ISSN 1512-1232

Momentum Based radial basic function neural controller for Pitch control of an Aircraft

C.S. Mohanty[a],P.S. Khuntia[b],D.Mitra[c]

[a]*C.S.Mohanty,Konark Institue Of Science and Technology,Bhubaneswar and 752050,India*
[b]*P.S.Khuntia, Konark Institue Of Science and Technology,Bhubaneswar and 752050,India*
[c]*D.Mitra, Indian School Of Mines,Dhanbad and 826004,India*

Abstracts:

In this paper Momentum based Radial Basic Function Neural Controller (MRBFNC) is designed for the pitch controller of an aircraft to obtain the desired pitch angel as required by the pilot. This controller utilizes a Momentum Factor α *, which adjusts the weights of RBFNC and controls the output of the Neural network. The performance of the MRBFNC is demonstrated for various conditions with change in the aircraft dynamics caused due to change in speed of the aircraft .A comparison between MRBFNC and conventional RBFNC is also establish to discuss the superiority of the former techniques.*

Keywords: *RBFNC, MRBFNC, Fuzzy Inverse Model, Pitch Control System*

1. Introduction

The conventional design methods of a control system often require a mathematical model describing the dynamic behavior of the plant to be controlled. When such a mathematical model is difficult to obtain due to uncertainty or complexity of systems the conventional techniques based on a mathematical model are not well suited. Artificial Neural Networks (ANN) in last decade has become popular for plant identification and control [1-2]. An advantage of the ANN is its ability to handle the nonlinear mapping of the input–output space It is well known that back propagation based ANN suffers from local minima and over fitting problems which is difficult to be implemented in real time due to a large number of neurons in the hidden layer in comparison to the RBFNC [3-4]. Locally tuned and overlapping receptive fields [5] have been found cerebral cortex visual cortex and in other parts of the brain. The concept of localized information processing in the form of receptive fields suggests that such local learning offers alternative computational opportunities to learning with global basis functions.

A novel and efficient method is proposed which implements a Radial Basic Function Neural Controller (RBFNC) with learning mechanism to control the pitch angle of an aircraft and to obtain the desired pitch angel as required by the pilot. This controller utilizes a learning mechanism, which observes the plant outputs and adjusts the weights of RBFNC, so that the overall system behaves like a "reference model" [6].

An efficient algorithm was proposed which based on Intrusion Detection, which utilizing both Artificial Immune Network and RBF neural network. The proposed method using multiple granularities artificial immune network algorithm to get the candidate hidden neurons firstly, and then, we training a cosine RBF neural network base on gradient descent learning process [7].

2. Radial Basic Function Neural Network:

Radial basic function networks are two-layer feed-forward. In RBF Networks the hidden nodes are implementing a set of radial basis functions (e.g. Gaussian functions).

In RBF the network training is divided into two stages:

- Weights from the input to hidden layer are determined.

ISSN 1512-1232

- Weights from the hidden to output layer is also determined.

The training/learning in case of RBF is very fast and networks are very good at interpolation. A radial basic function neural network is shown below

