Small-Scale Helicopter System Identification Model Using Recurrent Neural Networks

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Abstract— **Designing a reliable flight control for an autonomous helicopter requires a high performance dynamics model. This paper studies the recurrent neural network nonlinear model identification of a small scale helicopter. We have selected a Nonlinear AutoRegressive with eXogenous Inputs Series-Parallel (NARXSP) network model which identifies the dynamics model of an unmanned aerial helicopter from real flight data. The identification process is conducted by using the well known Levenberg-Marquardt learning algorithm. The obtained dynamics model shows good fitness with the actual data. This accuracy might be used to realize a reliable flight control for an autonomous helicopter.**

Keywords— **Dynamics model, Recurrent Neural Network (RNN), System Identification, Small-Scale Helicopter**

I. Introduction

Designing flight controller for unmanned aerial vehicles (UAVs) represents a great challenge for engineers because of their platforms complexity and nonlinear dynamics. Model Helicopters are popular platforms for unmanned aerial vehicles (UAVs) in both academic and military domains. Their ability to take off and land vertically, sideslip, hover and low speed cruise, make them useful for wide research applications. They can be used for agricultural crop dusting, search and rescue missions, traffic monitoring, inspection of bridges or power line and surveillance of larger areas etc. [1], [2].

A common problem in the design of high performance flight control for unmanned aerial helicopter is obtaining the dynamics model with high fidelity. Earlier, first principle modelling based on Newton's law and Euler's angle, have been applied in [3] to develop a nonlinear model. Then in order to design a linear controller, linearization of the nonlinear model is required [3]. Helicopters are well known to have complicated dynamics model. Therefore, their dynamics models are usually obtained through system identification techniques, using experimental collected data. The US army/NASA have developed a tool named CIFER (Comprehensive Identification from Frequency Response) to identify the model of full Rotorcraft dynamics. This method has been applied in [4], and successful obtain linear model for a Thunder Tiger Raptor-90 helicopter platform. The Prediction Error Method (PEM) was used in [5] as an estimation algorithm, which is based on minimizing the quadratic error between the predicted output and the experimental data. Artificial Intelligence control methods, such as neural networks, fuzzy logic and fuzzy/neural controllers have possibilities of high performance without large computing overhead to identify and control an unknown nonlinear dynamic system [6], [7], [8], [9], [10].

In recent years application of artificial neural network (ANNs) has received an increasing attention for identification and control of unknown nonlinear dynamic systems [11], [12], [13].

By taking into account the high nonlinearity of the helicopter system, we proposed Nonlinear AutoRegressive with eXogenous Inputs Series-Parallel Neural Network structure model to learn the dynamics model of a RUAV. Based on NARXSP structure a nonlinear dynamics model of helicopter plant is identified off-line from the collected data.

The present work is organized as follows, section II deals with describing the experimental platform we have used to collect flight data. Section III explains the methodology achieved for system identification to generate the dynamics model of an autonomous helicopter. We then deal with the simulation results in Section IV and finally, section V is the conclusion.

II. Platform Description

Experiments in this research were conducted on a size 50 HIROBO SCEADU R/C helicopter. Due to its ability payload capability and manoeuvrability, adding autopilot system, sensors and communication devices make it easy to upgrade onto UAV helicopter. The helicopter actuation is performed by five onboard servo actuators. The swash plate is controlled by the Cyclic Collective Pitch Mixing (CCPM) method, to execute all the swash plate movements (collective, aileron and elevator). The main centrepiece of the helicopter onboard systems are: 1) - an onboard flight computer (PC/104). However, in the experiments PC/104 is used as memory for data storage. 2) - The Inertial Measurement Unit (IMU) connected directly to the flight computer through a special serial port. This latter provides measurement of the airframe accelerations (a_x, a_y, a_z), which are then integrated to obtain velocities (u, v, w), angular rates (p, q, r) and Euler angles ($\emptyset, \theta, \varphi$). 3) - A diamond GPIO-MM Timer/Counter card is used to capture the PWM duty cycle signals coming from the onboard receiver. Table 1 shows some important parameters of the HIROBO SCEADU helicopter platform.

TABLE I
50 SIZE HIROBO SCEADU HELICOPTER DESCRIPTION

Rotor diameter	1348 mm
Gross weight	3.9 kg
Gear ratio	8.7 : 1 : 8.7
Engine ratio	OS 50 Class

III. SYSTEM IDENTIFICATION

As mentioned earlier, helicopters have a very complex dynamics system, MIMO characteristics and highly nonlinearity. Therefore, their dynamics model is not easily represented in terms of first principles. System identification is an experimental approach to generate dynamics model which identify the unknown model parameters. One approach known as Gray-box system identification combines physical modelling and numerical methods integration to estimate the unknown parameters in the model equations. This approach has been applied in several researches for helicopter dynamics identification [4], [5]. But this approach needs to be decoupled the physical model into subsystems due to higher orders. The insufficient model structure may complicate the design of the controller. Black box identification, without physical model integration is considered as a critical tool which is mostly used in intelligent control systems.

