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Direct Inverse Control of A 3 DOF Tandem Helicopter Model using Wavelet Neural Network

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Abstract

The control and guidance of autonomous vehicles has become a common topic of research amongst control theory mathematicians and engineers. There exist several control strategies, which can handle nonlinearities in the system, for controlling unmanned vehicles. In this paper a neural network based control strategy implemented on a 3DOF tandem helicopter model is discussed. This controller can handle systems with non-linear dynamicswith necessary changes in the neural network parameters. The focus of this paper is to perform system identification by learning the inverse model of the system. While most such algorithms use an artificial neural network,a wavelet neural network has been improvised upon in this work.

Keywords: TRMS, Non-linear control, Artificial Neural Networks, Wavelet Neural Networks, Direct Inverse Control, Arduino.

1 Introduction

The Twin Rotor MIMO System (TRMS) replicates the 3 degrees of freedom(DOF) of a helicopter with rotors connected in a tandem fashion. The 3 DOF of the model are along the roll, pitch and the yaw axes. These three motions are referredas change in elevation, pitch and travel angle. Testing of high speed motor systems in the aerial vehicle prototype is advisable under secure conditions. The laboratory built table top trainer model enables us to test the control strategies in secured conditions.

Many strategies have been proposed and tested for the control of unmanned aerial vehicles in the past. Conventional PID and LQR [1]control are some of the most utilized control schemes. Tuning of these controllers require an accurate mathematical model of the process. Also these controllers use the linearized model of the system for designing. This could limit the implementationof the control scheme to specific operating zones. Thereforea controller which can handle nonlinearity,independent of the operating conditions is required. Control strategies such as Model Predictive Control (MPC) [2], intelligent controllersbased on neural network, fuzzy and evolutionary algorithms are gaining popularityin non-linear control domain [3]. In a Direct Inverse Control(DIC) approach, the necessary control action will be generated from the inverse model of the system [4]. Such inverse model could be built using available knowledge on the forward dynamics of the system or using experimental data.

Artificial neural network (ANN) has been successfully used for building model based controllers for nonlinear systems [5, 6,7] in process control domain. Neural networks [8, 9] are mathematical models that mimic the functioning of human brain to learn and respond. Neural networks consist of nodes which act as neurons. These nodes have specific activation functions and nodes are interconnected among different layers via weights. The values of these weights are updated according to the learning algorithm for training the network.

Wavelet Neural Network(WNN) fuses the benefits of ANN and Wavelets in function approximating and multi resolution processing [10 -12]. WNN has the architecture similar to that of an ANN with the exception that the node's activation functions are wavelet functions. While training the network, the translation and dilation parameters of the wavelet activation function are updated along with the weights. This improves the nonlinear function learning capability of the network with reduced network architecture and faster convergence. In this work a Wavelet Neural Network based Direct Inverse Control (WNN-DIC) was designed and tested on the TRMS setup. The objective is to control the elevation and pitch angles of the tandem rotor system.

2 System Description

The TRMS is a laboratory set-up,resembling a helicopter [13- 15], used for control experiments is driven by two propellers actuated by DC motors. The free body diagram of the setup is shown in *Fig. 1.*The propellers $M_f$and M_b are mounted on a frame ***FE*** that mimics a helicopter. This frame is attached to a linking arm ***BC***. This linking arm links the frame to the base and also allows the system to move freely in elevation (ε), pitch (θ) and travel (φ) angles. A counter weight is attached on the other end of the linking arm for balancing the angular momentum. The cross-coupling between the arms and the nonlinear movement challenges the controller designing task.

