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Nonlinear Lateral Command Control Using Neural Network for F-16 Aircraft

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Abstract— **A discrete time neural network based lateral controller design for an F-16 nonlinear model is presented. The controller is designed using model reference indirect adaptive control and the input output representation and control law for nonlinear model are established using system theory. The input-output representation and control law are approximated using neural networks with linear filters. The design takes into account the multi input multi output nature of the lateral model. Roll rate and side slip commands are used to generate reference signals and the neural networks are trained to follow the reference signals. Nonlinear simulation results are given to prove the effectiveness of the controller.**

I. INTRODUCTION

Research in adaptive feedback control of nonlinear systems is motivated by many real time applications like high performance flight control systems, active control of flexible structures, fluid flow and combustion process. Accurate estimation of the system nonlinearities of present day high performance fighter aircraft under stringent flying quality requirements and complex maneuvers is especially difficult. The classical control system for modern aircraft are designed to give satisfactory performance under nominal operating conditions and are unable to cope with severe unknown nonlinearities including inertial and kinematic couplings and control surface failures. Although the conventional controller may assure stability, the tracking performance will be poor under such conditions. Hence, new design tools need to be explored to control such systems.

The emergence of the neural network paradigm as a powerful tool for learning complex mappings from set of examples has generated a great deal of research in using neural network models for identification and control of dynamical systems with unknown nonlinearities [1]–[3]. Due to their approximation capabilities as well as their inherent adaptivity features, neural networks present a potentially appealing alternative to modeling of nonlinear systems. Furthermore, from a practical perspective, the massive parallelism and fast adaptability of neural network implementations provide incentive for further investigating the connectionist approach in problems involving dynamical systems with unknown nonlinearities.

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In [4], a neural control scheme based on inversion of a linearized plant model is proposed. Inversion errors are compensated through multilayer perceptron neural networks. This method is proven to be effective in many applications including systems operating in a highly nonlinear aerodynamic regime [4], systems with rapidly varying nonlinear dynamics [5], [6] and systems with high levels of uncertainties [7]. This approach is commonly referred as feedback error learning technique, where the inner conventional controller stabilizes the aircraft while the outer neural network is expected to compensate for any deviation from command signal under uncertainties. Recently, in [8], [9], it is shown that neural networks with on-line learning capabilities can adapt to changes in aircraft dynamics undergoing highly nonlinear maneuvers. Use of neural networks for nonlinear flight control system is summarized in [10]. Apart from nonlinearities and uncertainties, restructurable flight control systems for sensor and actuator failures have also gained attention in recent times [11]. Reconfigurable flight control law for tailless aircraft has been investigated with off-line - online learning strategy in [12], [13]. A complete survey of adaptive neural control systems for various applications is presented in [14].

A single reconfigurable neural controller to achieve simultaneous stabilization and tracking is presented in [15], where an indirect adaptive strategy based neural controller is designed for an unstable unmanned air vehicle. A fault tolerant controller is designed using a neural network for the linear model of the aircraft. In order to overcome bounded input bounded output stability constraint for neural controller design an off-line (finite time interval) - online training strategy is used. However, linearisation often leads to loss of information about nonlinearity effects and is often valid only in the small neighborhood of equilibrium point.

The present work aims to design a discrete time lateral neural controller using model reference adaptive control for a nonlinear MIMO model of an F-16 aircraft. The neural network architecture and the corresponding learning algorithm used in this paper are similar to [15]. The reference inputs are roll rate and side slip commands and the reference models are chosen to satisfy flying quality requirements. The advantage of the present work is that simultaneous decoupling of roll rate and side slip responses can also be incorporated in the design to achieve coordinated turn.

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This paper is organized as follows: Mathematical preliminaries required to design a neural controller for nonlinear plant is given in section II. Section III deals with Model Reference Indirect Adaptive Neural Control and its different stages. In section IV the nonlinear model of F-16 and its linearized lateral model at level flight condition are presented. This section also describes the selection of reference model based on flying quality requirements. Simulation results are presented in section V and section VI concludes the paper.

