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Flight control system design using neural networks

Abstract

The paper considers the problem of applying a neural design to the flight control of an aircraft. Simulation results are displayed in the case of a longitudinal autopilot for a remotely piloted vehicle.

Keywords: tracking, control, neural networks, aircraft, longitudinal, acceleration, altitude

Volume 5 Issue 3 - 2019

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Received: February 17, 2019 | **Published:** May 06, 2019

Introduction

In the last years, several control theories have been widely developed.[1–3] They are generally applied to control task such as trajectory tracking and optimization. In most cases, the control approaches are based on linear methods and on the assumption that precise analytical model of the controlled system is available. However, relationships between physical variables are non linear and only represented by discrete numerical tables. Recently, neural networks have been proposed as feed-forward inverse dynamics controllers. In addition, a number of flight control applications illustrated the on-line learning capability of neural networks.[4,5] This paper presents the design of a flight controller using neural networks. Emphasis is placed on the use of a command and stability augmentation system using an off-line trained network. The application is focused on a remotely piloted vehicle (RPV). The paper is organized as follows: Section 2 presents the longitudinal dynamics of a rigid airplane. The third section outlines the principles of a linear controller. The design of a neural controller is given in section 4. The effectiveness of the proposed approach is displayed by simulation results in the case of a longitudinal control.

Dynamics of flight

The equations governing the motion of an aircraft are a very complicated set of non-linear coupled differential equations. However, under certain assumptions, they can be decoupled into the longitudinal and lateral equations. Altitude control is a longitudinal problem, and in this application, we will design an autopilot that controls the altitude of an *RPV* aircraft.

The non linear equations of the longitudinal motion of a rigid aircraft can be written[6,7]

$$\begin{pmatrix} \dot{v} \\ \dot{\gamma} \\ \dot{\alpha} \\ \dot{q} \\ \dot{z} \end{pmatrix} = \begin{pmatrix} \dfrac{-D+T\cos\alpha - mg\sin\gamma}{m} \\ \dfrac{L+T\sin\alpha - mg\cos\gamma}{mv} \\ q-\dfrac{L+T\sin\alpha - mg\cos\gamma}{mv} \\ \dfrac{M}{I_y} \\ -v\sin\gamma \end{pmatrix} \qquad (1)$$

With v: airspeed, γ : flight path angle, α: angle of attack, q pitch rate, z: altitude, D: drag force, L: lift force, M: pitching moment, I_y: y-axis moment of inertia, m: aircraft mass, g: gravity acceleration and δm: elevator angle, T: thrust. δm is taken as the control input of the airplane longitudinal motion.

By using the complete model (eq. 1), we can simulate the longitudinal responses of the considered airplane at a flight point, $z_0 = 2500\ m$ and $v_0 = 40\ m/s$. Examples of simulation results are given in figures (Figure 1&2).

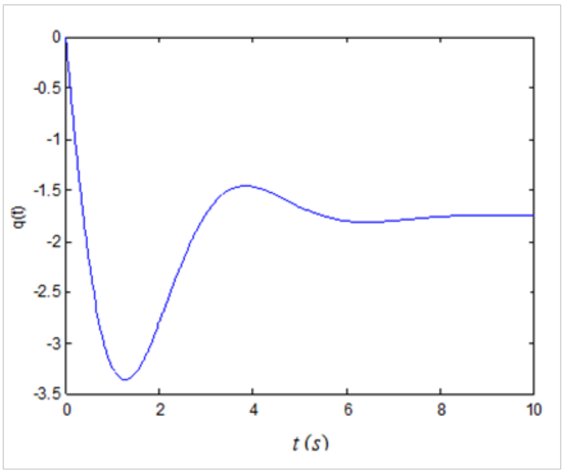

Figure 1 Pitch rate response in an open loop of a RPV system.

