due to the strong coupling that exists between all degrees of freedom and make the control difficult. The same strong coupling of the degrees of freedom and the same (maybe even more, due to smaller helicopter size, greater sensitivity to control inputs and disturbances as well as higher bandwidth of dynamics) amount of experience and skills are also required for flight of small-size remote controlled helicopters. The use of such small-sized helicopters is increasing for surveillance purposes by the police, filming industry, hobby, the army, etc., and therefore, the need for assistance of non-experienced helicopter pilots has also increased. These reasons triggered the initiation of research for development of autopilots that were able to navigate a helicopter autonomously according to commands that were given by an inexperienced user.

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Most of the existing results for helicopter control have been based on the linearization model or through several linearization techniques [1, 2]. A very thorough survey of linear techniques for helicopter control has been given by Garrad and Low [1]. Miniature helicopter control problems have also been discussed by Furuta et al. [3]. The work of Pallett et al. [4] has served as the basis for our understanding of the helicopter model.

Helicopter is a highly nonlinear dynamical system for which linear control designs are far from adequate. The classical control systems designed to provide satisfactory performance under nominal operating conditions, are unable to cope with severe unknown nonlinearities including inter-axis couplings and variation in helicopter model due to difficulty in accurate modeling. We have been exploring nonlinear controllers to provide automatic vehicle control for a helicopter. In recent years theory and applications of intelligent control systems have been a focus of attention in control engineering. Intelligent control of uncertain, unknown dynamical systems with ever changing dynamics, where conventional model-based control theory fails because of low information and data about the plant dynamics, has been studied extensively and several strategies have been addressed [5-7]. Among intelligent control techniques, there are Artificial Neural Networks [8], Fuzzy Control [9], and Genetic Algorithms [10]. Recently, a computational model of emotional learning in mammalians brain has been developed [11, 12]. Using the proposed model, a control algorithm has been introduced, which is called Brain Emotional Learning Based Intelligent Controller (BELBIC), and has been successfully employed for decision making and control of non-linear systems.

In this paper we apply two methods to the system and compare their performance. First method is an intelligent controller named BELBIC. This controller has a certain structure, but it can be changed to achieve the control objectives. There are both continuous and discrete time BELBIC controllers [13, 14]. We use the continuous one to compare that with another continuous time control method (PID controller). To design the BELBIC controller, we should choose the appropriate reward function according to physical aspects of the control problem, and tune the training coefficients of the controller to achieve the desired control objectives.

The sections of the paper are as follows. Section 2 describes the nonlinear model of the helicopter. Theoretical aspect and controller design PID method and autopilot policy has been elaborated on in the section 3. Section 4 contains a brie review of the general formulation of BELBIC. Section 5 shows the controller setup and simulation results. Finally, conclusions are presented in section 6.

2 Helicopter mathematical model

2.1 Rigid Body Dynamic

This section presents the dynamic model of a single main rotor and tail rotor Model helicopter equipped with a Bell-Hiller stabilizing bar. We based the control system design on a nonlinear model of the helicopter valid in the hover and low velocity regime. A number of researchers [15,16] have proposed nonlinear models for the aerodynamics of the main rotor and the tail rotor in hover or in forward fight. In this paper we used the dynamic model that was developed by Mokhtari et al [17]. The equations of motion are obtained by equating the sum of force and moment terms in each direction to the time derivatives of the linear and angular momentum. We treat the helicopter as the lumped parameter system that consists of main rotor, tail rotor, fuselage and horizontal and vertical stabilizers. In near-hover condition, the effect of fuselage and stabilizers are neglected and the forces and moments generated by the main rotor,tail rotor and control rotor are substituted into the equation of motion described in the body-coordinate system. The rigid body fuselage dynamics are modeled using equations of motion that describe the motion of the helicopter body. These are the three force, three moment equations and three kinematic equations that are derived using Newtonian mechanics. The derivation of these equations is discussed in detail in [18], which are given below:

$$\begin{aligned} \dot{u} &= -(wq - vr) + \frac{X}{M} - g\sin\theta \\ \dot{v} &= -(ur - wp) + \frac{Y}{M} + g\cos\theta\sin\phi \\ \dot{w} &= -(vp - up) + \frac{Z}{M} + g\cos\theta\cos\phi \end{aligned} \tag{1}$$

$$\begin{aligned} I_{XX}\dot{P} &= (I_{YY} - I_{ZZ})qr + I_{XZ}(\dot{r} + pq) + L \\ I_{YY}\dot{q} &= (I_{ZZ} - I_{XX})rp + I_{XZ}(r^2 - p^2) + M \\ I_{YY}\dot{r} &= (I_{XX} - I_{YY})pq + I_{XZ}(\dot{p} - qr) + N \end{aligned} \tag{2}$$

$$\begin{aligned} \dot{\varphi} &= p + q\sin\varphi\tan\theta + r\cos\varphi\tan\theta \\ \dot{\theta} &= q\cos\varphi - r\sin\varphi \\ \dot{\psi} &= q\sin\varphi\sec\theta + r\cos\varphi\sec\theta \end{aligned} \tag{3}$$