II. Mathematical Preliminaries

Consider a class of discrete-time, time-invariant dynamical systems ($\sum$), with input-state-output representation:

$$\sum : \quad \begin{aligned} x(k+1) &= F\left[x(k), u(k)\right] \\ y(k) &= G\left[x(k), u(k)\right] \end{aligned} \tag{1}$$

where $x(k) \in X$, is the state vectors of dimension n, $y(k) \in Y$, the output vector of dimension p and $u(k) \in U$ the bounded input of dimension m.

For deriving the input-output representation of the dynamical system and unique control law, we impose mild assumptions on the nonlinear dynamical system:

A1 Given a class U of admissible inputs $u \in U := \{u : \|u(k)\| \leq \Delta\}$, where Δ is any positive real number, then for any $u \in U$ and for any finite initial condition $x^0 \in \Omega_x$ where Ω_x is a small neighborhood around the equilibrium point, the state and output trajectories do not escape to infinity in finite time, i.e., for any finite $T > 0$, we have $\|x(k)\| + \|y(k)\| \leq \infty$.

A2 The functions $F[.,.]$ and $G[.,.]$ are continuous with respect to their arguments. Furthermore, the function $F[.,.]$ satisfies a local Lipschitz condition so that the solution is unique for all finite initial conditions and bounded inputs.

In order to derive the unique control law, the nonlinear system defined in equation 1 can be linearized about a given equilibrium point using the assumption **A2** as:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + f(x, u, k) \\ y(k) &= Cx(k) + Du(k) + g(x, u, k) \end{aligned} \tag{2}$$

where $f(.,.,.)$ and $g(.,.,.)$ are higher order functions [18].

In [3], it has been shown that if the linear system derived from the nonlinear model is controllable and observable, the stabilization and regulation problems for nonlinear systems are solvable. Therefore, the state vector of nonlinear systems can be reconstructed from the input and output together with their past values. In such a case, a local Nonlinear Auto-Regressive Moving Average (NARMA) model exists for the plant described by equation (1).

$$\begin{aligned} y(k+d) = \; & F[u(k), u(k-1), \cdots, u(k-n_1+1), \\ & y(k), y(k-1), \cdots, y(k-n_2+1)] \end{aligned} \tag{3}$$

where n_1 and n_2 are the order of past inputs and outputs and d is the relative degree of the system.

Now, the objective of our problem is to design a control law such that for any arbitrary bounded reference output sequence $y^m(k)$, $y^m(k) \in \Omega_y := \{y^m : \|y^m(k)\| \leq \Delta_2, \forall k \geq 0\}$ determine u^* that results in,

$$\lim_{k \to \infty} \|y(k) - y^m(k)\| \to 0 \tag{4}$$

It has been shown in [3] that the asymptotic stability of the zero dynamics together with a well defined relative degree assures the existence of control input that can make the dynamical system follow any arbitrary bounded signal y^m. In such case, the control law has the following form

$$\begin{aligned} u^*(k) = \; & \bar{G}[u(k-1), u(k-2), \cdots, u(k-n_1+1), \\ & y(k), \cdots, y(k-n_2+1), y^m(k+d)] \end{aligned} \tag{5}$$

where $\bar{G}(.,.)$ is known to exist and is unique.

A. Reference Model

The reference signal $y_m(k)$ is generated from the stable dynamical system

$$\begin{aligned} x_m(k+1) &= A_m x_m(k) + B_m r(k) \\ y_m(k) &= C_m x_m(k) \end{aligned} \tag{6}$$

where A_m, B_m and C_m are system matrix and $r(k)$ is the reference input signal. The NARMA representation of the observable reference model is given by

$$\begin{aligned} y_m(k+d) = \; & \bar{F}_m[y_m(k-1), \cdots, y_m(k-n), \\ & r(k), .., r(k-n)] \end{aligned} \tag{7}$$

where $\bar{F}_m[.]$ is a smooth and continuous function.