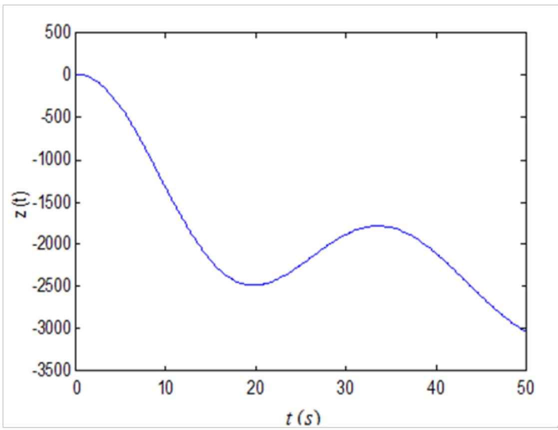

Figure 2 Altitude response in an open loop of a RPV system.

Linear flight control system design

As we can see from the time responses of the path angle and the altitude displayed for a RPV (Figure 1&2), the longitudinal motion of the considered airplane is unstable. A controller needs to be designed so that the time responses satisfy all design requirements. The central function of a controller is to implement a control law, which plays an important role in determining the accuracy and the rapidity of a control system in following a command. Control of non linear systems by feedback linearization is well known and has been applied to control of a wide variety of non linear dynamic systems. In classical *PID* controllers (Figure 3), the linear control laws are related to the time integral and time derivative of the error (eq. 2.). By error we mean the difference between the command input and the output of a system. In the case of an altitude control, we have $\varepsilon = z_c - z$.

$$\delta \ddot{u}\ddot{u}(\ddot{u}) = {}_p.\varepsilon(\ ) + {}_i\int_0^t \varepsilon(\tau).\ \tau + {}_d \frac{d\varepsilon(t)}{dt} \qquad (2)$$

Another alternative approach to controller design is the state feedback method. With this technique, control laws are obtained by feeding back all the state variables through a constant gain matrix (Figure 4) such that:

$$\delta m = Y_c - KX \qquad (3)$$

Where X = (v, q, α, γ, z) is the state vector, K gain matrix, Y_c command input.

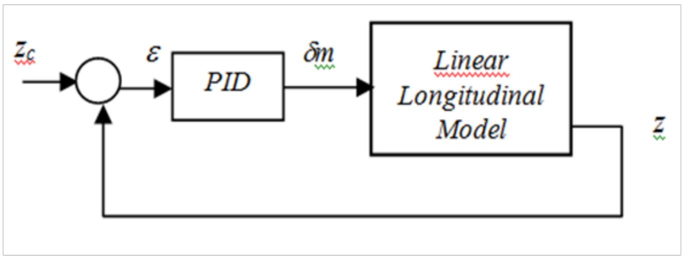

Figure 3 PID controller of a linear longitudinal system.

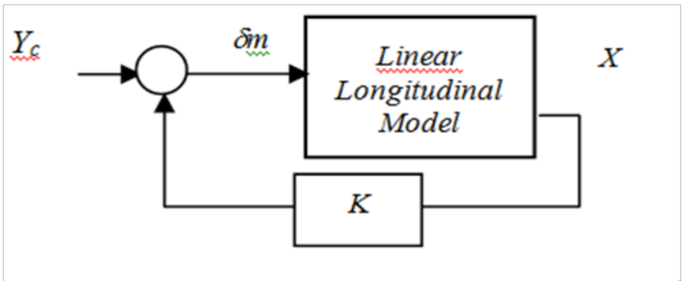

Figure 4 State feedback controller of a linear longitudinal system.

Non linear flight control system design using neural network

In this application we will train a neural network controller which will drive the longitudinal flight system to follow a linear reference model. Figure 5 depicts the architecture of a neural controller system design using the complete (non linear) equations of longitudinal motion of an aircraft.