Total forces and moments in three directions obtained as following:

$$\begin{aligned} X &= X_R + X_T + X_{TP} + X_{FN} + X_F \\ Y &= Y_R + Y_T + Y_{TP} + Y_{FN} + Y_F \\ Z &= Z_R + Z_T + Z_{TP} + Z_{FN} + Z_F \end{aligned} \tag{4}$$

$$\begin{aligned} L &= L_R + L_T + L_{TP} + L_{FN} + L_F \\ M &= M_R + M_T + M_{TP} + M_{FN} + M_F \\ N &= N_R + N_T + N_{TP} + N_{FN} + N_F \end{aligned} \tag{5}$$

The various subscripts that accompany the forces and torques are: $()_R$ for Main Rotor, $()_T$ for Tail Rotor, $()_F$ for Fuselage, $()_{FN}$ for Vertical Fin and $()_{TP}$ for Horizontal Stabilizer. As it was said before, we can neglect the effect of fuselage and stabilizers.

The helicopter is controlled by four inputs: main rotor collective U_{col} , longitudinal U_{long} and lateral U_{lat} cyclic pitch, and tail rotor collective pitch U_{ped}. Servo actuators are linked to these control surfaces and are modeled by first-order transfer functions. A separate engine governor regulates the throttle in order to maintain a constant rotor speed.

2.2 Main rotor Thrust Magnitude

To determine main rotor thrust magnitude, two complimentary methods are used: momentum and blade element theory. The first method presented is momentum theory which yields an expression for thrust based on the induced velocity through the rotor disk. Because this is a single equation with two unknowns, a second expression is needed to make a solvable set of equations. This second equation is generated using blade element theory, which is based on the development of thrust by each blade element. The result of this section is a set of thrust equations that are solved by a recursive algorithm. The final thrust equation derived from momentum theory becomes: [15]

$$T = \rho . A . \sqrt{V^2 + (v_1 - \omega_r)^2} . 2 v_1 \tag{6}$$

Again, partially solving the equation for the induced velocity v_1 we get

$$v_1 = \sqrt{\frac{\hat{V}^2 + w_r(w_r - 2v_1)}{2} + \sqrt{\left(\frac{\hat{V}^2 + w_r(w_r - 2v_1)}{2}\right)^2 + \left(\frac{T}{2\rho A}\right)^2}} \tag{7}$$

In the final expression both thrust and induced velocity are unknown, in order to solve this, another expression for either thrust or velocity is needed. Therefore, blade element theory is used. The new total thrust equation that is generated by the main rotor blades is:

$$T = b.L = \frac{\rho}{4}.(\Omega.R)^2.b.c.R.a.(\theta_t - \phi_t) \tag{8}$$

Finally the results of the thrust generation section are obtained using the following equations:

$$\hat{V}^2 = u^2 + v^2 + (w . \beta_{1c} . \beta_{1s})^2 \tag{9}$$

$$w_r = w + u.\beta_{1c} + v.\beta_{1s} \tag{10}$$

$$v_1 = \sqrt{\frac{\hat{V}^2 + w_r(w_r - 2v_1)}{2} + \sqrt{\left(\frac{\hat{V}^2 + w_r(w_r - 2v_1)}{2}\right)^2 + \left(\frac{T}{2\rho A}\right)^2}} \tag{11}$$

$$T = \frac{1}{6}.\rho.\Omega^2.R^3.b.c.a.[(\theta_{col} + \frac{3}{4}.\theta_{tw}) - v_1 + w_r] \tag{12}$$

2.3 Thrust Vector

Here the main rotor and control rotor flapping equations are derived. The outputs of these equations are the TPP inclination described by the angles β_{1s}, β_{1c}, $\beta_{cr,1s}$ and $\beta_{cr,1c}$ for the main rotor and control rotor, respectively. The inputs to these equations are the moments affecting each blade element about the effective flapping hinge. The moments are comprised of the following: Gyroscopic Moments, Aerodynamic Moment Centrifugal Moments, Spring Moments, Inertial Moments and Gravitational Moments. By finding the equilibrium point between all moments affecting the blade, TPP angles can be found. [17]

$$\beta = \beta_{1s} \sin\psi_{MR} + \beta_{1c} \cos\psi_{MR}$$
$$\ddot{\beta}_{MR} + \Omega^2_{MR} \beta_{MR} = \frac{M_{a_{MR}}}{I_{b_{MR}}} \tag{13}$$

2.4 Rotor control

The control rotor acts as a lagged rate feedback in the pitch and roll axes, reducing the bandwidth and control sensitivity to cyclic inputs. From the swash plate, the control rotor receives longitudinal and lateral inputs, much like the main rotor. But unlike the main rotor, it does not receive any collective input, and thus does not produce any lift which would result in a coning angle of the control rotor. The control rotor tip path plane flapping can be modeled by [17]:

$$\beta_{cr} = -\beta_{cr,1s} \sin(\psi) + \beta_{cr,1c} \cos(\psi) \tag{14}$$

The procedure for obtaining the flapping angles are the same for the control rotor as was followed by the main rotor. By equating all of the moments that act on each paddle or rotor blade, it is possible to find the blade flapping angle.

