

PAPER 74 – ACCURATE PREDICTION OF QUADCOPTER DYNAMICS THROUGH INCREMENTAL EVOLUTION OF GRNN MODEL DEVELOPMENT

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ABSTRACT

This paper discusses the use of incremental evolution of generalized regression neural networks (GRNN) in the development of dynamic models of quadcopter systems. 11,835 flight datasets comprising attitude and altitude data were collected using quadcopter model F450 fitted with a PIXHAWK flight controller. The data were normalized and 70% was used for training and testing, while 30% was used for model validation. The results obtained show that for an MSE threshold of 0.1, a 98% reduction in the size of the hidden layer of the network is achievable for the attitude (roll, pitch and yaw) and altitude identification. The MSE values of 0.0268, 0.0514, 0.1627 and 0.2033 for the roll, pitch, yaw and altitude models respectively also indicated that the networks have higher accuracy compared with the GRNN models. Also, the R^2 values of 0.9732, 0.9484, 0.8373 and 0.7967 obtained for the validation of the roll, pitch, yaw and altitude models indicate that the models are well-fitted. The results showed that the incremental evolution-based GRNN algorithm reduces the size of the network's hidden layer by pruning neurons that do not contribute to error minimization between the actual flight output and the trained output, which results in higher accuracy compared to conventional GRNN models.

KEYWORDS: Quadcopter, GRNN, System Identification, Incremental Evolution

21. INTRODUCTION

The design of robust controllers for high performance operations of the quadcopter in constrained environments require an accurate model of the quadcopter system. These accurate models can also be used for design and development of advanced control strategies for trajectory planning control, fault-tolerant control, fault diagnosis and autonomous missions planning (Navarro *et al.*, 2017). The development of a robust controller with the ability to adapt itself to the dynamic behaviour of the quadcopter system in the event of performance degradation of the actuators can be achieved with the aid of suitable system identification techniques, hence, an accurate identification of the system plays an important role in model reference adaptive control design. System identification and parameter estimation of any dynamic system produces a model of the system that can be used for the design, development and validation of control algorithms for the system. The mathematical model of quadcopter unmanned aerial vehicle systems derived from first principle contains un-modelled dynamics and model uncertainties arising from dynamic perturbations such as high frequency dynamics on parts of the system (Noormohammadi-asl *et al.*, 2020). Furthermore, parametric and non-parametric uncertainties, noise and disturbances can affect the accuracy of models developed from experimental data. Neural networks are used in many applications including image recognition, classification, control and system identification, function approximation and regression (Tutunji, 2016). Neural identification offers a promising direction towards higher understanding of systems and the ability to solve some of the challenges in control design problems, especially in the determination of accurate dynamic models, and the development of intelligent control algorithms. Furthermore, there has been a paradigm shift in model identification of dynamic systems with the attention now focusing on the use of neural network techniques for improved accuracy in the determination of system models (Wang and Zhao, 2013).

Many researchers have worked on the development of neural networks for system identification. Abas *et al* (2011) investigated a method for parameter identification of a quadcopter using state estimation method with the implementation of Unscented Kalman Filter (UKF). In a related work, Navarro *et al* (2017) carried out a research on flight dynamics model development of a multi-copter using system identification techniques by using Comprehensive Identification from Frequency Response (CIFER) software for frequency response analysis. Al-Mahasneh *et al* (2017) carried out a study on the effect of evolutionary algorithms in improving neural network capabilities in identification of nonlinear multi input multi output dynamic systems such as quadcopters. Similarly, Al-Mahasneh *et al* (2018) carried out a comparative analyses between Generalized Regression Neural Network (GRNN) technique and Back Propagation Neural Networks (BPNN) technique in system identification and control of dynamic systems by comparing their training time and training error. Ives *et al* (2015) carried out system identification of the attitude of a quadrotor using experimental data. Furthermore, several other methods of system identification give better results, like the work of (Wang and Zhao, 2013) which is based on the white-