Design requirements

Suppose that we would like the altitude, path, pitch angles, angle of attack, and velocity closed loop system to respond with the dynamics given by the following transfer functions:

$$\frac{z}{z_c} = \frac{0.36}{p^2 + 0.84\,p + 0.36} \qquad (4)$$

$$\frac{\gamma}{\gamma_c} = \frac{\alpha}{\alpha_c} = \frac{3.22}{p^2 + 2.51\,p + 3.22} \qquad (5)$$

$$\frac{q}{\delta m_p} = \frac{9}{p^2 + 4.2\,p + 9} \qquad (6)$$

$$\frac{v}{\ddot{u}\ddot{u}\ddot{u}\ \ +} = \frac{1}{\ } \qquad (7)$$

The above transfer functions are equivalent to the following design requirements:

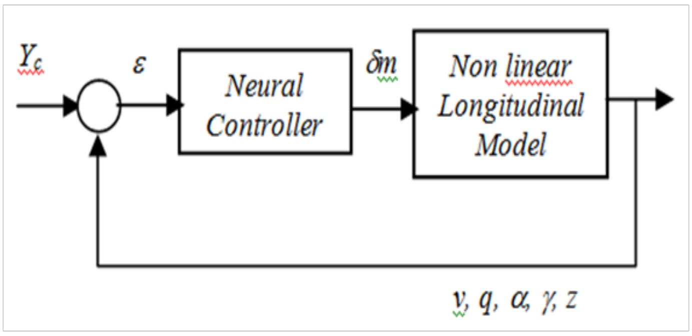

Figure 5 Neural controller of a nonlinear longitudinal system.

Velocity: 1st order behaviour, with a rise time of less than 1s and a zero steady-state error.

Pitch rate: 2nd order behaviour, with a damping ratio of 0.7, a rise time of 1s and a zero steady-state error.

Path angle and angle of attack: 2nd order behaviour, with a damping ratio of 0.7, a rise time of 2s and a zero steady-state error.

Altitude: 2nd order behaviour, with a damping ratio of 0.7, a rise time of 5s and a zero steady-state error.

We would like to find a controller network which takes the current (v, q, α, γ, z) variables of the airplane, and the command constants $Y_c = (v_c, q_c, \alpha_c, \gamma_c, z_c)$ as inputs, and outputs a signal δm which can be applied to the airplane. This current signal value δm should make the airplane's next state (in 0.01 seconds) identical to that defined by the desired linear reference model.

Network training

Now let us train a neural network to help perform this model reference control. The desired linear reference model, described mathematically above by a transfer function, takes the current time *t* and the *δm* angle and returns the values of the outputs (*v, q, α, γ, z*). We can simulate the desired linear reference model during *20 econds* with a period of *0.01 second.* The results can be regrouped in a matrix $A(kT, v_d(kT), q_d(kT), \alpha_d(kT), \gamma_d(kT), z_d(kT)\ , k=1, \ldots, 2000\ )$.

$$A(kT\ddot{u}\ddot{u}\ddot{u}_d(kT)\ \ q_d(kT)\ \alpha_d(kT)\ \gamma_d(kT)\ \ z_d(kT)) = A(kT, x_d(kT))\ , k = 1, \ldots,\ 2000 \qquad (8)$$

First, take a look at the following diagram of the entire neural controller/airplane system (Figure 6).

The neural controller is a three layers back-propagation network. Its architecture is (10, 8, 1). Each input vector is represented by the 5 state variables x (kT) and the 5 constant command Y_c. The rules for

Citation: Mjahed M. Flight control system design using neural networks. *Int Rob Auto J.* 2019;5(3):96‒99. DOI: 10.15406/iratj.2019.05.00180

computing the output δm are:

$$\delta m = \sum_i w_{im}^{ho} h_i \quad (9)$$

$$h_i = f\left(\sum_j w_{ji}^{xh} x_j - \theta_i\right) \quad (10)$$

$$f(x) = \frac{1}{1+e^{-2x}} \quad (11)$$

Where w^{kl}_{ij} are synaptic weights of the connection between neuron i (of layer k) and neuron j (of layer l), and θ_i thresholds. These parameters are adjusted by minimizing the error function *E,* using the *Levenberg-Marquardt* training recipe.[8,9]

$$\text{üüüi} \sum_{ki} (\ _{di}(\quad) - \ _{i}(\quad))^2 \quad (12)$$

The problem is that the error between the actual airplane behavior and the desired linear behavior occurs on the outputs of the airplane. As the non linear model is known, for each neural output *δm*, the responses of the airplane x ((k+1)T), are computed.