$$\beta_{CR} = \beta_{C_{CR}} \cos\psi_{CR} + \beta_{S_{CR}} \sin\psi_{CR}$$
$$\ddot{\beta}_{CR} + \Omega^2_{CR} \beta_{CR} = \frac{M_{a_{CR}}}{I_{b_{CR}}} \tag{15}$$

The moments that have an effect on flapping angle are aerodynamic, inertial, centrifugal and gyroscopic. To find the flapping angle, the moments are equated to zero. From the longitudinal (M_{cosine}) and lateral (M_{sine}) moments, two differential equations describing longitudinal and lateral flapping are isolated. This gives the final result of the control rotor flapping equations.

$$\begin{aligned}\dot{\beta}_{cr,ic}(t) &= -\frac{1}{16}\Omega\gamma\varepsilon B_{sw,l} - \frac{1}{16}\gamma\varepsilon p(t) \\ &\quad -q(t) - \frac{1}{16}\gamma\varepsilon\beta_{cr,lc} - \frac{1}{16}\gamma\varepsilon\Omega\dot{\beta}_{cr,ls}(t)\end{aligned} \tag{16}$$

And

$$\begin{aligned}\dot{\beta}_{cr,ls}(t) &= \frac{1}{16}\Omega\gamma\varepsilon A_{sw,l} - P(t) + \frac{1}{16}\gamma\varepsilon q(t) \\ &\quad -\frac{1}{16}\Omega\gamma\varepsilon\beta_{cr,ls} + \frac{1}{16}\gamma\varepsilon\dot{\beta}_{cr,lc}(t) - \frac{\ddot{\beta}_{cr,lc}(t)}{2\Omega}\end{aligned} \tag{17}$$

Where the term ε is equal to:

$$\varepsilon = (-1 + \frac{R_1^4}{R^4}) \tag{18}$$

The flapping of the control rotor is mixed with the input from the swash plate ($A_{sw,l}, B_{sw,l}$) to form the complete pitch input of the main rotor. The mixing ratio between swash plate input and the control rotor input is governed by the mechanical links connecting the swash plate, control rotor and the main rotor. These gains (K_{sw} and K_{cr}) can be found by measurements of the pitch responds to a swash plate tilt or a control rotor flapping angle. The resulting inputs are thus:

$$\begin{aligned}A_1 &= K_{sw}A_{sw,l} + K_{cr}\beta_{cr,ls} \\ B_1 &= K_{sw}B_{sw,l} - K_{cr}\beta_{cr,lc}\end{aligned} \tag{19}$$

2.5 Main rotor Forces

After obtaining thrust magnitude, rotor control flapping angles and main rotor control angles, the total force produced by main rotor can be obtained by following equations:

$$\begin{aligned}X_{MR} &= -T_{MR}.\sin\beta_{1c} \\ Y_{MR} &= T_{MR}.\sin\beta_{1s} \\ Z_{MR} &= -T_{MR}.\cos\beta_{1c}.\cos\beta_{1s}\end{aligned} \tag{20}$$

2.6 Tail rotor

The equations defining the magnitude of the thrust are derived with respect to the main rotor blades; however, the same principles apply to the tail rotor, where β_{1s} and β_{1c} are zero. Furthermore the tail rotor rotational direction and the yaw rate, r, must be considered with respect to $w_{r,tr}$ and $\hat{V}_{tr}$; thus the tail rotor thrust equations are [15]:

$$\begin{aligned}\hat{V}_{tr}^2 &= u^2 + w^2 \\ w_{r,tr} &= v - l_t.r\end{aligned} \tag{21}$$

$$u_{1,tr} == \sqrt{-\frac{\hat{V}_{tr}^2 + w_{r,tr}(w_{r,tr} - 2u_{1,tr})}{2} + \sqrt{(\frac{\hat{V}_{tr}^2 + w_{r,tr}(w_{r,tr} - 2u_{1,tr})}{2})^2 + (\frac{T_{tr}}{2.\rho.A_{tr}})^2}} \tag{22}$$

$$T_{tr} = \frac{1}{6}.\rho.\Omega_{tr}^2.R^3.b_{tr}.c_{tr}.a_{tr}.[(\theta_{col,tr} + \frac{3}{4}.\theta_{tw}) - u_{1,tr} + w_{r,tr}] \tag{23}$$

The force produced by tail rotor is shown as follows:

$$Y_{tr} = -T_{tr} \tag{24}$$

2.7 Tail plane and vertical fin

As it was stated before, tail plane produces force in Z direction and vertical fin produces force in Y direction [15].

$$\begin{aligned}u_0 &= u - u_{wind} \\ v_0 &= v - v_{wind} - l_{tr} - V_{1tr} \\ v_0 &= v - v_{wind} + l_{hr}.q - V_{1mr}\end{aligned} \tag{25}$$

$$\begin{aligned}v_0 &= v - v_{wind} - l_{tr} - V_{1tr} \\ v_0 &= v - v_{wind} + l_{hr}.q - V_{1mr}\end{aligned} \tag{26}$$

$$\begin{aligned}Y_{vf} &= 0.5\rho S_{vf}(C_{L_a}^{vf}|u_0|v_0 + |u_0|u_0) \\ Z_{ht} &= 0.5\rho S_{ht}(C_{L_a}^{ht}|u_0|w_0 + |w_0|w_0)\end{aligned} \tag{27}$$

The overall model is implemented in MATLAB & SIMULINK environment for the design and evaluation of the controllers introduced in the following chapters.