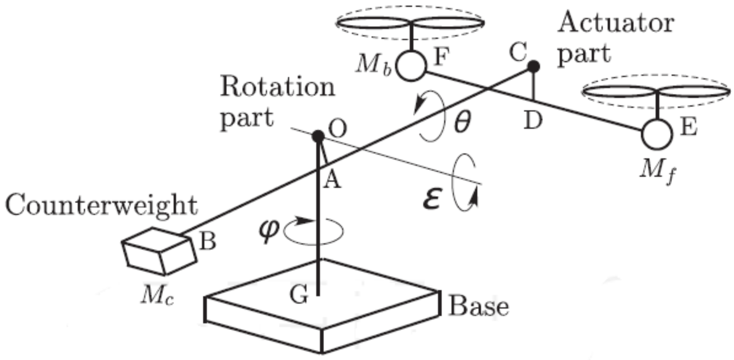


Fig.1. Complete Free Body Diagram

The system dynamics can be expressed using nonlinear equations of motion [15] given by equations (1), (2) and (3).

$$J_\varepsilon \ddot{\varepsilon} = -(M_f + M_b)g \frac{L_a}{\cos\delta_a}\cos(\varepsilon - \delta_a) + M_c g \frac{L_c}{\cos\delta_c}\cos(\varepsilon + \delta_c) - \eta_\varepsilon \dot{\varepsilon} + K_m L_a (V_f + V_b)\cos\theta \quad (1)$$

$$J_\theta \ddot{\theta} = -M_f g \frac{L_h}{\cos\delta_h}\cos(\theta - \delta_h) + M_b g \frac{L_h}{\cos\delta_h}\cos(\theta + \delta_h) - \eta_\theta \dot{\theta} + K_m L_h (V_f - V_b) \quad (2)$$

$$J_\Phi \ddot{\Phi} = -\eta_\Phi \dot{\Phi} - K_m L_a (V_f + V_b)\sin\theta \quad (3)$$

Here,

$$\delta_a = \tan^{-1}\left\{\frac{L_d + L_e}{L_a}\right\};\ \delta_c = \tan^{-1}\left\{\frac{L_d}{L_c}\right\};\ \delta_h = \tan^{-1}\left\{\frac{L_e}{L_h}\right\}$$

V_f, V_b : Voltage applied to the front and rear motors
M_f, M_b : Mass of the front and rear sections of the helicopter
M_c :Mass of the counter-balance
L_d, L_c, L_a, L_e, L_h : Distances OA, AB, AC, CD, DE=DF
g : gravitational acceleration
$J_\varepsilon, J_\theta, J_\Phi$: Moment of inertia about the elevation, pitch and travel axes
$\eta_\varepsilon, \eta_\theta, \eta_\Phi$: Coefficient of viscous friction about the elevation, pitch and travel axes.

The custom built model, *Fig. 2,* which is based upon the setup manufactured by Quanser, holds the following system parameters.
M_f= 32g, M_b= 32g,M_c= 125g.
L_d,=L_c,=31cm, L_a,=36cm, L_e=0 cm,L_h =25cm

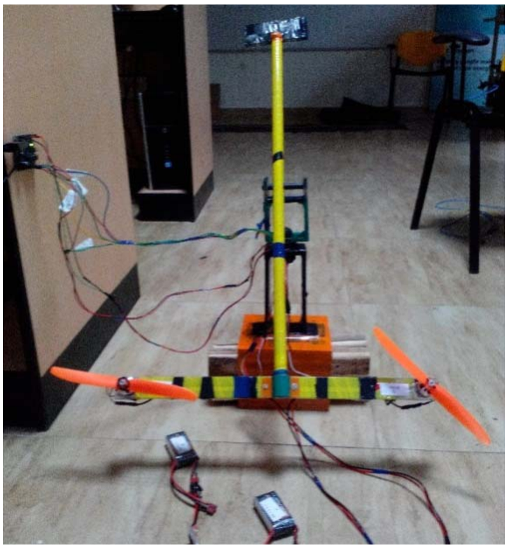


Fig. 2.The Custom Built Model

The proposed controller was implemented in MATLAB – Simulink®. Arduino [16], which is a microcontroller board based on the ATmega328 microcontroller, was configured to act as a data acquisition medium. This board collects system parameters from a 3-axis accelerometerADXL335 [17] and serially transfers to the controller.Also the microcontroller was used to transfer the controller output to two electronic speed controllers which are controlling two BLDC motors. The detailed control system schematic is shown in *Fig. 3*.

