Altitude Control of Heavy-Lift Hexacopter using Direct Inverse Control Based on Elman Recurrent Neural Network

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ABSTRACT
This paper proposes the use of Direct Inverse Control (DIC) with Elman Recurrent Neural Network (ERNN) learning algorithm for the altitude control of a heavy-lift hexacopter. The study was conducted analytically using the real flight data obtained from real plant experiment. The results showed that the ERNN can successfully control the altitude of the heavy-lift hexacopter, where the response generated by the DIC system was in good agreement with the test data with low error. Furthermore, the proposed DIC system can also control the attitude, e.g. roll, pitch and yaw of the hexacopter which are also crucial for the hexacopter movement control.

CCS Concepts
• **Computing methodologies → Artificial intelligence → Control methods →. Computational control theory**

Keywords
Heavy-Lift Hexacopter; DIC; Neural Networks; Elman Recurrent Neural Networks; Altitude Control.

1. INTRODUCTION
Hexacopter is one type of multirotor that is widely studied due to its maneuverability, flexibility and the ability to effectively lift heavy loads. It is a six rotors nonlinear system than can be operated like a helicopter, but it is more secure than a UAV fixed wing. Like a helicopter, it is capable to do vertical take-off and landing (VTOL) and can fly at low altitudes [1, 2]. The common application of hexacopter includes surveillance, military needs, monitoring purposes, search and rescue operations and mobile sensor networks [1]. In hexacopter, the acceleration during takeoff is not directly proportional to the rotational speed of the rotor. However, the rotor rotational speed produces direct proportional lift and torque which determines the hexacopter movements such as hovering, maneuvers and maintains altitude.

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A special kind of hexacopter is a heavy-lift hexacopter, which is designed specifically to be able to lift heavy loads. The control of this heavy-lift hexacopter remains a challenge due to the significant necessity to maintain stability and prevent the vehicle from any possible failures due to its weight. Altitude is one of the important factors in controlling a heavy-lift hexacopter. The control of altitude is required so that the hexacopter is able to move to a certain height and also able to maintain its stability at such height. This is done by increasing or decreasing the speed of the rotor and maintaining the coordination of the coupling rotor, which is difficult to accomplish since controlling altitude should also involve controlling its attitude, in which the coupling parameter and the characteristics of the nonlinear system play a very important role.

Several researchers have performed altitude control by using a Proportional Derivative (PD) cascade [2, 3], Sliding Mode Controller (SMC) [4], Proportional Integral Derivative (PID) [5], etc. All of the mentioned controllers rely on complex mathematical models, where the nonlinearity problem becomes the main disadvantage, so that these methods cannot work properly for a nonlinear, multivariable and highly coupled system.

Some Neural Network methods have been recently proposed to overcome this problem [6, 7]. The advantage of neural network control is that it is capable to work in a system that is dynamic, nonlinear and uncertain [6,7]. The neural network is a parallel processor that has the ability to memorize and stores knowledge, and then use that knowledge to improve the process of learning [8]. The learning process is basically a process of changing the connection weight between neurons in the network systematically to achieve the capability of mapping a set of the input pattern to a corresponding set of output pattern.

In our previous work [9], attitude control of heavy-lift hexacopter using Elman Recurrent Neural Network (ERNN) Direct Inverse Control (DIC) has been conducted. However, the data used for training and testing were taken from a test bed system where the altitude is fixed, so that the data are only valid at a fixed altitude. This paper analyzes the use of ERNN DIC to control the altitude of a heavy-lift hexacopter. The utilized data for both training and testing were the real flight data obtained from real heavy-lift hexacopter flight experiment.

This paper is presented in five sections. The next section explains about the dynamic model of the heavy-lift hexacopter. The experimental data acquisition is also presented in this section. Section III discusses the development of the neural networks based control system using DIC scheme method and Elman Recurrent

Neural Network learning algorithm. The experimental results and the analysis of the proposed controller's output response will be discussed in Section IV. The conclusion is given in Section V.

2. HEXACOPTER MODELLING

2.1 Dynamic model of Heavy-Lift Hexacopter

The dynamic model of a hexacopter can be derived from the layout and rotation of its six rotors as depicted in Figure 1. The six rotors are analyzed on two reference frames, i.e. the body-fixed frame (B) and the earth-fixed frame (E). The hexacopter is moved by these coupling rotors. In the figure, the hexacopter's center of mass is OB and the center of gravity in the earth-fixed frame is OE.