3 PID Controller Design

It is well known that the elimination of offset is a major objective in the control of any system. The PID controller has been widely applied in engineering. Apart from its simple structure and relatively easy tuning, one of the main reasons for its popularity is that it provides the ability to remove offset by using integral action. Moreover, since PID (PI or PD) controllers are so widely used, one might expect that the structure should arise naturally, given reasonable assumptions of system internal dynamics and control performance specifications. A single-variable PID controller is composed of three terms, namely, (1) proportional, (2) integral, and (3) derivative [19]. Controller commands are executed in four channels. Two channels are controlled by longitudinal and lateral motion of cyclic and the two another are controlled by pedal and collective, respectively.

$$u = \left\{ u_{col} \quad u_{lat_{cyclic}} \quad u_{lon_{cyclic}} \quad u_{ped} \right\} \tag{28}$$

Input commands are defined separately in the two different phases of flight. For the first phase, vertical climbing, the commands are defined as follows:

$$\psi_{com}, \varphi_{com}, \theta_{com} = 0, \tag{29}$$

$V_{z_{com}}$ is determined so that helicopter vertical velocity is increased in the first one third of climbing. After that, vertical velocity remains constant and in the last one third, helicopter gains negative acceleration to reach to purposed height at $V_{z_{com}} = 0$. Define

$$e(t) = X_{comm} - X_{Meas} \tag{30}$$

$$X = [\varphi, \psi, \theta, V_z] \tag{31}$$

$$u_j(t) = Ke(t) + K_d \frac{d}{dt} e(t) + K_i \int e(t) dt, \; j = 1,2,3,4 \tag{32}$$

As mentioned, the goal of the second phase is to change the yawing angle from zero to 90 deg. Input commands are defined as:

$$\varphi_{com}, \theta_{com} = 0,$$
$$V_z, V_x, V_y = 0 \tag{33}$$

ψ_{com} is selected as follows:

$$\psi_{com}(t) = \begin{cases} 0 & t \le 20 \\ \frac{\pi}{2}(t - 20) & 20 < t \le 30 \\ \frac{\pi}{2} & 30 < t \end{cases} \tag{34}$$

3.2 PID controller verification

The Ziegler–Nichols tuning method has been used for tuning PID controllers. For verifying designed pid controller, we check the step response of both control channels. As shown below, the result of step response reveals good tuning of pid controller for both vertical speed and yaw channel.

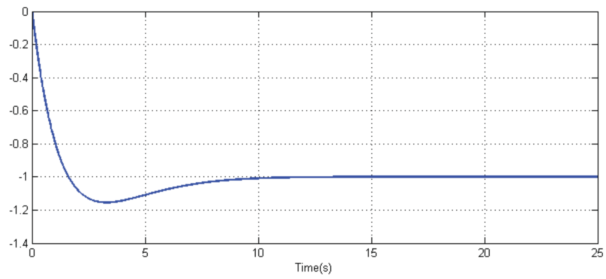


Figure 1. Step response of vertical speed controller channel V_z

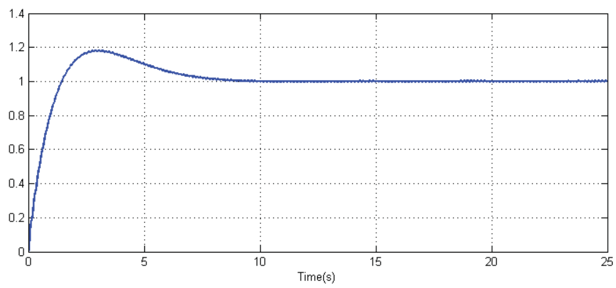


Figure 2. Step response of yaw controller channel

4 Brain emotional based intelligent controller (BELBIC) [20-21]

Emotions and their nature have been studied for a long time and psychologists have proposed a wide-range of different theories of emotion. Emotion has traditionally been conceived as something that is irrational and detractive from reasoning. But scientists have recently learned about the surprisingly positive roles played by human emotions especially in decision-making processes. A major motivation to mimic emotions in control engineering applications is the belief strongly held by the authors that in the development of intelligent control systems, too much attention has been focused on fully rational deliberative approaches, whereas in many real world decision-making situations human agents select their action via bounded rationality. Various factors like computational complexity, multiplicity of objectives, and prevalence of uncertainty leads desirability of more ad hoc rule-of-thumb decisions. Emotional decision-making is particularly appealing since it is neither completely cognitive nor entirely behavioral.

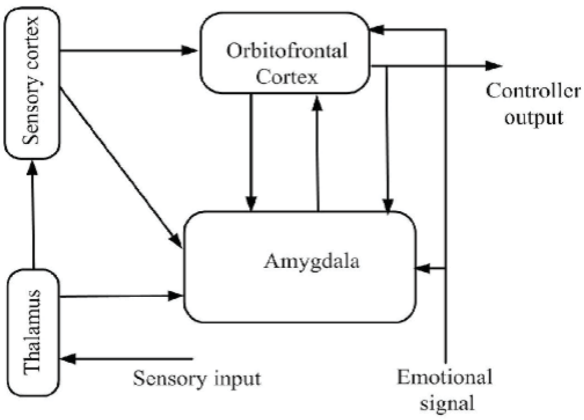


Figure 3. The abstract structure of the computational model mimicking some parts of mammalian brain.