A number of experimental test flights have been made to collect flight data via a human operator pilot. The flight data were collected at sampling interval of 30ms rate. During the flight data test, the IMU sends back the airframe data of the vehicle to PC/104. Whereas, the Counter/Timer captures the PWM signals sent by the receiver to the actuators. For the identification purpose, the selected data were taken in near hover conditions.

A. Helicopter model system representation

A standard NARX discrete time nonlinear multivariable model system with *m* outputs and *r* inputs, which is a general parametric form for modelling nonlinear systems [14] can be described by the following equation

$$y_m(t+d) = N[y_m(t), y_m(t-1), \dots, y_m(t-n_y+1), u_r(t), u_r(t-1), \dots, u_r(t-n_u+1) \tag{1}$$

where,

$$y_m(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \\ \cdot \\ \cdot \\ \cdot \\ y_m(t) \end{bmatrix}, \quad u_r(t) = \begin{bmatrix} u_1(t) \\ u_2(t) \\ \cdot \\ \cdot \\ \cdot \\ u_r(t) \end{bmatrix} \tag{2}$$

The above mentioned vectors are the system output, the input system and the noise respectively, n_y and n_u are the maximum lags in the output and input. t is time and d is the step time. *N(.)* represent unknown nonlinear function, which needs to be approximated.
According to the basic state of the IMU model frame-out back to the system, the helicopter coordinates can be represented as nine outputs. This model has three accelerators, three angular rates and three angles all can specify by a 9x9 dynamics model parameters.

B- Neural Networks Architecture

Fig.1 shows the overall of the NARX Series Parallel Recurrent Neural Networks structure which is commonly has three layers (input, hidden and the output). Since we have collected both inputs and outputs flight data (Actual model). The series parallel networks have chosen rather than the feedback networks. A nonlinear transfer function used in the hidden layer, and a linear function in the output layer. The nonlinear function given as a sigmoid function:

$$\sigma(x) = \frac{1+e^{-ax}}{1-e^{-ax}} \tag{3}$$

The relationship between input-output of a generic node, the *i*th node in the *l*th layer is given by:

$$n_i^{(l)} = \sum_{j=1}^{n_{l-1}} w_{ij}^{(l)} x_j^{(l-1)} + b_i^{(l)} \tag{4}$$

$$y_i^{(l)} = f\left(n_i^{(l)}\right) \tag{5}$$

where, $w_{ij}^{(l)}$ and $b_i^{(l)}$ are the connections weights and the biases respectively. $x_j^{(l-1)}$ is the input vector coming from the previous layer, $y_i^{(l)}$ is *i*th node output and $f(.)$ is the activation function.

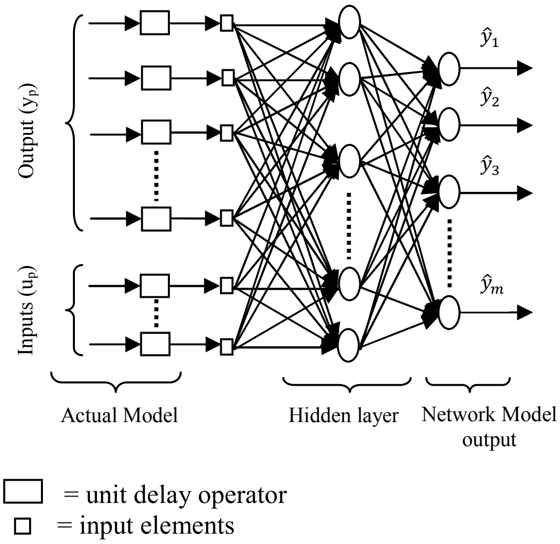


Fig. 1 Series Parallel Recurrent Neural Network Structure

From Fig. 1 we can expressed the identification model as the follows equation

$$\hat{y}_m(t+d) = \hat{N}[y_m(t), y_m(t-1), \dots, y_m(t-n_y+1), u_r(t), u_r(t-1), \dots, u_r(t-n_u+1) \quad (6)$$

where $\hat{y}_m$ is the model output, y_m is the actual output, $\hat{N} = g(w_{ij}^{(l)}, b_i^{(l)}, w_{ij}^{(l+1)}, b_i^{(l+1)})$ is the neural network approximation function which involves the adjustment of the weights through the back propagation.