box technique, which requires a mathematical model of the system to be presented. Pairan *et al* (2020) carried out a review of neural network-based techniques for quadcopter dynamic modelling. Sa and Corke (2012) carried out system identification, estimation and control for a cost effective open-source quadcopter by using autoregressive moving average (ARMAX) model. Pairan and Shamsudin (2017) performed recursive system identification of a quadcopter based on radial basis function (RBF) neural network structure trained with constant trace (CT) and minimum resource allocation neural network (MRAN) algorithms for attitude model of quadcopters. The generated model was validated by checking the RMSE, training time and R^2 values. Salameh *et al* (2015) developed system models for a quadcopter hovering operation using experimental flight data. The models developed were autoregressive with extra input (ARX) – based models for the attitude and altitude single input single output. Filho *et al* (2016) developed a test bench to be used for identification of system parameters of a quadcopter. Chovancová *et al* (2014) carried out mathematical modelling and identification of parameters of the non-linear model of a quadcopter. Kantue and Pedro (2018) investigated the identification of unmanned quadcopter in accelerated flight using grey box modelling approach. Similarly, Kantue (2018) investigated nonlinear identification of an unmanned quadcopter rotor dynamics using radial basis function neural networks. Abdolahi and Rezaeizadeh (2018) carried out a black-box identification and iterative learning control of a quadcopter. Gandhi *et al* (2019) carried out a comparative analysis of multiple algorithms used for system identification of an unconventional UAV. Ayyad *et al* (2020) carried out a parametric system identification for linear system model of an unmanned aerial vehicle using deep learning and modified relay feedback test (MRFT). Amiruddin *et al* (2021) performed a comparative analyses of several deep learning techniques for system identification of quadcopter unmanned aerial vehicle. They compared gated recurrent units (GRUs), Long-short term memory and Convolutional neural networks (LSTM-CNN) in the identification of single-input-single-output (SISO) and multi-input-multi-output (MIMO) quadcopter system using a black-box approach. This paper focuses on the development of black-box quadcopter dynamic models using incremental evolution of generalized regression neural networks with a view to reducing the size of the hidden layer of the network while improving the accuracy of the trained models.

22. THEORETICAL FRAMEWORK

The quadcopter is a four rotor fixed pitch propeller unmanned aerial vehicle. **Figure 1** shows the typical set-up of a quadcopter system.

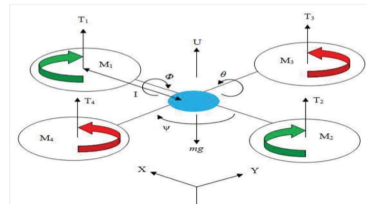


Figure 1: A Quadcopter Schematic Diagram

The thrust generation by the motors is directly proportional to the square of the angular speed as provided in equation (1)

$$T_i = c\omega_i^2 \quad \dots(1)$$

where T_i and ω_i are the thrusts and angular velocities exerted by the i^{th} motor respectively, and c is the drag coefficient of each of the identical propellers.

In the inertial frame, the acceleration of the quadcopter is due to thrust, gravity and linear friction. The thrust vector in the inertial frame can be obtained by using the rotation matrix R to map the thrust vector from the body frame to the inertial frame. The position and velocity in the inertial frame $\dot{X} = (x, y, z)^T$ and $\ddot{X} = (\dot{x}, \dot{y}, \dot{z})^T$, and the attitude in the body frame and the corresponding velocities $\Theta = (\phi, \theta, \psi)^T$ and $\dot{\Theta} = (\dot{\phi}, \dot{\theta}, \dot{\psi})^T$. The angular velocity in the body frame is given by;

$$\omega = \begin{bmatrix} 1 & 0 & -\sin \theta \\ 0 & \cos \phi & \cos \phi \\ 0 & -\sin \phi & \cos \phi \end{bmatrix} \quad \dots (2)$$