The limbic system is seen as the seat of emotion, memory and attention in the brain [21]. Researchers have found that the amygdala and OFC, parts of the limbic system, play an important role in the coding of the emotional significance of sensory stimuli [22, 23, and 24]. Also neurons in the amygdala are driven particularly strongly by stimuli with emotional significance. During experiments to investigate the role of emotion in brain mechanisms, the amygdala and OFC have been implicated as the focal points that determine the emotional significance of many kinds of emotional stimuli [22, 23, and 24]. The emotional learning model in amygdala and OFC is illustrated in Fig. 1. BELBIC is essentially an action generation mechanism based on sensory inputs and emotional cues (reward signals). The emotional learning occurs mainly in amygdala. The learning rule of amygdala is given in following formula:

$$\Delta V_i = \alpha_a S_i \max(0, REW - \sum_i A_i) \tag{35}$$

Where is the gain in amygdala connection, α_a is the learning step in amygdala, S_i is sensory input at each instance, and *REW* and *A* are the values of reinforcing signal and amygdala output at each time. The term max in the formula (13) is for making the learning changes monotonic, implying that the amygdala gain can never be decreased as it is modeled to occur in biological process in amygdala [11]. Similarly, the learning rule in OFC is shown in formula (14).

$$\Delta W_i = \alpha_a S_i (E' - REW) \tag{36}$$

Where W_i the weight of OFC connection and α_a is OFC learning rate. The E' node sums the outputs from *A* except A_{th} (thalamic connection (4)) and then subtracts from inhibitory outputs from the *O* nodes, where it can be calculated as formula (15):

$$E' = \sum_i A_i - \sum_i O_i \quad \text{(not including } A_{th}\text{)} \tag{37}$$

in which, *O* represents the output of OFC. The thalamic connection (A_{th}) is calculated as the maximum overall stimuli *S* and becomes another input to the amygdala part:

$$A_{th} = \max(S_i) \tag{38}$$

There is one output node common in 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:

$$E = \sum_i A_i - \sum_i O_i \quad \text{(including } A_{th}\text{)} \tag{39}$$

In fact, by receiving the sensory input, the model calculates the internal signals of amygdala and OFC by the relations in (18) and eventually yields the output:

$$\begin{aligned} A_i &= S_i V_i \\ O_i &= S_i W_i \end{aligned} \tag{40}$$

Since amygdala does not have the capability to unlearn any emotional response that it ever learned, inhibition of any inappropriate response is the duty of OFC. Controllers based on emotional learning have very good robustness and uncertainty handling properties, while being simple and easily implementable. To utilize our version of the Moren–Balkenius model as a controller, it should be noted that it essentially converts two sets of inputs (sensory input and emotional cue) into the decision signal as its output. Closed loop configurations using this block (termed BELBIC) in the feed-forward-loop of the total system in an appropriate manner have been implemented so that the input signals have the proper interpretations. The block implicitly implemented the critic, the learning algorithm and the action selection mechanism used in functional implementations of emotionally based (or generally reinforcement learning based) controllers, all at the same time. In utilization of BELBIC, it should be pointed out that since this model has originally been proposed for descriptive purpose with no control engineering motivation, the model is essentially open-loop. To be used as a controller, the designer has to choose the sensory input fed back from the system response as well as the reward function in accordance with the control engineering requirements of the problem on hand and not merely from neuro-cognitive insights. The design of BELBIC, is therefore, no different from the design of any other non-linear and adaptive control schemes. The structure of the control circuit we implemented in this study is illustrated in Fig. 2.

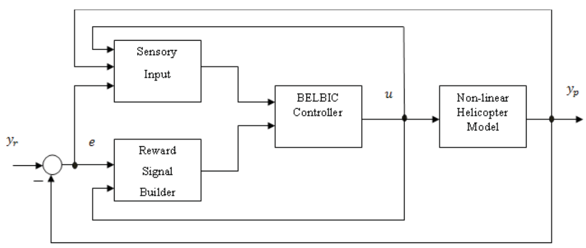


Figure 4. Control system configuration using BELBIC.

The implemented functions in emotional cue (REW) and sensory input blocks are given in (19):

$$\begin{aligned} REW &= J(S_i, e, y_p) \\ S_i &= f(u, e, y_p, y_r) \\ O_i &= S_i W_i \end{aligned} \tag{41}$$

As it is illustrated in (19), sensory input and reward signal can be arbitrary function of reference output, y_r, controller output, u and error (e) signal, and the designer must find a proper function for control.

5 BELBIC Controller setup and simulation results

In this section, the design procedure for intelligent Helicopter vertical speed, yaw channel control, and obtained simulation results are presented. V_z and yaw programs were explained in PID controller section.