Fig. 2 photograph of Collecting Flight Data for System Identification

C. Neural Networks Learning Algorithm

The training process used to approximate the helicopter dynamics model plant is illustrated in Fig. 3. The system identification diagram based on back propagation learning algorithm with the approximation of Levenberg-Marquardt function is used. Levenberg-Marquardt training algorithm is applied for the speed of convergence. The algorithm adjusts the weights to minimize the cost function (e) Fig. 3. The performance of the approximate plant model is shown to outperform the Recurrent Neural Networks in terms of convergence speed and mean squared error (MSE). The mean square error is given as

$$e = \frac{1}{n}\sum_{t=1}^{n} (\hat{y}_m(t) - y_m(t))^2 \quad (7)$$

where, $\hat{y}_m$ is the output of the model from networks, y_m represents the actual (measured) output at index time t and n is the number available patterns. The idea of the algorithm in this study is to obtain an approximation for the function $\hat{N}$ in the equation (6) that minimizes the error between the measured outputs and the networks outputs. The flexibility of Levenberg-Marquardt learning algorithm between Gradient descent and Guass Newton Methods make it more useful [15].

The weights updated via Levenberg-Marquardt learning algorithm can be written as follows

$$W(t+1) = W(t) - [J^T \ J + \mu I]^{-1} \ J^T \ e \quad (8)$$

where J is the Jacobian matrix which can be written for a single neuron as:

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial w_1} \cdots \frac{\partial e_1}{\partial w_{n-1}} & \frac{\partial e_1}{\partial w_n} \\ \vdots & \\ \frac{\partial e_m}{\partial w_1} \cdots \frac{\partial e_m}{\partial w_{n-1}} & \frac{\partial e_m}{\partial w_n} \end{bmatrix} \quad (9)$$

and μ is the adaptive parameter which can modified based on the development of the error e.

In the proposed neural network architecture, one input layer with five nodes corresponding to the five servo control signals, one hidden layer with twenty five units (neurons) and one output layer with eight nodes corresponding to angular rates, translation velocities and Euler angles of the helicopter system out-frame are used in the proposed structure (Fig. 1). The yaw angle has eliminated, because it is already controlled by the gyro system. As mentioned earlier the hidden layer has a sigmoid nonlinear transfer function, and the output layer has linear function. By using a forward selection method to decide the number of neurons in the hidden layer which begins with small number of neurons, then train and test the neural networks outputs up to get a better convergence between the network outputs and the experimental data set.

Before starting the training of the identifier neural networks plant, the collected data requires some filtering to screen out noises, moving average filter is used in this study.

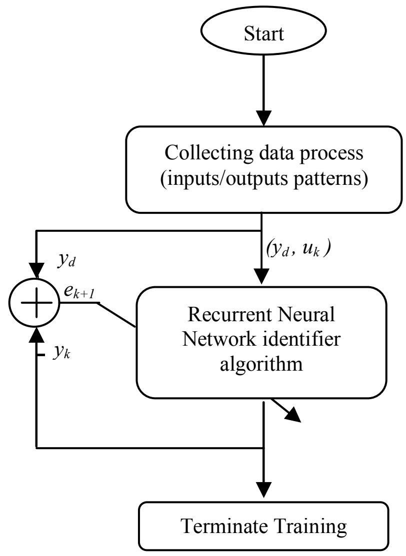


Fig. 3 System identification diagram procedure

IV. Simulation Results & Discussion

A- Results

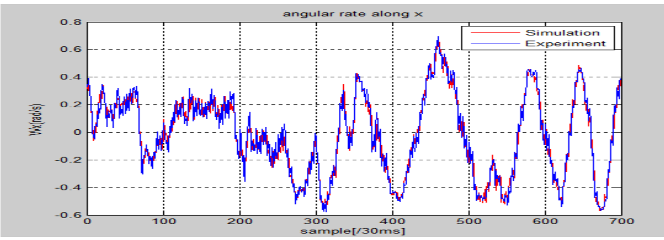
Fig. 4 shows a comparison of the recurrent neural network output with the experimental data. The upper left panel displays the predicted angular rates output response about the rigid body axis (x, y, z) which is almost close to the measured output variance. The upper right panel displays the translation velocities along the three directions. The lower panel displays the predicted Euler angles (roll and pitch angles). The results demonstrate that the proposed neural network computation structure is capable to generate the dynamics model with high accuracy for a small-scale helicopter. The training performances are shown in table II.