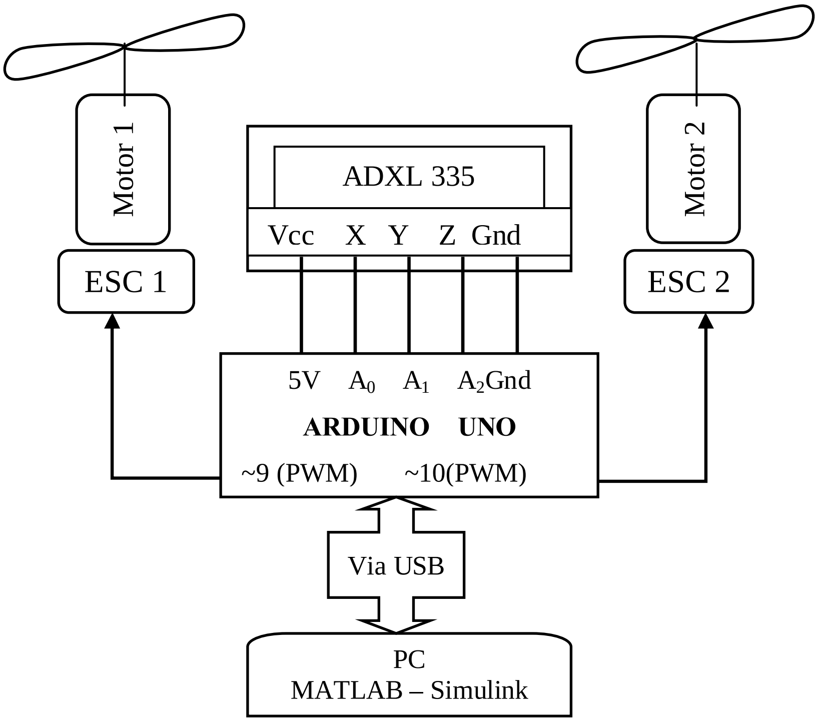


Fig. 3.Control System Schematic

3 WNN-DIC

Direct inverse control,shown in *Fig. 4* is a control scheme which uses the inverse model of the system under control. Inverse model of a system, whose dynamics is given by (4), will take the dynamics given by (5). Such inverse model could be built using neural networks, which were trained using input-output data collected from the system.

$$y(n+1) = f[y(n), y(n-1), y(n-2), \ldots, x(n), x(n-1), x(n-2), \ldots] \quad (4)$$

$$\hat{x}(n) = \hat{f}^{-1}[y(n+1), y(n), y(n-1), \ldots, x(n-1), x(n-2), \ldots] \quad (5)$$