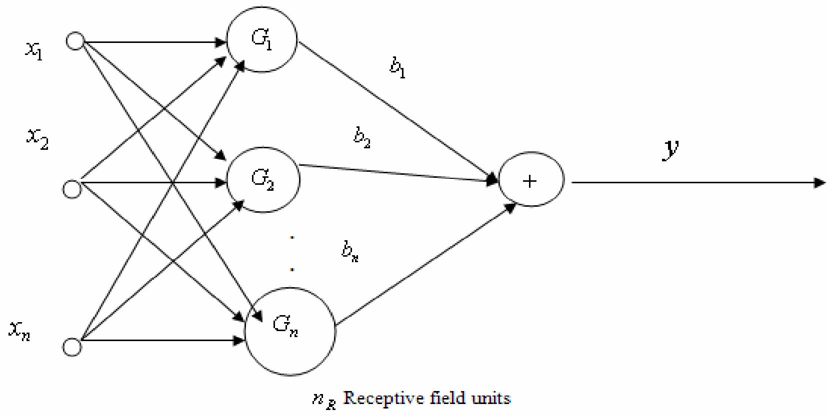

Figure 1: RBFNC for Aircraft Pitch Control

The proposed RBFNN model with single neuron output y is presented in figure-1 consists of three-layers [6]. Each input values are assigned to a node and passed directly to the hidden layer without weights. The hidden layer nodes are called Radial Basic Function (RBF) units which are determined by a parameter vector called center and a scalar called width. The Gaussian density function is used as an activation function for the hidden neurons. The RBFNN shown in Figure 1 has inputs $x_i, i = 1, 2, 3 \ldots n.$ and output $y = F_{rbf}(x)$. $x = [x_1, x_2, x_3, \ldots x_n]^T$ is the input and $R_i(x)$ is the output of the ith receptive field with strength denoted by b_i .Assuming n_R receptive fields present in the RBFNN, the output y can be written as

$$y = F_{rbf}(x,\theta) = \sum_{i=1}^{n_R} b_i R_i(x) \quad , \tag{1}$$

where θ holds the parameters of the receptive field units which consist of the parameters b_i and possibly the parameters of the $R_i(x)$. The Gaussian-shaped functions are preferred for analytical convenience i.e.

$$R_i(x) = \exp\left[\left|x - c^i\right|^2 \Big/ (\sigma^i)^2\right] \quad , \tag{2}$$

where $c_i = [c_1{}^i, c_2{}^i, \ldots c_n{}^i]^T$ parameterize the locations and σ decides the spreading of the receptive fields in the input space

The weighted average output of the RBF neural network can be written as

$$y = F_{rbf}(x,\theta) = \sum_{i=1}^{n_R} b_i R_i(x) \Big/ \sum_{i=1}^{n_R} R_i(x) \quad . \tag{3}$$

3. Problem Formulation:

Here the pitch control system of delta aircraft [8] is taken as plant whose pitch angle is to be controlled.

Longitudinal dynamics of a aircraft [8-9] can be described by the following equations.

$$\dot{u} = X_u u + X_w + W_0 q - g \cos \Theta_0 \theta \quad , \tag{4}$$

$$\dot{w} = Z_u u + Z_w w + U_0 q - g \sin \Theta_0 \theta + Z_{\delta_E} \delta_E \quad , \tag{5}$$

ISSN 1512-1232

$$\dot{q} = M_u u + M_w w + M_{\dot{w}} \dot{w} + M_q q + M_{\delta_E} \delta_E \quad , \tag{6}$$

$$\dot{\theta} = q \quad . \tag{7}$$

Substituting the values of stability derivatives of the aircraft for flight condition -3 in the above equations gives the following transfer function

$$\frac{\theta(s)}{\delta_E(s)} = \frac{1.5\,s + 1.386}{s^3 + 2.198s^2 + 1.222s} \quad . \tag{8}$$

4. Design of Momentum based RBF Neural Controller

The RBFNC for aircraft pitch control system is shown in the figure 2 tracks the desired pitch angle $\theta(kT)$ .The system has a Momentum factor [10] that is used to tune the output of the RBF network.

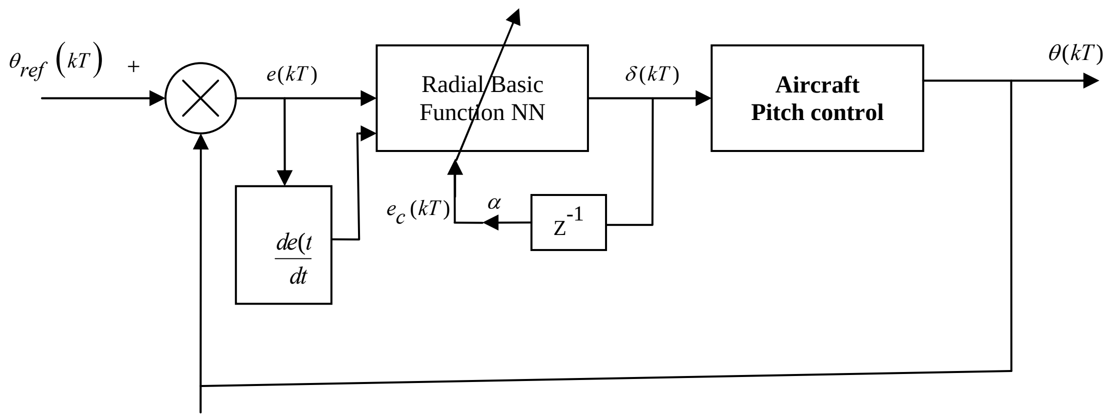

Figure-2: Proposed RBFNC Control for aircraft pitch control

As shown in Figure 2 the α , $e(kT)$, $e_c(kT)$ and $\theta(kT)$ is used to adjust the weights of the neural controller i.e. $b_{i.,}$ where