If the plant output follows the reference signal accurately then the control law given in equation (5) can be simplified using equation (7) as

$$u^*(k) = \bar{G}\left[y(k-1), ..., y(k-n), r(k), \cdots, r(k-n)\right] \tag{8}$$

The above function map ($\bar{G}[.]$) is known to exist and is unique. The function form of the controller equation is known, hence, neural networks architecture can be used to approximate the function map $\bar{F}[.]$ and $\bar{G}[.]$ using input output data set. For this purpose, we use model reference indirect adaptive control scheme.

III. Model Reference Indirect Adaptive Neural Control

The objective of Model Reference Indirect Adaptive Neural Control (MRIANC) scheme is defined quantitatively as: Given an aircraft model, a reference model (R_M) and a pilot input (r), determine the input to the aircraft (u^*) (which will be the output of the neural network controller) so that the response of the aircraft (y) follows the reference model. The architecture of the MRIANC is shown in the Figure 1, where two neural networks namely identifier network (N_I) and controller network (N_c) are used. The identifier neural network is used to approximate the input/output relationship of the aircraft dynamics and the controller network is used to approximate the unique control

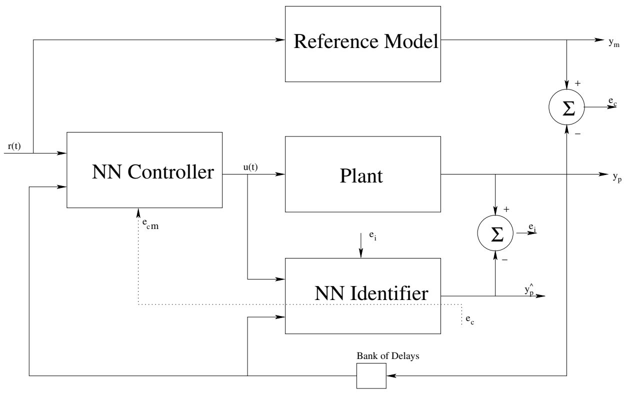

Fig. 1. Block Diagram of Model Reference Indirect Adaptive Control

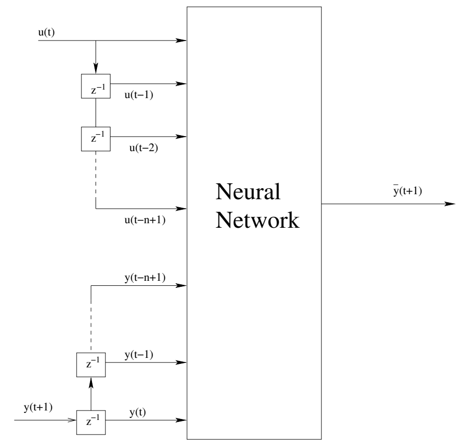

Fig. 2. Neural Network Architecture

law given in equation 8. In this paper, we use an off-line and on-line learning strategy presented in [15], to stabilize the aircraft and also to provide a good tracking performance. The off-line training procedure will be used to augment the stability of the aircraft and also provide the necessary tracking performance. The off-line trained neural network is than adapted online for unknown nonlinearities.

Now, the problem essentially has two parts, the first part of which is to derive the identifier model such that the neural model follows the aircraft dynamics accurately in some sense.

$$\|\hat{y}(t) - y(t)\| \quad < \quad \epsilon \ \forall t \in [0, T]$$

where $\hat{y}(k)$ is the neural model predicted output and ϵ is a small positive integer. The second part is to determine the controller network for the given identifier model, and to ensure that the aircraft output follows the reference model outputs accurately. The convergence of the controller neural network depends on the accurate modeling of the identifier network.

A. Neural Identifier

One of the basic requirements in using the neural network architectures to identify the nonlinear dynamical systems is the capability of these architectures to accurately model the behavior of a large class of dynamical systems that are encountered in real world problems. This leads to the question of whether a given neural network architecture would be able to approximate the input-output response of an unstable aircraft in some appropriate sense. The input-output response of the aircraft is represented in terms of network architecture and its weights. Therefore the representation capabilities of the given network depend on whether there exist a set of weight matrix (w_f) such that the neural network configuration approximates the behavior of a given system.