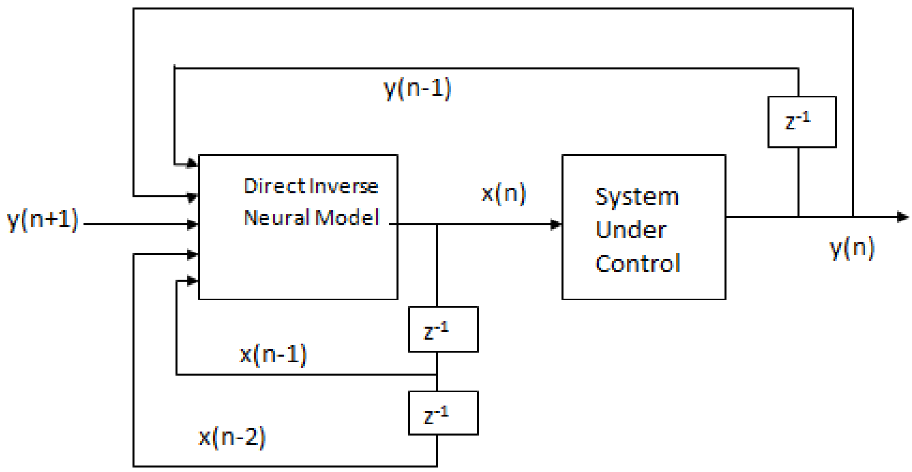


Fig. 4. Direct Inverse Control Schematic

The nonlinear function approximation capability of an artificial neural network depends on the selection of activation functions. In Wavelet neural network the activation function of all hidden layer neurons will be a wavelet function as in (6). The m^{th} hidden neuron's output is formulated by a dilation factor $a_k$and a translation factor b_k.

$$\psi(\boldsymbol{\tau}_m) = \psi\left(\frac{(t-b_m)}{a_m}\right) \tag{6}$$

The WNN structure, shown in *Fig. 5*, maps the inputs to output using the relationship given in (7). Training a WNN involves adjustment of these dilation and translation parameters along with adjustment of interconnecting weights. This results in a unique activation function for each hidden layer neuron in the trained WNN model.

$$\mathbf{Y}_k = \sum_m W_{km}\, \psi\left(\frac{\sum_n W_{mn} X_n - b_m}{a_m}\right) \tag{7}$$

Where,

W_{mn}	–	Weight between input and hidden layer
W_{km}	–	Weight between hidden and output layer
X, Y	–	Input and Output vectors