$$e(kT) = \theta_{ref}(kT) - \theta(kT) \, , \; e_c(kT) = \frac{e(kT) - e(kT - T)}{T}$$

and T is the sampling time. The output of the RBF neural controller $\delta(k)$ is computed by taking $e(k)$ and $e_c(k)$ as the argument to the radial basic function

$$\delta(k) = F_{rbf}\left(e(k), e_c(k), \alpha, \delta\left(k-1\right)\right) \, , \tag{9}$$

where α = Momentum Factor,
$\delta(k-1)$ = Previous output of neural controller.

It is decided in the designing of pitch controller that elevator should not to exceed more than $\pi/2$ radian in either upward or downward direction or the change of error should not be more than 0.01 radian/sec. It concludes range of error $e(kT)$ and change of error $e_c(kT)$ are $e(k) \in [-\pi/2, \pi/2]$ and $e_c(k) \in [-0.01, 0.01]$. A uniformly grid is created by taking the error and the change of error with the corners of the grid are placed at $(-\pi/2, -0.01)$, $(-\pi/2, 0.01)$, $(\pi/2, 0.01)$ and $(\pi/2, -0.01)$. Each point on the grid contains a receptive field which is a Gaussian function . The error and change of the error's spreading (σ) are taken differently as

$$\sigma_c = 0.7\frac{0.02}{\sqrt{n_G}}, \quad \sigma_e = 0.7\frac{\pi}{\sqrt{n_R}}$$

where n_G is the no of partitions on the grid (n_G=11 here), n_R is the no of receptive field units in RBFNC which is equal to, $n_R = nG^2$ (n_R=121). Each center which represents a RBF is represented by circle shown in the Figure 3.

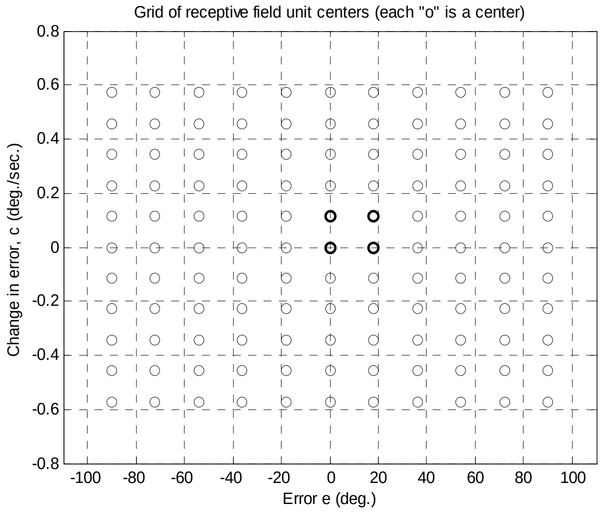

Figure 3: Receptive Field Unit Centers

The left most bottom circle $(-\pi / 2, -0.01)$ is counted as 1 and the counting increases by 1 making the left most top circle $(-\pi / 2, 0.01)$ to be numbered as 11.Next counting starts from bottom circle of the next column with number as 12 and the top most circle in that column is represented as 22.So the right most bottom circle $(\pi / 2, 0.01)$ is counted as 111 and top most circle is counted as 121 $(\pi / 2, -0.01)$. The input and output mapping of the radial basis function neural network is shaped by choice of scaling parameters b_i . Assuming the scaling and summation of the receptive field units with centers at the four dark shaded circles shown in Figure-1(the indices here are assumed to be 61, 62, 72 and 73) is $2R_{61}(e,c) + 3R_{62}(e,c) + R_{72}(e,c) + 2R_{73}(e,c)$. The scaling and summing is computed and shown in Figure 4.