The body and inertial frames are related by the rotation matrix R , which goes from the body frame to the inertial frame. Using the Z-Y-Z Euler angle conversion;

$$R = \begin{bmatrix} \cos \phi \cos \theta & \cos \psi \sin \theta - \sin \psi \cos \phi & \cos \psi \sin \theta \cos \phi + \sin \psi \sin \phi \\ \sin \psi \cos \theta & \sin \psi \sin \theta \sin \phi + \cos \psi \cos \phi & \sin \psi \sin \theta \cos \phi - \cos \psi \sin \phi \\ -\sin \theta & \cos \theta \sin \phi & \cos \theta \cos \phi \end{bmatrix} \quad \dots (3)$$

The first set of differential equations that describe the acceleration of the quadcopter can be written as;

$$\begin{pmatrix} \ddot{x} \\ \ddot{y} \\ \ddot{z} \end{pmatrix} = g \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} - R \frac{T}{m} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \quad \dots (4)$$

where T is the total torque generated by the quadcopter, m is the mass of the quadcopter system and g is the acceleration due to gravity.

With the inertia matrix I , which is a diagonal matrix with the inertias I_x , I_y and I_z on the main diagonal, the rotor inertia I_r , the vector M that describes the torque applied to the vehicle's body and the vector M_G of the gyroscopic torques, a second set of differential equations is obtained;

$$I \ddot{\omega} = -(\dot{\omega} \times I \dot{\omega}) - M_G + M \quad \dots (5)$$

The vector M is defined as;

$$M = \begin{pmatrix} Lb(\omega_3^2 - \omega_4^2) \\ Lb(\omega_1^2 - \omega_2^2) \\ b(\omega_1^2 + \omega_2^2 - \omega_3^2 - \omega_4^2) \end{pmatrix} \quad \dots (6)$$

Generalized Regression Neural Network (GRNN), also called general regression neural network, is a single pass associative memory feedforward type neural network, and uses normalized Gaussian kernels in the hidden layer as activation functions (Al-Mahasneh *et al* 2018). It is similar to radial basis function neural network, but the output is a special linear function. It is made up of the input layer, hidden layer, summation, division and output layer. **Figure 2** shows the structure of generalized regression neural network, unlike in feedback neural networks, the data in a GRNN can only flow from the input layer to the hidden layer and finally to the output layer. When GRNN is trained, it memorizes every unique pattern because it is a single pass network and does not require back propagation. After training GRNN with adequate training patterns, it will be able to generalize for new inputs. The output of GRNN can be calculated using equations (7) and (8).

$$D_i = (X - X_i)^T (X - X_i) \quad (7)$$

$$\hat{Y} = \frac{\sum_{i=1}^N Y e^{\left(\frac{-D_i}{2\sigma^2}\right)}}{\sum_{i=1}^N e^{\left(\frac{-D_i}{2\sigma^2}\right)}} \quad (8)$$

where D_i is the Euclidean distance between the input X_i and the training sample input X and Y is the training sample output, and σ is the smoothing parameter of the GRNN.

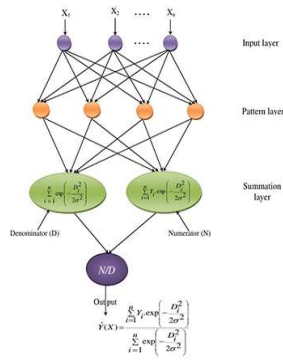


Figure 2: Structure of GRNN

23. MATERIALS AND METHODS

The quadcopter model F450 is a prototype quadcopter developed by Da-Jiang Innovations in Nanshan, Shenzhen, China initially for hobbyists, but later, it became useful in many areas of application of UAVs including photography, search and rescue, agriculture and control design and validation. Its frame structure is rigid and light in weight, and can be assembled with less difficulty. It can accommodate a wide variety of off-the-shelf flight controllers like the PIXHAWK flight controller family, a wide range of GPS modules, electronic speed controllers, Lithium-Polymer (Li-Po) battery, and brushless DC motors. It has a diagonal length of 450mm from the centre of one DC motor to the other. **Plate 1** shows the quadcopter model F450 with the PIXHAWK 2.4.8 flight controller, the GPS module and the four propellers attached to the individual motors. The quadcopter has six degrees of freedom, three translational (movement along x , y and z directions) and three rotational (roll, pitch and yaw movements), making it an under-actuated system (Norouzi Ghazbi *et al*, 2016). There are two basic configurations of the quadcopter; the ‘+’ configuration and the ‘x’ configuration. The ‘x’ configuration is considered more stable (Gupte *et al* 2012).