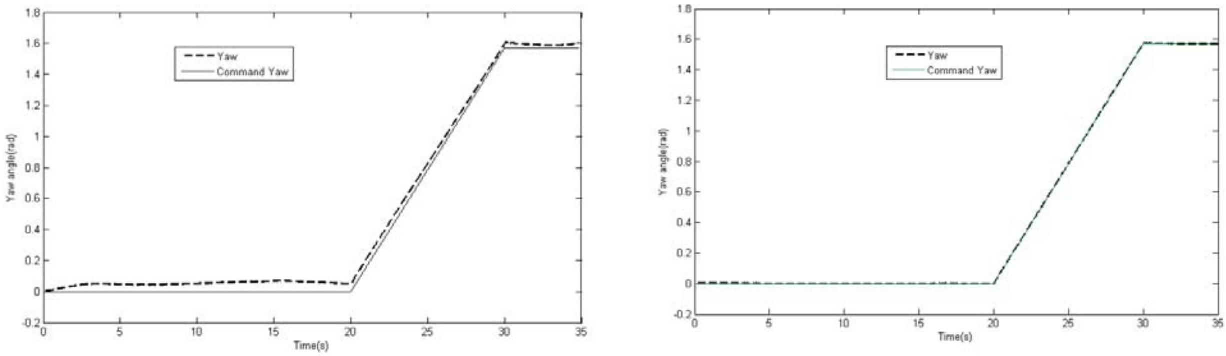
It was mentioned in Section 4 that the BEL based controller must be provided with a set of sensory input signal in addition to a reward signal. To accomplish the desired performance we have used sensory input and reward signal for V_z control channel as follows:

$$S = [100(V_{zc} - V_{zm}), 10\ V_{zc}] \tag{42}$$

$$REW = 10(V_{zc} - V_{zm}) + 5\int (V_{zc} - V_{zm})dt + 10\frac{d}{dt}(V_{zc} - V_{zm}) \tag{43}$$

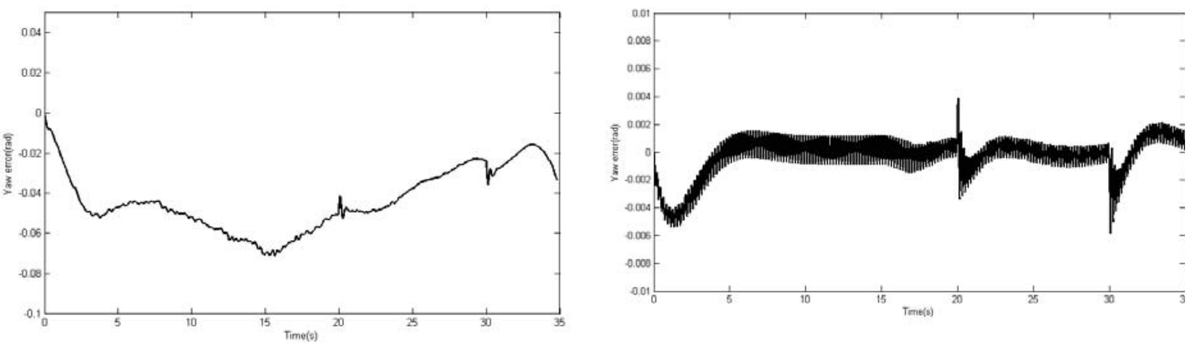
While the learning rate in amygdala and OFC was set at $\alpha_a = 1e-3$ and $\alpha_o = 1e-1$, respectively. The sensory input chosen for the helicopter control (20) has the reference command signal and the feedback error signal as its two components. The coefficients are chosen via trial and error. The reward function (21) is similar to a PID control scheme seeking a suitable tradeoff between quick adjustment of error and long-time elimination of the steady-state error. Using above data we can now proceed with simulations. The inputs to the controllers are V_z and yaw programs are illustrated in Fig.3and Fig.5 which have been previously designed in PID controller section. Simulation results for nominal trajectory following, in absence of any disturbance, are shown in Fig. 3-6. It can be seen clearly that the command signal is followed by BELBIC very closely with slight error in both V_z and yaw programs in respect to PID controller.

To demonstrate the robustness of proposed BELBIC, the control algorithm was executed in presence of a high frequency disturbance. The examination of simulation results (Fig. 9(b)) reveals that the proposed BELBIC is quite robust facing exerted disturbances and is able to reject them. While using PID controller, the system is not able to cope with the disturbances and instability occurs (Fig. 9(a)). The disturbance diagram is depicted in Fig. 8.



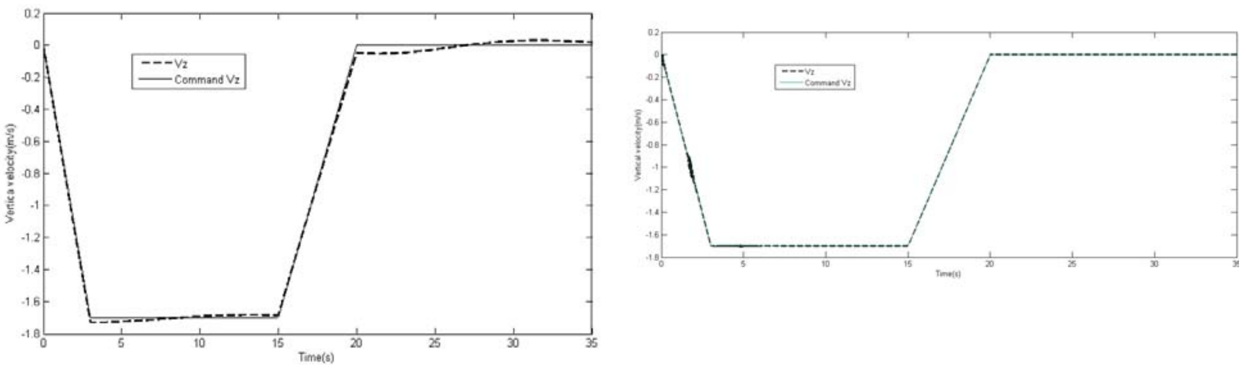
(a) (b)