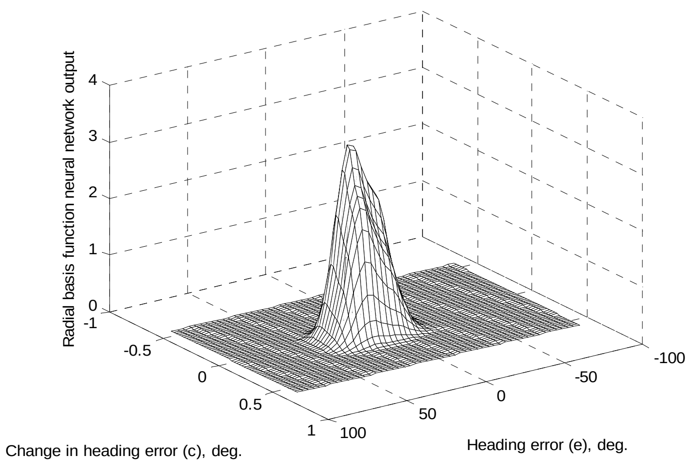

Figure 4: Scaling and Addition of many Receptive Fields

$2R_{61}(e,c) + 3R_{62}(e,c) + R_{72}(e,c) + 2R_{73}(e,c)$

ISSN 1512-1232

A single receptive field $R_{73}(e,c)$ without scaling is shown in Figure 5.

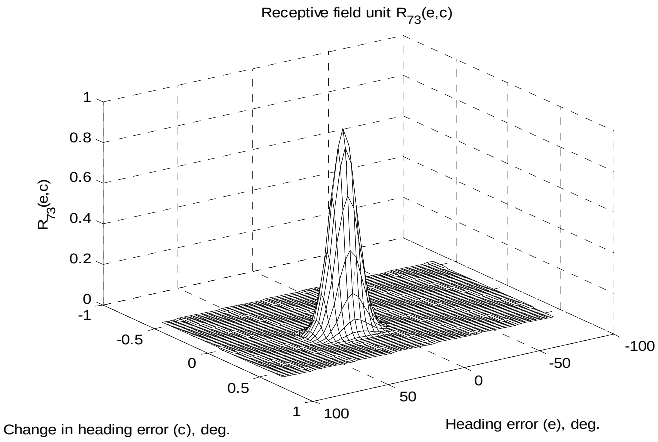

Figure 5: Single receptive field $R_{73}(e,c)$

For the receptive field the parameter σ of the Gaussian function decides the spreading of the Gaussian function. The error and change of the error's spreading (σ) are different and are taken as

$$\sigma_c = 0.7 \frac{0.02}{\sqrt{nG}}, \sigma_e = 0.7 \frac{\pi}{\sqrt{nR}}$$

where nG is no of partitions on each edge of grid (here nG =11), nR is the no of receptive field units in RBF Neural Controller which is equal to, $nR = nG^2$ (here nR =121).

5. Simulation Results

The reference signal is a pulse signal of duration 25 seconds and the flight travels with constant speed of 253 m/sec of a delta aircraft (flight condition-3) .A reference pitch angle of 5 degree is given as input to the aircraft and to the reference model simultaneously. The output which is the actual pitch angle follows the reference trajectory of reference model output .The following figures illustrates the responses of the flight condition-3 with momentum factor and without momentum factor. The figure-6 explains the trajectory of the actual pitch angle $\theta(kT)$ and the desired input and the output of the RBF Neural controller to the plant to maintain the reference trajectory.
Closed Loop Response of the proposed system without momentum ($\alpha = 0$)