Based on the input/output representation given in equation (3), following the approach given in [17], one can construct a neural network model as shown in the Figure 2. The inputs to the neural network are the present input and past n inputs and outputs/response of the aircraft. The interconnection of static multilayer perceptron and dynamic elements (past inputs and outputs) is proposed for modeling the input-output response of the system described by (3). Such networks are called as neural network with linear filter (also known as time delayed neural networks). The input-output behavior ($u \rightarrow \hat{y}$) of a two-layer sigmoidal neural network ($N_I^{l,n_h,m}$) with l inputs, m outputs and n_h hidden neurons is given by

$$\begin{aligned} \hat{y}(k+d) &= N_I[y(k), \cdots, y(k-n_2+1), \\ &\qquad u(k), \cdots, u(k-n_1+1), w_f] \\ \hat{y}(k+d) &= N_I\left[V, w_f\right] \end{aligned} \tag{9}$$

where w_f is the weight matrix, V is the input to the neural network at any instant k and $N_I[.]$ is the neural network approximation for the function $F[.]$.

If we suppose that the system and the neural network model are initially at the same state, then we have to prove that there exists an optimal weight vector w_f^* such that the input-output behavior ($u \rightarrow \hat{y}$) of the neural network model (Equation. 9) approximates, in some sense, the input-output behavior ($u \rightarrow y$) of the aircraft dynamics (Equation. 3). The optimal weight vector w_f^* that approximates the system is given as

$$w_f^* \quad := \quad \min_{w_f \in B(w)} \left\{ \sup_{V \in \aleph} \|\hat{y}(k+d) - y(k+d)\| \right\} \tag{10}$$

where $\aleph$ is the set consisting of all network inputs V and target vector y_p. $B(w)$ is a (large) compact set of weight vector, $B(w) := \{w_f : \|w_f\| \leq \delta\}$ denotes a ball of radius δ. In adaptive law, the estimated weight vector w_f is also restricted to $B(w)$. The neural network weights are adapted based on the identification error $e(k)$ between the actual aircraft response and the neural network model.

$$e(k) \quad = \quad \hat{y}(k) - y(k) \tag{11}$$

Since, the inputs to the neural networks are independent of the present output of the aircraft, static backpropagation training algorithm is used to adapt the network weights.

B. Neural Controller

In this section we consider a strategy to choose an appropriate controller network to stabilize the unstable aircraft dynamics and also follow the arbitrary reference output signal generated from the reference model. The objective of the controller network is to approximate the control law given in equation (8). The mapping $\bar{G}[.]$ is not known. Hence, it is difficult to calculate the target $u^*(k)$ to train the controller network (N_c). The neural network architecture shown in figure 2 is used to approximate the unknown function $\bar{G}[.,]$. The input to the network (N_c) are the past reference inputs and response of the aircraft. The parameters of controller network are updated using a dynamic backpropagation algorithm [17]. The error (e_c) between the reference output (y^*) and aircraft response (y) is back propagated through the identifier network (N_I) to calculate the error at the output neurons of network N_c. Figure 2 shows explicitly the delayed inputs that are fed to the network (N_I). Let us suppose that the aircraft response depends on $u(k)$, $u(k-1)$, $u(k-2)$ and $u(k-3)$, and hence these are fed to the network N_I by delays from the single output (δ_e) of N_c. Initially we do not consider the other inputs such as past outputs of the aircraft to N_I, as they are not important to this discussion. For training N_c, we need to find the error at the output node of N_c, which is directly connected to the input node 1 of the network N_I. So, the error e_c is backpropagated through N_I to reach the node 1 in its input layer. Since the aircraft response depends on many previous inputs, the correct procedure to calculate the error at output node of N_c is dynamic backpropagation [17], i.e., propagate the error through delay line (z^{-1}). In practice this would mean that we have to backpropagate the error e_c up to all input nodes of N_I, and then add appropriately delayed versions of these errors to get the error at the output node of N_c. The performance index (J) for training process is defined as

$$J = \frac{1}{N}\sum_{k=1}^{N}(y(k) - y^*(k)) \tag{12}$$

The network weights are adjusted such that the performance index (J) is minimized.