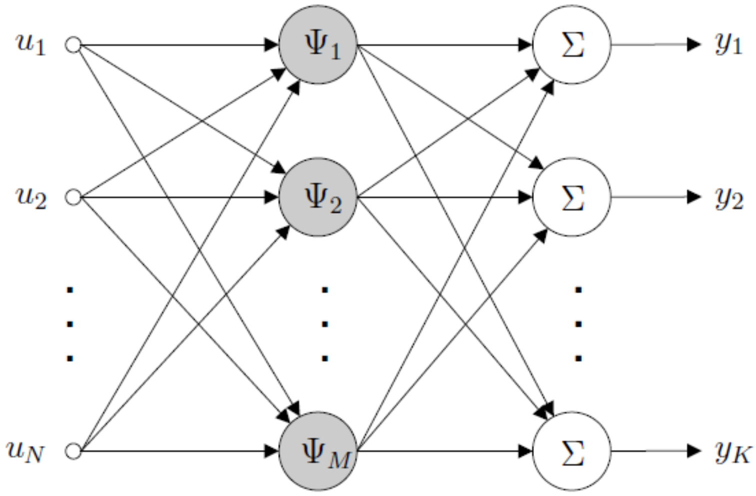


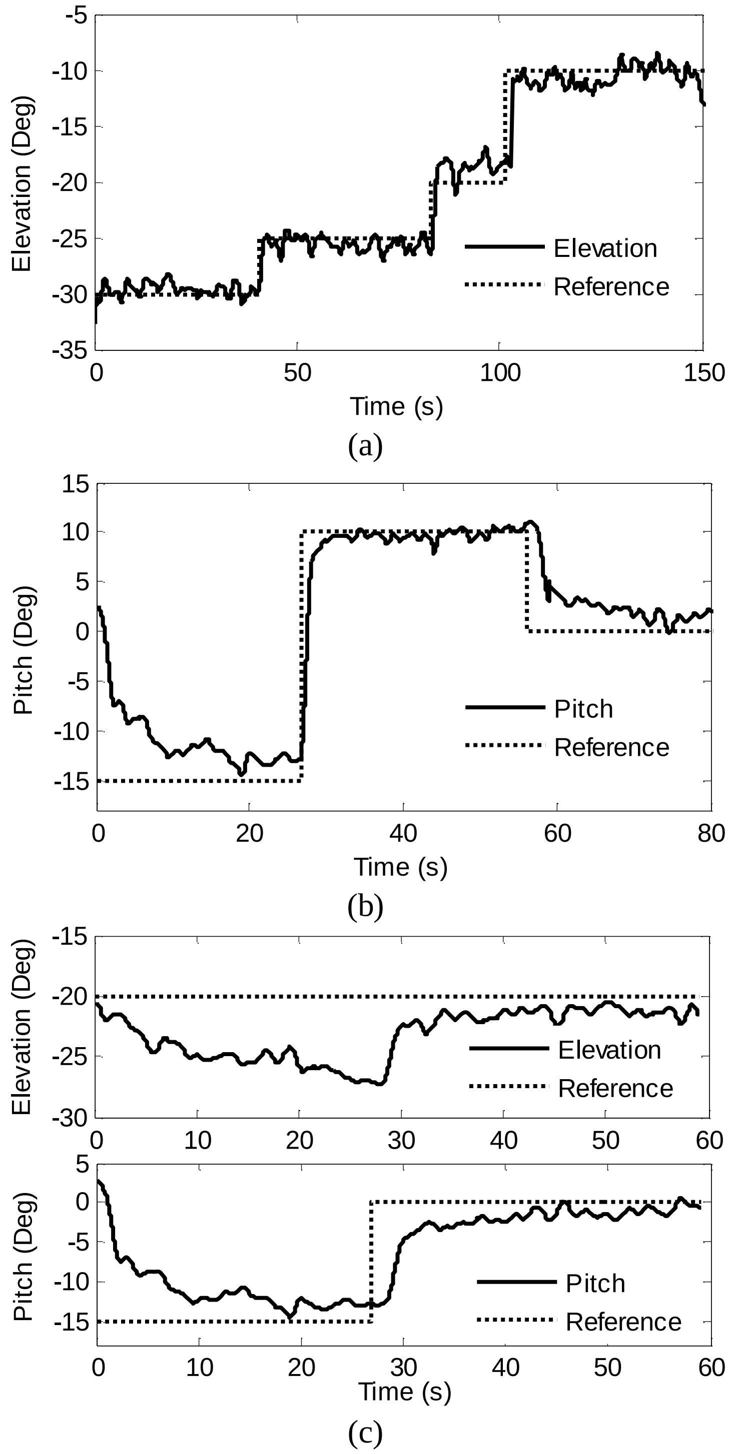
Fig. 5. Wavelet Neural Network – Structure

4 Results

The data set used to train the controller was obtained by manually running the system under safe operating conditions.The motors were given different combination of voltage signals and the feedback was collected from the accelerometer for the values of elevation and pitch angles. From this data set the training pattern was generated to meet the structure of the inverse model used for DIC. The custom build TRMS was tested for elevation and pitch angle controls, both individually and together. The inverse model was constructed using ANN with sigmoidal activation function and WNN with Morlet wavelet activation function for each case and trialed.

For controlling both pitch and elevation angles the inverse model was built with a network having 12 input nodes and 21 hidden nodes. The network structure for individual angle controller was selected to have 6 input nodes and 11 hidden nodes. Both neural models have 2 outputs for the front and rear motors of the TRMS setup.

The servo responses obtained from the system for the controller built with ANN having sigmoidal activation functions are given in *Fig. 6*. The responses obtained using WNNDIC are shown in *Fig. 7*.When the TRMS is in resting position the pitch angle will be 0^0 and Elevation will be -35^0.



(a)

(b)

(c)

Fig. 6.DIC using ANN. (a) Elevation control, (b) Pitch control (c) Both together controlled