TABLE II
training algorithm performance

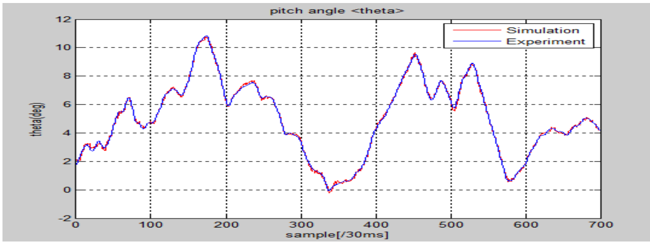
MSE (performance)	0.00273692/0
Levenberg-Marquardt performance	0.000232992/1e-006

B. Discussion

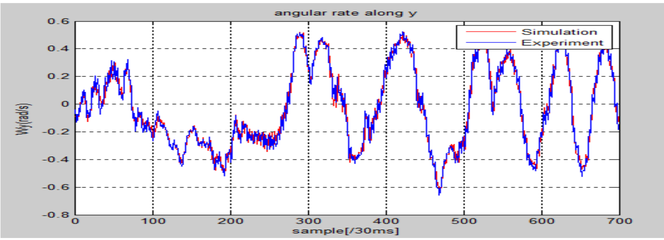
The simulation results demonstrate that the recurrent neural network as a black-box computation tool is useful for modeling and analyze the dynamics model of a small-scale helicopter. From the study in Section III. *A*, the NARXSP model having a structure of 5 inputs and 8 outputs inferred respectively from the Counter/Timer signals and the IMU airframe outputs of an autonomous helicopter, on this model structure, the recurrent neural network computational tool were implemented in Section III. *C,* with the suggested parameters: learning rate $\mu = 0.01$, training performance goal is zero and training epoch of 700. The method successfully minimizes the error to identify an accurate model structure for an autonomous helicopter. Additionally, this computational structure tool is capable of training a large data set.



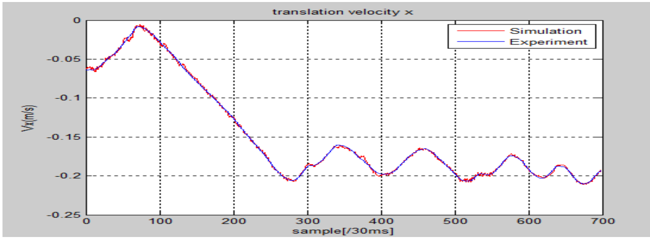
Angular rate along x axis



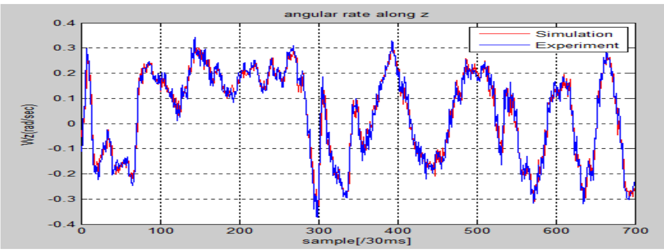
Pitch Angle



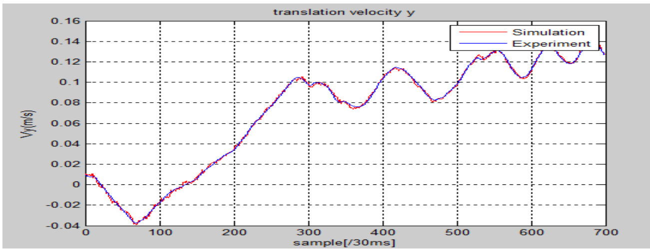
Angular rate along y axis



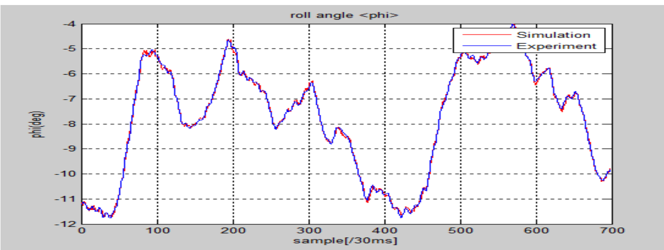
Translation velocity along x axis



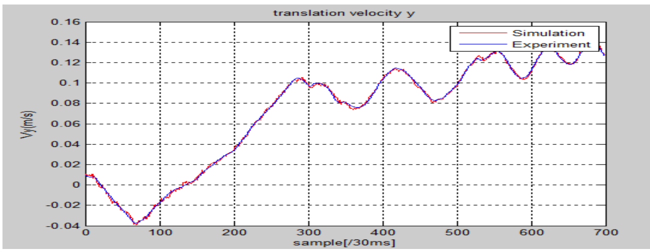
Angular rate along z axis



Translation velocity along y axis



Roll angle



Translation velocity along z axis

Fig. 4 comparison of recurrent neural network output with experimental flight data set

V. CONCLUSION

It has been successfully shown that a model small-scale helicopter dynamics plant can be identified using NARXSP neural network model as a system identification approach. The NARXSP has been implemented in a recurrent neural network structure which is based on the Levenberg-Marquardt learning algorithm. This latter algorithm was trained to map the relationship between the input and output patterns.

The identified model of the small-scale helicopter did not require the physical model parameters calculation. These results may have practical significance in analysis of the helicopter dynamics model and it could lead to more efficient intelligent flight control strategies.

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