IV. Aircraft Model

The aircraft model used in this study is similar to high-performance fighter aircraft model (F-16) [16]. Rigid body dynamics of aircraft is described globally (over the full-flight envelope) by a set of 12 nonlinear differential equations, corresponding to the six degrees of freedom. The continuous time equations are summarized as follows,

$$\frac{dx}{dt} = F_1(x, u, t) \quad y(t) = H_1(x, t)$$

where the symbols, $F_1(.,.)$ and $H_1(.,.)$, denote nonlinear functions known reasonably accurately as a mix of analytic expressions and tabular data [16]. The elements of *body-axes state vector* will comprise, the components of the velocity vector v_B, the vector of Euler angles Φ, the angular rate vector ω_B, and the position vector P_{NED}. The state vector can be described as

$$X^T = [U\ V\ W\ \phi\ \theta\ \psi\ P\ Q\ R\ p_N\ p_E\ h]$$

The aerodynamic forces and moment components are function of control surface deflections and these deflections form inputs to the model. The control input vector comprises of throttle setting, elevator deflection, aileron deflection and rudder deflection.

$$U^T = [\delta_t\ \delta_e\ \delta_a\ \delta_r]$$

The complete aerodynamic data acquired from wind tunnel tests cover a wide range of angle of attack $-10° < \alpha < 45°$ and slideslip angle $-30° < \beta < 30°$. The aircraft is powered by an afterburners turbofan jet engine. The deflection limits of aileron and rudder are $\pm 21.5°$ and $\pm 30°$ respectively.

In this section, the performance results of the proposed neural controller developed in previous section is presented based on a nonlinear fighter aircraft (F16) model executing coordinate turn command. For this purpose, the aircraft is trimmed at velocity of $V_t = 500$ft/sec, angle of attack of $\alpha = 2.837°$ and altitude of 5000ft. The linear continuous time lateral model of the F16 aircraft at this flight condition is,

$$A = \begin{bmatrix} -3.598 & 0.1968 & -35.180 & 0 \\ -0.0377 & -0.3579 & 5.884 & 0 \\ 0.0688 & -0.9957 & -0.2163 & 0.0733 \\ 0.9947 & 0.1027 & 0 & 0 \end{bmatrix}$$
$$B = \begin{bmatrix} 14.65 & 6.538 \\ 0.2179 & -3.087 \\ -0.0054 & 0.0516 \\ 0 & 0 \end{bmatrix} \tag{13}$$

where the states of the system are roll rate, yaw rate, roll angle and side slip. The pole at -0.0258 corresponds to the stable spiral mode, $-0.396 \pm 2.74i$ to the dutch roll mode and -3.35 to the roll subsidence mode. The system dynamics satisfy both conditions of controllability and observability for the outputs of roll rate, roll angle and yaw rate [17], [18]. Hence, the input output representation and unique control law to meet tracking requirements exist at this flight condition.

A. Flying Quality Requirements

Any flight control system performance is evaluated by its ability to satisfy the flying quality requirements of the vehicle, to ensure mission completion and safety. The reference model used in this study is based on the Military Specification standards (MIL-STD-1797A) [19]. These specifications describe the required aircraft responses in terms of transfer functions from the pilot stick to aircraft output. The requirements for lateral directional mode are as follows:

- Spiral time to double < 12 seconds

- Roll time constant (T_r) is less than one second
- Dutch roll damping (τ_d) is greater than 0.4 and dutch roll frequency is greater than 1.