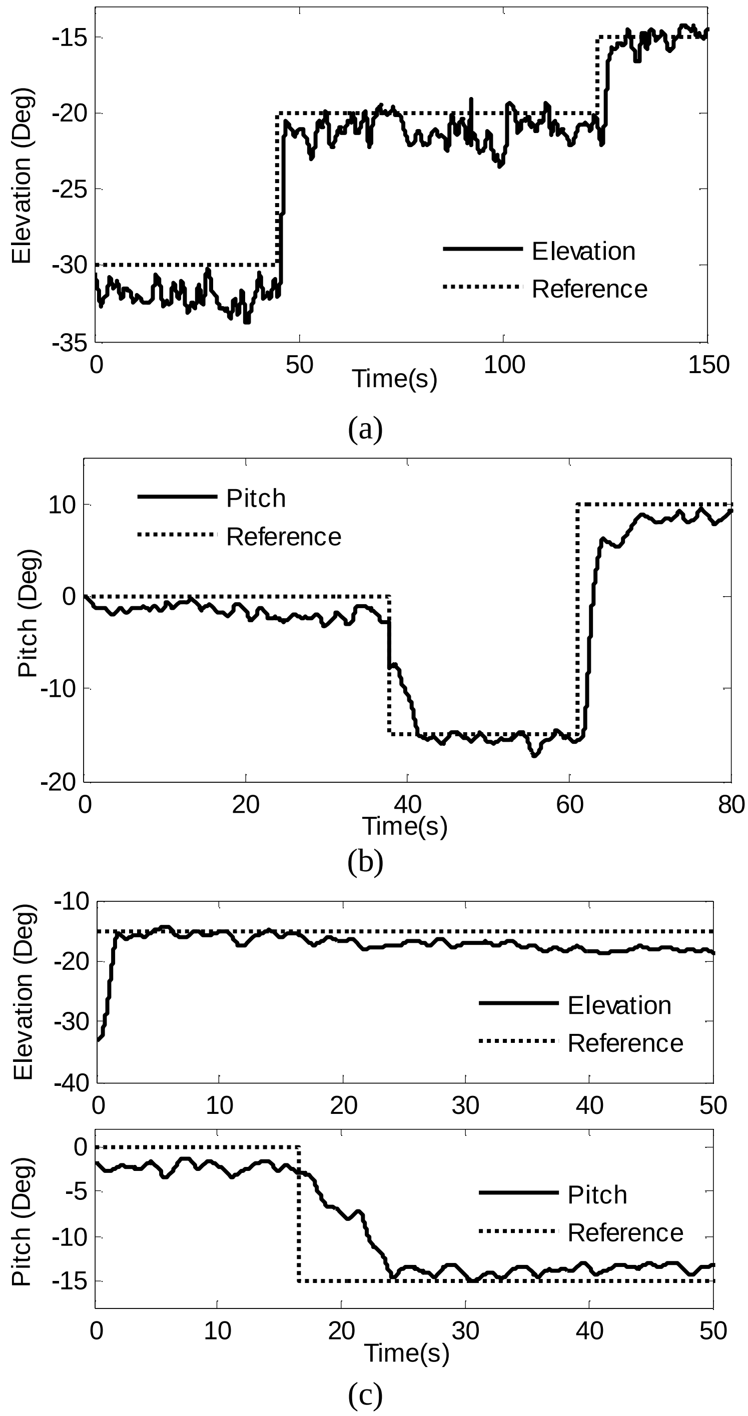


Fig. 7.DIC using WNN. (a) Elevation control, (b) Pitch control (c) Both together controlled

Table 1. Standard Deviation about Set-Point

Control	**WNN-DIC**	**ANN-DIC**
Elevation control	0.957°	1.6306°
Pitch control	0.9237°	1.9606°
Elevation and Pitch Controlled Together	Elevation=1.251° Pitch= 0.4654°	2.0369° 0.9002°

5 Conclusions

In this work the DIC strategy was implemented using both ANN and WNN based inverse models. The results indicate the WNN based controller outperforms the ANN based one. The impact of pitch variations on elevation is much reduced in WNN-DIC. WNN based control is also quick in reacting to change in set-point value. The performances of the controllers were measured by computing the standard deviation of the corresponding angles about their reference set point value, Table.1.

In a real time autonomous helicopter control, the inverse model could be further expertized by operation the system under different operating situations during the data collection period.

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