Plate 1: The Quadcopter Model F450

a. INCREMENTAL EVOLUTION ALGORITHM

The training of the neural network was carried out using MATLAB 2019b software. HP Pavillion 24 Intel(R) Core™ i5 – 8400T CPU @1.70GHz, 1704MHz 6 cores logical processor and 12GB RAM was used for the simulation. Eleven Thousand, Eight Hundred and Thirty-Five (11,835) data sets were collected from attitude and altitude flight data, the data was divided in two with 70% for neural identification, 30% for model validation. The GRNN is initialized with one hundred (100) datasets of four (4) pulse with modulated (PWM) inputs and one (1) output each for the attitudes and altitude data of the quadcopter with a spread of 0.1. The GRNN inputs are the four plant inputs $u_1(k), u_2(k), u_3(k), u_4(k)$ and the target is the current plant outputs $y_1(k), y_2(k), y_3(k), y_4(k)$ for the roll, pitch, yaw and altitude respectively. The GRNN then predicts the next outputs $y_{1,2,3,4}(k+1)$ in a one-step-ahead mode as shown in **Figure 3(a)**, while **Figure 3(b)** shows the flowchart of the incremental evolution algorithm.

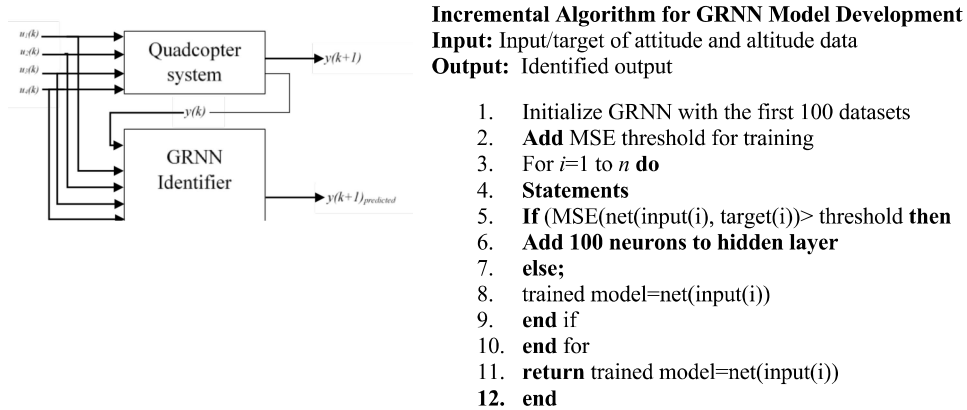


Figure 3 (a) One-Step Ahead Prediction (b). Flowchart of Incremental Algorithm

24. RESULTS AND DISCUSSION

The results shown in figures 4 and 5 of the identification of the quadcopter model F450 using GRNN and IE-GRNN. The results depict the predicted data and the target data. The GRNN takes 0.0244 seconds to train and generate the roll, pitch and yaw models, while the IE-GRNN takes 71.7300 seconds to train. The GRNN model is a forward path model, and a new node is assigned for every input/output data, that is why it takes only 0.0244 seconds to train, while the IE-GRNN trains the data in batches of 100 and discards any set of data which does not help improve the overall accuracy of the model. Hence the training time increases significantly