From equation (13) the damping of the dutch roll mode is 0.143 and the undamped natural frequency is 2.77 rad/sec. It is obvious that the dutch roll frequency satisfies the flying quality specifications. However, the dutch roll damping is lower than the specifications and needs improvement. Based on the flying quality requirements, the reference model for roll rate and side slip reference models are chosen (in continuous time) as:

$$
\begin{aligned}
A_m &= \begin{bmatrix} -2.5 & 0 \\ 0 & -2.5 \end{bmatrix} \\
B_m &= \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \\
C_m &= \begin{bmatrix} 1.25 & 0 \\ 0 & 1.25 \end{bmatrix}
\end{aligned}
$$

The inputs to the reference model are in inches of pilot stick deflections and the outputs are in radians. The diagonal nature of the reference model ensures decoupling of roll response and side slip response.

V. Simulation Results

The objective of the closed loop nonlinear simulation is to prove the effectiveness of the neural controller to follow reference roll rate command. The level of achieved decoupling between roll and side slip responses can also be monitored in this setup. The reference command inputs are in the form of a 4 second pulse of amplitude 0.2in and doublet of duration 1 second and amplitude 0.2in. The pulse command is required to monitor the bank angle hold capability of the closed loop system, while the doublet is need to confirm that the aircraft banks back to zero degrees.

The MRIANC developed for tracking the reference signal consists of two parts, identifier and controller. The off-line training strategy consists of training both the identifier and controller networks for finite time interval. The identifier network has 22 input neurons corresponding to 4 states and 2 inputs, 35 hidden neurons and 2 output neurons corresponding to roll rate and sideslip. The controller network consists of 16 input neurons, 55 hidden neurons and 2 output neurons corresponding to aileron and rudder commands. A 4th order difference equation is used to approximate the aircraft dynamics and control law. Both the controller and identifier networks are trained with a learning rate of 0.3, using pseudo random signals at various initial conditions.

The nonlinear F-16 dynamics and neural controller are implemented in MATLAB with a sampling period of 0.05 seconds. Figure 3 shows the roll rate, roll angle and side slip responses to a pulse roll rate command. The roll rate response follows the reference model output closely. The roll angle response shows that the aircraft can indeed hold a steady bank angle as is intended. The ratio of maximum side