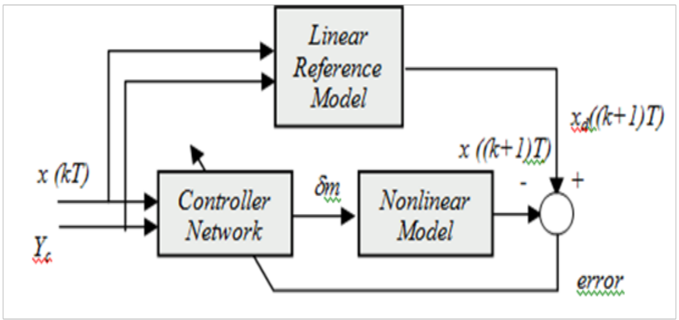

Figure 6 Diagram of the entire neural controller/ nonlinear longitudinal system.

The derivatives of the error are then back-propagated through the controller and used to adjust its weights and biases. Thus the control network must learn how to control the airplane so that it behaves like the linear reference model. It is used to obtain a minimization of the error. The network is trained for up to 600 epochs (Figure 7).

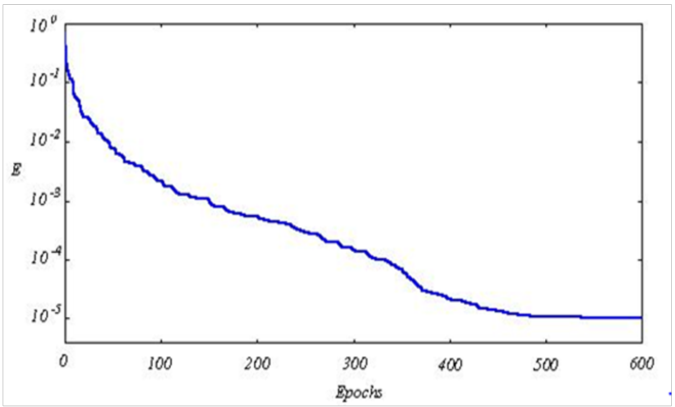

Figure 7 Error minimization vs number of epochs.

Network testing

To test the control network, the neural controller/airplane system is simulated and its response compared to the linear reference model. Figure 8–Figure 11 depict the results of simulating the linear reference model from an initial zero position, and a constant command vector *Yc*=(1, 1, 1, 1, 1).

The network does a near perfect job of making the non linear airplane system, *NCA,* (solid line) act like the linear reference model, *RM* (dashed line).

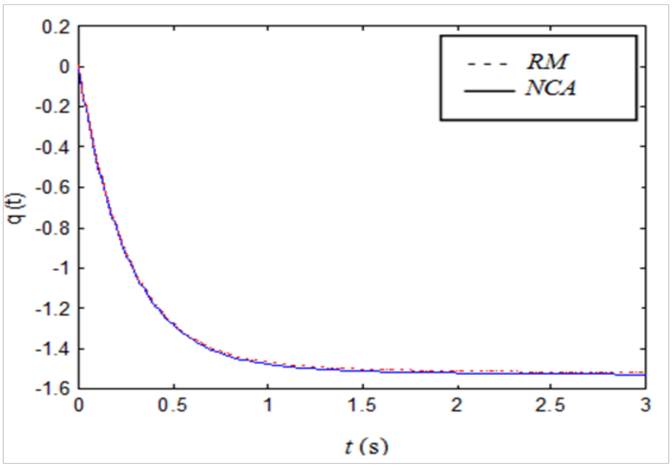

Figure 8 Pitch rate response of the entire neural controller/airplane-closed loop system.