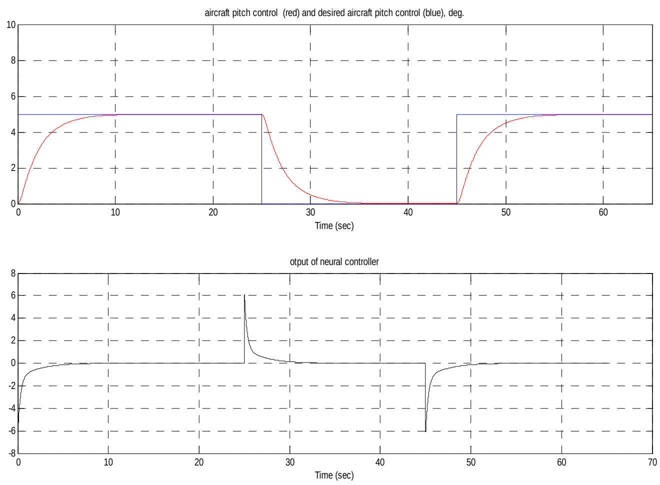

Figure 6: Response of Simulation Without momentum

ISSN 1512-1232

Closed loop response of proposed system with momentum ($\alpha = 0.9$).

The figure-7 explains the trajectory of the actual pitch angle $\theta(kT)$ and the desired input with momentum factor $\alpha = 0.9$, and output of the RBF Neural controller to the plant to maintain the reference trajectory.

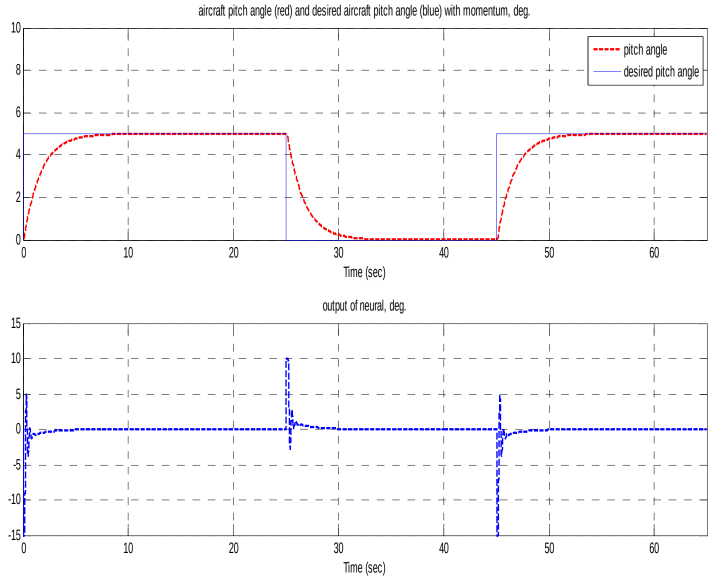

Figure 7: Response of Simulation with momentum

Comparison of closed loop response (without and with momentum) for $(\alpha = 0, \alpha = 0.9\ )$

The figure-7 explains the comparison of pitch angle $\theta(kT)$ without and with momentum ,comparison output of the RBF Neural controller to the plant.

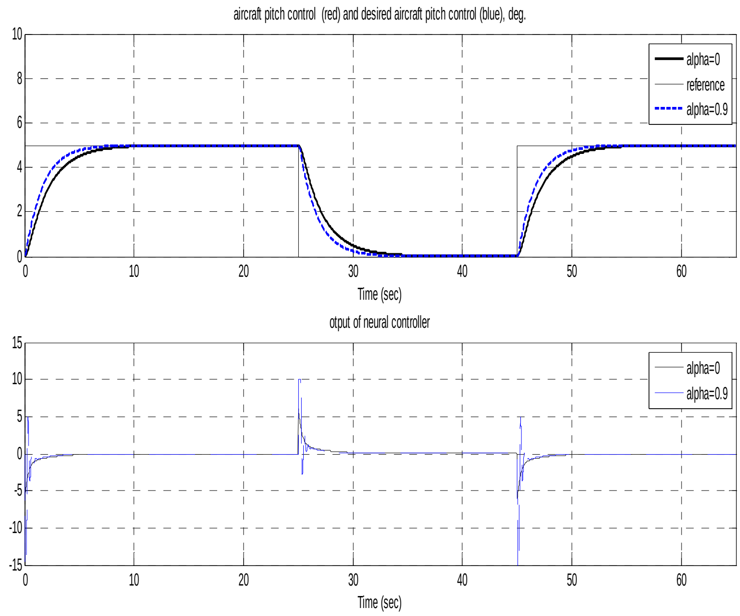

Figure 8 Comparison Response of Simulation between with and without momentum

Comparison of closed loop system of Aircraft for different values of momentum factor