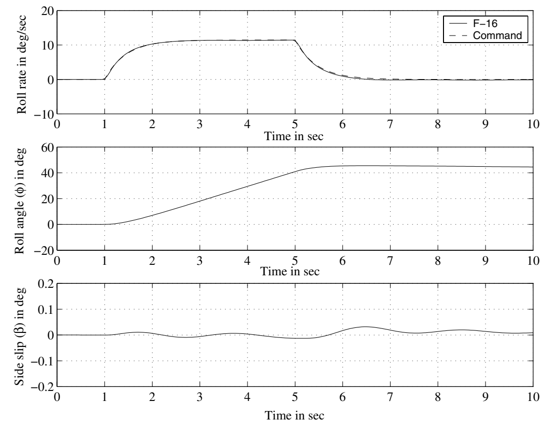

Fig. 3. Aircraft response for pulse command input

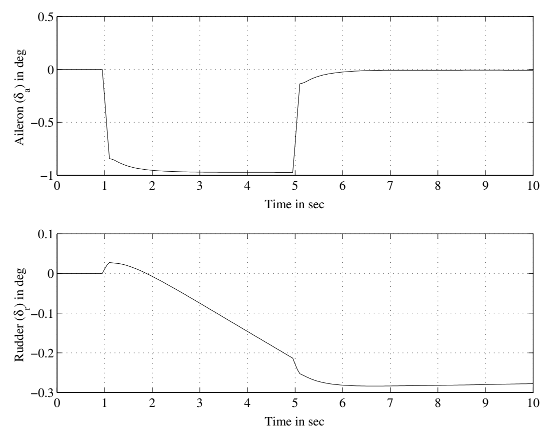

Fig. 4. Aircraft surface deflections for pulse command input

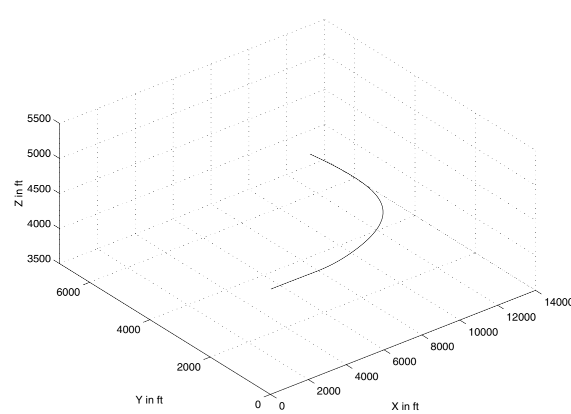

Fig. 5. Trajectory traced by the aircraft

slip angle to maximum roll angle is 0.0007 indicating very good decoupling. Figure 4 shows the aileron and rudder deflections. The maximum aileron and rudder deflections are 1 degree and 0.3 degrees respectively, which shows that the control surface deflections are well within limits. The trajectory traced by the aircraft to pulse response is shown in Figure 5. It can be seen that the aircraft executes a turn maneuver without any side motion. The aircraft also loses height due to loss in lift component as it banks.

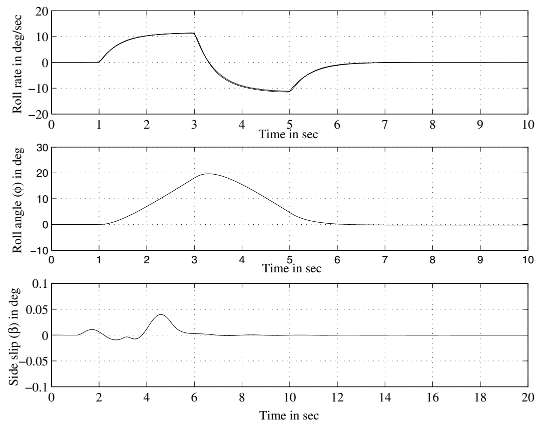

Fig. 6. Aircraft response to a doublet command input

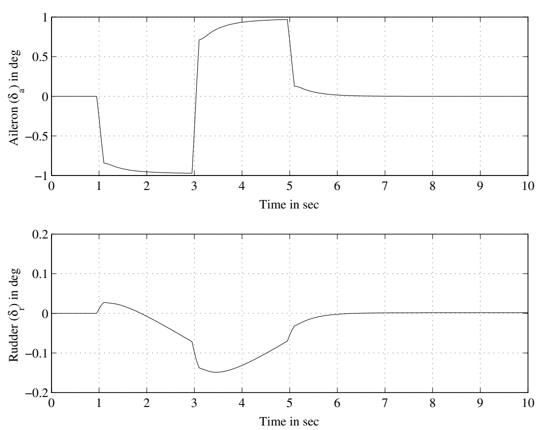

Fig. 7. Control surface deflection to a doublet command input

Figure 6 shows the aircraft response to doublet command input. The roll rate reaches a steady value of 12 degrees/sec during the first pulse and then reaches -12 degrees/sec before coming back to 0 degree. The roll angle reaches a maximum of 20 degrees before banking back to zero degrees. Again the ratio of maximum roll angle to side slip angle is small (0.004), indicating good decoupling. The aileron and rudder responses are shown in Figure 7. The maximum deflections are again seen to be within limits.

VI. Conclusion

A discrete time lateral neural controller based on model reference indirect adaptive scheme is presented for a nonlinear F16 model. The proposed scheme takes into account the multi input multi output nature of the aircraft model. The diagonal form of the reference model corresponding to roll rate and side slip commands helps in achieving complete decoupling of roll response and side slip response. Simulation studies prove the tracking ability of the closed loop system. Future work would involve incorporating longitudinal and lateral controllers in the nonlinear model to achieve altitude hold and coordinated turn.

References

[1] M. M. Gupta, and D. H. Rao, *Neuro-Control Systems: Theory and Applications*, New York, IEEE, 1994.