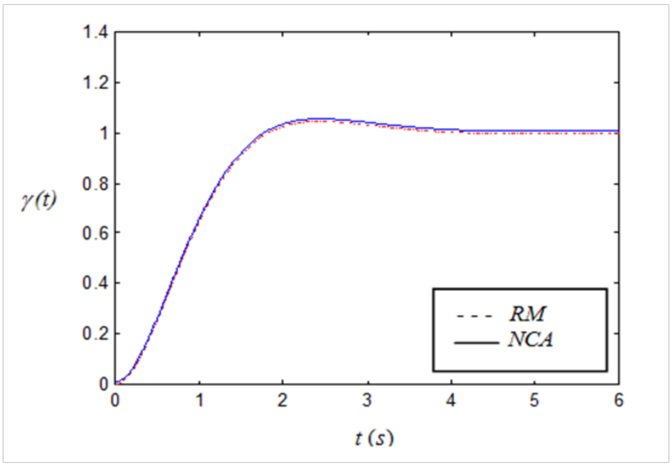

Figure 9 Path angle response of the entire neural controller/airplane - closed loop system.

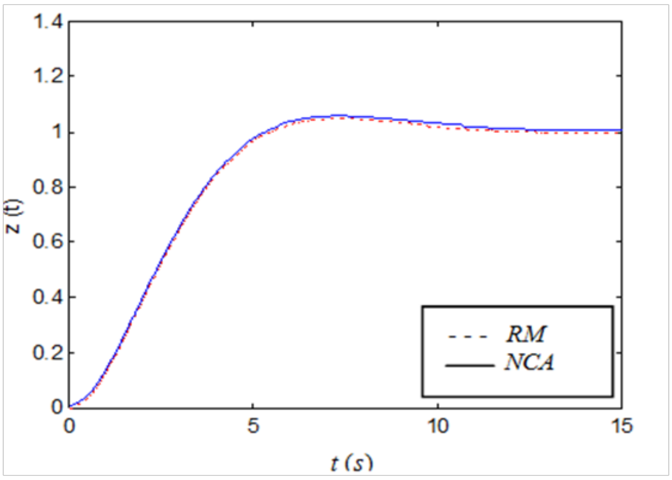

Figure 10 Altitude response of the entire neural controller/airplane - closed loop system.

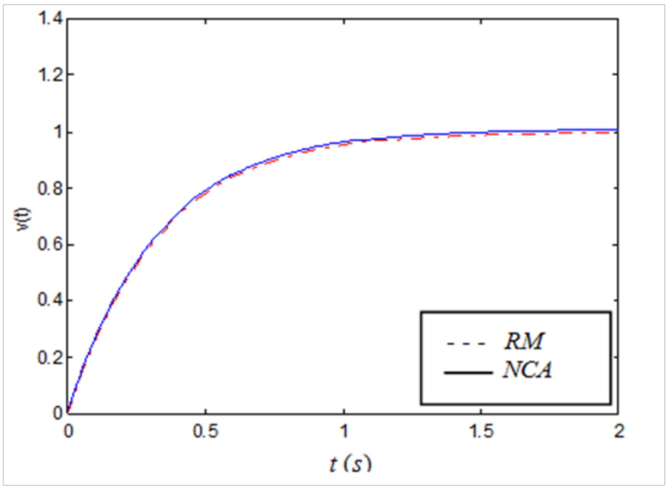

Figure 11 Velocity response of the entire neural controller/airplane - closed loop system

Conclusion

In this paper, to turn feasible the control of a nonlinear system a back-propagation neural network is proposed. A simulation study shows the effectiveness of this approach in the case of a longitudinal control of a remotely piloted vehicle. Additionally, attention has been given to the choice of the training data, where several flight conditions are considered.

Acknowledgments

None.

Conflicts of interest

Author declares that there is no conflict of interest.

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