($\alpha = 0.4, \alpha = 0.9, \alpha = 0$)

ISSN 1512-1232

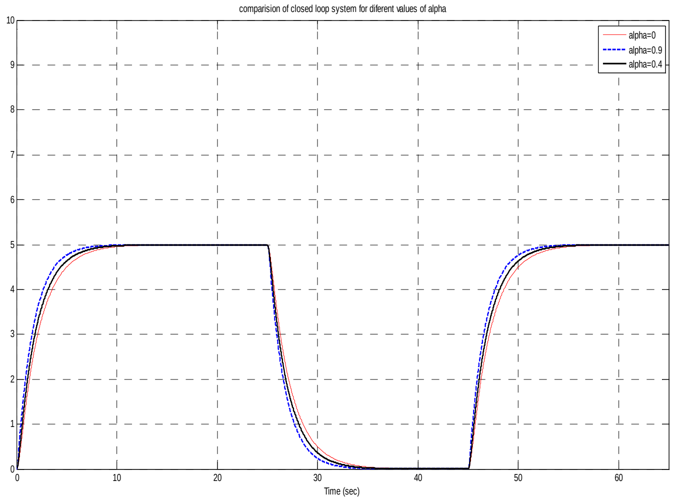

Figure 9 Comparison of Response for different value of momentum factors

6. Conclusion

The non zero value of the RBF neural network output exhibits its adoptive nature whenever the actual pitch angle differs from its reference value and at the time of transition of the reference signal. When the speed of the aircraft is changed the control signal to the pitch control system also changes to cope up with the speed change. It is also shown in this simulation the use of momentum factor tunes the output of the RBF neural network. The Figure 8 shows that a comparative analysis of closed loop response between conventional and momentum based RBF neural network which shows that the Momentum based system has a better response than the Conventional RBF network. In figure 9 the response of the Pitch control system varies according to the value of Momentum factor (α).It is concluded that with increase in value of α the response $\theta(k)$ becomes settles faster early to the reference value. Considering α beyond 1 results distorted value and does not fallow the trajectory.

References:

1. K.S.Narendra and K.Parthasarathy, "Identification and Control of Dynamical Systems using Neural Networks," *IEEE Trans. on Neural Networks*, vol. 1, no. 1, pp.4–27, Mar. 1990.
2. S. Suresh, N. Kannan, S. N. Omkar and V. Mani "Nonlinear Lateral Command Control Using Neural Network for F-16 Aircraft", American Control Conference, 2005. June 8-10 Portland, USA .
3. Y. Li, , N.Sundararajan and P.Saratchandran, ,"Neuro-Controller Design For Nonlinear Fighter Aircraft Maneuver Using Fully Tuned RBF Networks," *Automatica*, Vol. 37, No. 8, 2001.
4. Ming-guang Zhang, Xing-gui Wang, Man-qiang Liu" Adaptive PID Control Based on RBF Neural Network Identification" Proceedings of the *17th IEEE International Conference on Tools with Artificial Intelligence*,2005, IEEE Computer Society.
5. S.Schaal, and C.Atkeson, Constructive Incremental Learning from Only Local Information, *Neural Computation,* 10, 2047–2084, 1998.
6. P.S Khuntia and D.Mitra, Radial Basic Function Neural Controller for Pitch Control of an Aircraft, *Georgian Electronic Scientific Journal: Computer Science and Telecommunications*, No.2 (19), 2009.
7. YongJin Zeng and JianDong Zhuang, Construction cosine radial basic function neural networks based on artificial immune networks, Proceedings of the *6th international*

ISSN 1512-1232
conference on Advanced data mining and applications, 134-141, Springer-Verlag Berlin, Heidelberg, 2010.
8. Automatic Flight Control Systems, Mclean Donald, Prentice Hall International (UK) Ltd, 1990.
9. Advances in aircraft flight control, M. B. Tischler, UK: Taylor & Francis, 1996.
10. Yonghomg Tan, Dang xuanju, A.Cauwenberghe, Generalized nonlinear PID controller based on neural networks, Proceeding of information, decision and control 1999, 519-524,Adelaide,SA,1999.

Article received: 2013-12-30