Figure 5. Yaw channel tracking. (a) PID controller (b) BELBIC controller



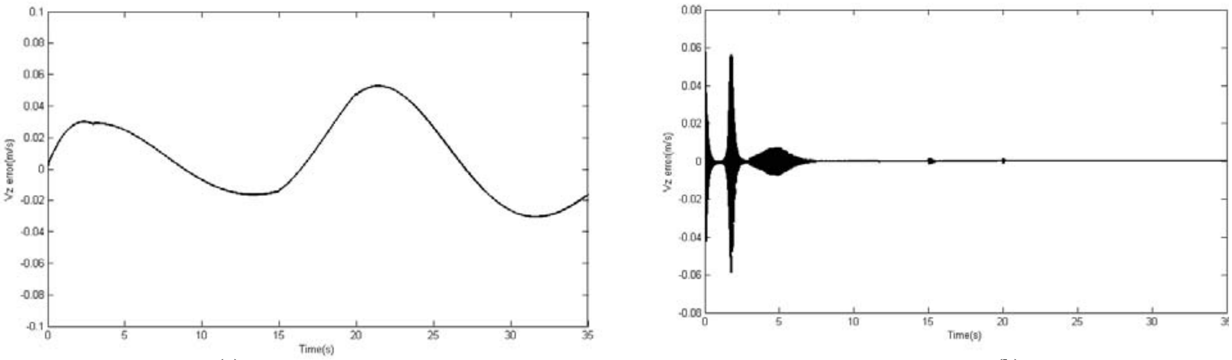
(a) (b)

Figure 6. Yaw angle error. (a) PID controller (b) BELBIC controller



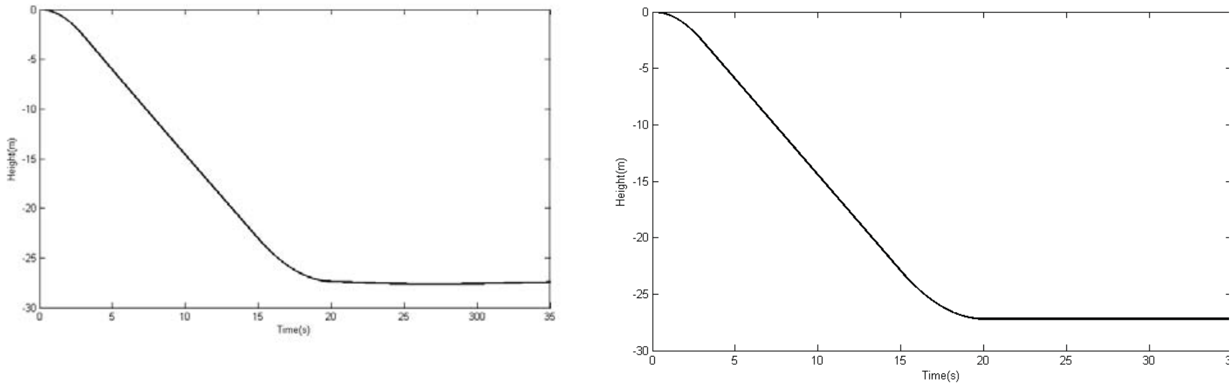
(a) (b)

Figure 7. Vertical Velocity program tracking. (a) PID controller (b) BELBIC controller



(a) (b)

Figure8. Vertical velocity tracking error. (a) PID controller (b) BELBIC controller



(a) (b)