[2] D. A. White, and D. A. Sofge, *Handbook of Intelligent Control: Neural, Fuzzy, and Adaptive Approaches*, New York: Van Nostrand and Reinhold, 1993.

[3] A.J. Calise, "Neural Networks in Non-Linear Aircraft Flight Control", *IEEE Aerospace and Electronic Systems Magazine*, Vol. 11, No. 7, July 1996, pp. 5-10.

[4] A. J. Calise, M. Sharma, and J. E. Corban, "An adaptive autopilot design for guided munitions," *AIAA Guidance, Navigation, and Control Conference*, vol. 3, AIAA, Reston, VA, pp. 1776-1785, 1998.

[5] J. Leitner, A. J. Calise, and J. V. R. Prasad, "A full authority helicopter adaptive neuro-controller," *IEEE Aerospace Conference Proceedings*, vol. 2, Int. Electrical and Electronics Engineers, NY, pp. 117-126, 1998.

[6] F. Nardi, R. T. Rysdyk, and A. J. Calise, "Neural network based adaptive control of a thrust vectored ducted fan," *AIAA Guidance, Navigation, and control Conference*, vol. 1, AIAA Reston, VA, pp. 374-383, 1999.

[7] M. B. McFarland, and A. J. Calise, "Robust adaptive control of uncertain nonlinear systems using neural network," *Proc. American Control Conference*, vol. 3, American Automatic Control Council, Evanston, pp. 1996-2000, 1997.

[8] Y. Li, N. Sundararajan, and P. Saratchandran, "Neuro-controller design for nonlinear fighter aircraft maneuver using fully tuned RBF networks," *Automatica*, vol. 37, pp. 1293-1301, 2001.

[9] N. Sundararajan, P. Sarachandran, and Zhifeng Wang, "Robust neuro-H- controller design for aircraft auto-landing," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 40, no. 1, pp. 158-168, 2001.

[10] A. J. Calise, "Neural networks in Nonlinear aircraft Flight Control," *IEEE Aerospace and Electronics System Magazine*, vol. 11, no. 7, pp. 5-10, 1997.

[11] A. J. Calise, S. Lee, and M. Sharma, "Development of a reconfigurable flight control law for tailless aircraft," *Journal of Guidance, Control and Dynamics*, vol. 24, no. 5, pp. 675-682, 2001.

[12] T. Lee and Y. Kim, "Nonlinear adaptive flight control using backstepping and neural networks controller," *Journal of Guidance, Control and Dynamics*, vol. 24, no. 4, pp. 675-682, 2001.

[13] M. R. Napolitano, S. Naylor, C. Neppach, and S. Pispitsos, "On-line learning nonlinear neuro-controllers for restructurable control systems," *Journal of Guidance, Control and Dynamics*, vol. 18, no. 1, pp. 170-176, 1995.

[14] G. W. Ng, *Application of neural networks to adaptive control of nonlinear systems*, Research Studies Press, Tauton, U.K., pp. 43-77, 1997.

[15] S. Suresh, N. Kannan, S. N. Omkar and V. Mani, "Time bounded neural network command control design for unstable aircraft," *42nd AIAA Aerospace Sciences Meeting and Exhibit*, USA, AIAA Paper 2004-773, 2004.

[16] Brian L. Stevens and Frank L. Lewis, *Aircraft Control and Simulation*, John Wiley and Sons, 2003.

[17] K. S. Narendra, and K. Parthasarathy, "Identification and control of dynamical systems using neural networks," *IEEE Transactions on Neural Networks*, vol. 1, no. 1, pp. 4-27, 1990.

[18] I. J. Leontartis and S. Billings, "Input-output parametric models for non-linear systems, Part I: Deterministic non-linear systems," *International Journal of Control*, vol. 41, no. 2, pp. 303-328, 1985.

[19] Military Standards-Flying Qualities of Piloted Vehicles, *MIL-STD-1797A*, 1990.