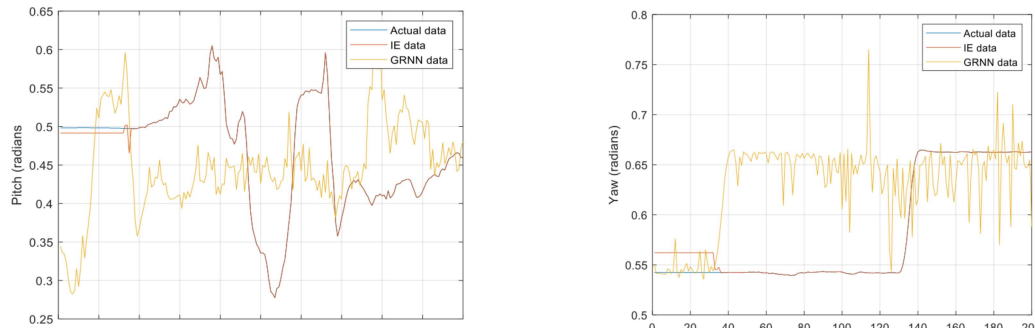


Figure 4(a) Pitch Identification for GRNN, IE-GRNN and Actual Data (b). Yaw Identification Responses for GRNN, IE-GRNN and Actual Data

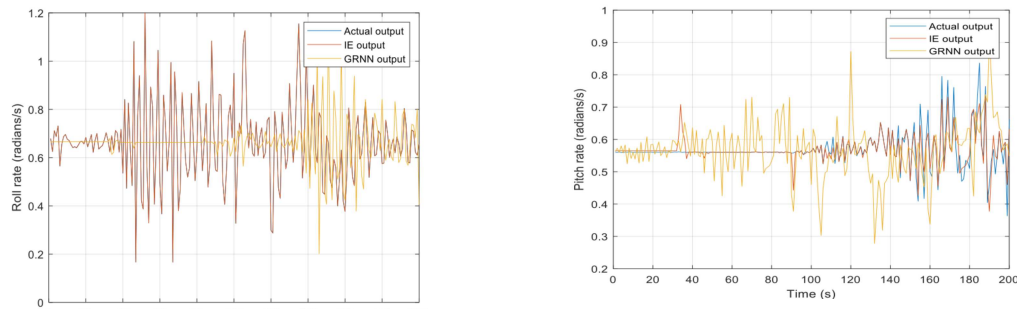


Figure 5 (a) Roll rate Identification comparison (b). Pitch rate Identification comparison

Furthermore, the mean squared error (MSE), root mean squared error (RMSE) and the R-squared values of the trained models in comparison with the actual data outputs are presented in table 1. The IE-GRNN provides better accuracy in terms of error minimization compared to the GRNN trained model. Also, the R^2 values closer to 1

also indicate that the models are well-fitted (Pairan & Shamsudin, 2017) (Dey et al., 2022) except for the altitude model, which has an R^2 value of 0.5. This is caused by the large disturbance experience while collecting data and the poor default controller developed for the quadcopter system which has poor disturbance rejection.

Table 1: Error Analysis of GRNN and IE-GRNN

Variable	MSE		RMSE		R^2	
	GRNN	IE-GRNN	GRNN	IE-GRNN	GRNN	IE-GRNN
Roll	0.0834	0.0268	0.29	0.16	0.9166	0.9732
Pitch	0.0691	0.0514	0.05	0.23	0.9975	0.9484
Yaw	0.9251	0.1627	0.10	0.40	0.9908	0.8373
Altitude	0.500	0.2033	0.71	0.45	0.7967	0.5000
Roll Rate	0.1570	0.0916	0.40	0.30	0.8430	0.9984
Pitch Rate	0.0857	0.0251	0.29	0.16	0.9143	0.9749
Yaw Rate	0.2330	0.1154	0.48	0.34	0.7670	0.8846

25. CONCLUSION

This work has shown the use of neural identification of quadcopters for large data samples and the impact of incremental evolution on generalized regression neural network with regards to over-fitting and under-fitting of the models. It also examined the accuracy of the developed models using the incremental evolution algorithm. The use of an improvised test bench for attitude data collection provides a cheap and alternative means to the use of expensive motion capture cameras, and the results obtained are comparable (Gandhi *et al.*, 2019). Incremental evolution – based generalized regression neural network is suitable for offline black-box identification of quadcopter attitude and attitude rates dynamic models due to the reduced computational complexities and hardware requirements for its implementation. Incremental evolution – based generalized regression neural network – based models provide more accurate models compared to models developed using conventional generalized regression neural networks in terms of model fit, and error minimization. However, the longer training time required makes it unsuitable for online model identification.

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