Figure 9. Vertical Position. (a) PID controller (b) BELBIC controller

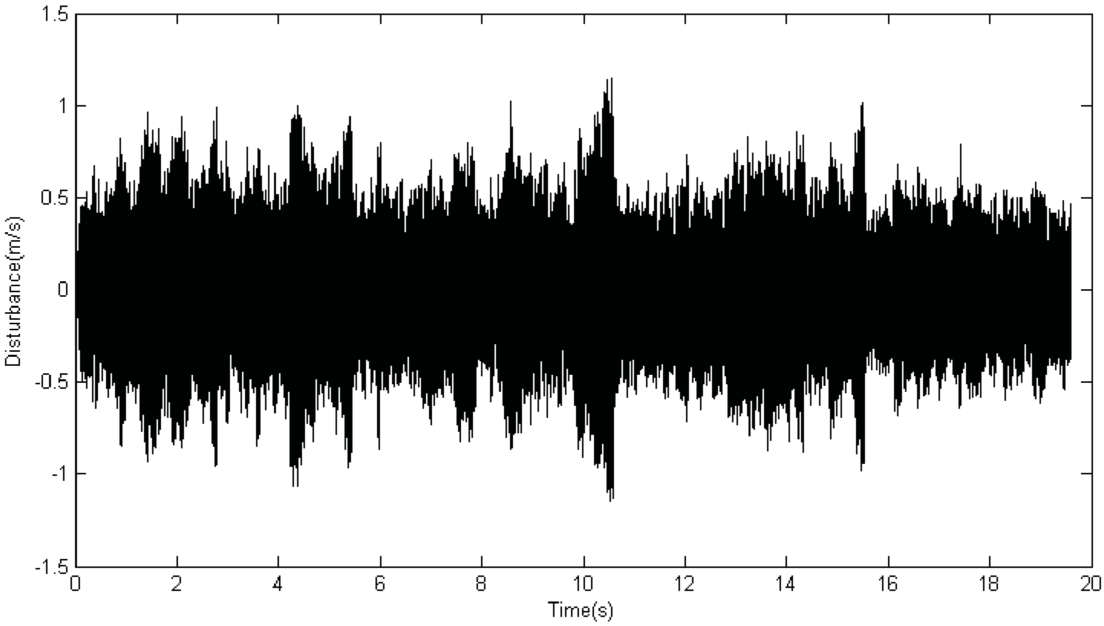
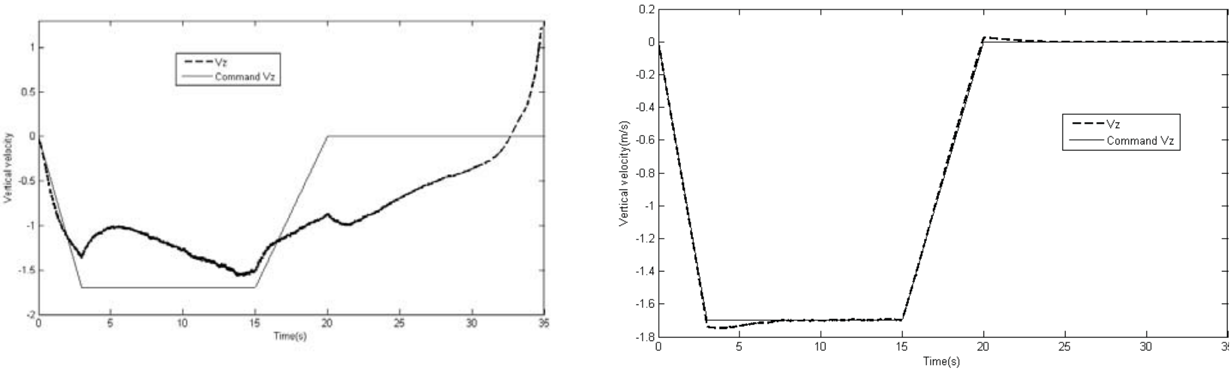
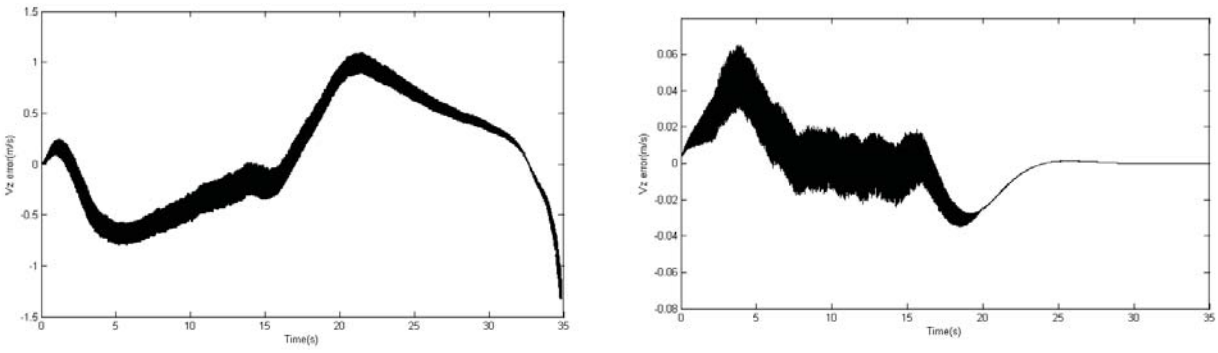


Figure 10. Exerted disturbance on vertical velocity



(a) (b)

Figure 11. Vertical velocity tracking in presence of high frequency disturbances. (a) PID controller (b) BELBIC controller



(a) (b)

Figure12- Vertical velocity tracking error in presence of high frequency disturbances. (a) PID controller (b) BELBIC controller

6 Conclusions

In this paper, application of on-line brain emotional learning based intelligent adaptive controller (BELBIC) has been introduced to maintain commanded attitude of a scale-model helicopter. A survey of results obviously implies that BELBIC shows effective performance in the presence of exerted uncertainties and disturbances when compared to classical PID controllers. Besides, due to simplicity of the proposed BELBIC which majorly is because of requiring little information about the system dynamics, implementing the controller is easily possible. Requiring less number of calculations compared to other adaptive controller strategies, meanwhile having better robustness performance are other advantages of BELBIC. The results show the applicability of the BELBIC for real world functions where high oscillated disturbances and unknown conditions make control process difficult for other controllers like classical PID. 10 Acknowledgment

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