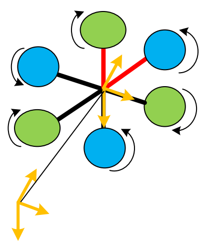

Figure 1. Orientation of Hexacopter

Figure 1 shows the direction of motor rotation for lift movement. In this movement, each adjacent motor have different directions of rotation so that they can simultaneously produce lift forces that are mutually reinforcing. Coupling motors (M1, M3 and M5, and M2, M4 and M6) have different rotation directions in order to provide balance for the hexacopter's movement [4]. Increasing or decreasing the rotation speed of one or more of the coupling motors will produce rotational and translational movement.

The translational and rotational position of hexacopter can be described by vector $\zeta = [x,y,z]^T$ and vector $\eta = [\phi, \theta, \psi]^T$, where ϕ is roll movement, θ is pitch movement and ψ is yaw movement. Given the linear and angular velocity vectors in the body fixed frame, $v^B= [u,v,w]^T$ and $w^B=[p,q,r]^T$, the relationship between (ζ, η) and (v^B, w^B) can be expressed as:

$$\zeta = R\, v^B \tag{1}$$

$$\eta = T\, w^B \tag{2}$$

where R is the rotation matrix and T is the transformation matrix of the body-fixed frame (B) to the earth-fixed frame (E) described as:

$$R = R(\psi, z)\, R(\theta, y)\, R(\phi, x) \tag{3}$$

$$R = \begin{bmatrix} \cos\theta\cos\psi & \cos\psi\sin\theta\sin\phi - \cos\phi\sin\psi & \cos\phi\cos\psi\sin\theta + \sin\phi\sin\psi \\ \cos\theta\sin\psi & \cos\phi\cos\psi + \sin\theta\sin\phi\sin\psi & \cos\phi\sin\psi\sin\theta - \cos\psi\sin\phi \\ -\sin\theta & \cos\theta\sin\phi & \cos\theta\cos\phi \end{bmatrix} \tag{4}$$

$$T = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi \;\; \tan\theta \\ 0 & \cos\phi & \sin\phi \\ 0 & \sin\phi\sec\theta & \sec\theta\cos\phi \end{bmatrix} \tag{5}$$

Therefore, the dynamic model of the hexacopter can be expressed as:

$$\begin{cases} \ddot{X} = -(\sin\psi\sin\phi + \cos\psi\sin\theta\cos\phi)\dfrac{u_1}{m} \\ \ddot{Y} = (-\cos\phi\sin\theta\sin\psi - \cos\psi\sin\phi)\dfrac{u_1}{m} \\ \ddot{Z} = -g + (\cos\theta\cos\phi)\dfrac{u_1}{m} \\ \ddot{\phi} = (\dot{\theta}\dot{\psi}(I_{yy} - I_{zz}) + \tau_x)/I_{xx} \\ \ddot{\theta} = (\dot{\phi}\dot{\psi}(I_{zz} - I_{xx}) + \tau_{yy})/I_{yy} \\ \ddot{\psi} = (\dot{\phi}\dot{\theta}(I_{xx} - I_{yy}) + \tau_z)/I_{zz} \end{cases} \tag{6}$$

where $\ddot{X}, \ddot{Y}, \ddot{Z}$ are the hexacopter's linear accelerations in the E axis, while $\ddot{\phi}, \ddot{\theta}, \ddot{\psi}$ are the hexacopter's angular accelerations in the B axis, m is the mass of the hexacopter, g is the gravity speed, and I_{XX}, I_{YY}, I_{ZZ} are the moments of body inertia at xyz-axis.

Meanwhile, the equation to reflect the relationship between the basic movement of a hexacopter and its rotor rotational speed can be expressed as:

$$\begin{cases} U_1 = b\left(\omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2 + \omega_5^2 + \omega_6^2\right) \\ U_2 = l\, b\left(-\omega_2^2 - \omega_3^2 + \omega_5^2 + \omega_6^2\right) \\ U_3 = l\, b\left(-\omega_1^2 - \omega_2^2 - \omega_6^2 + \omega_3^2 + \omega_4^2 + \omega_5^2\right) \\ U_4 = d\left(-\omega_1^2 + \omega_2^2 - \omega_3^2 + \omega_4^2 - \omega_5^2 + \omega_6^2\right) \\ \omega = -\omega_1 + \omega_2 - \omega_3 + \omega_4 - \omega_5 + \omega_6 \end{cases} \tag{7}$$

In equation (7), U_1 is the vertical thrust, U_2 is the roll torque, U_3 is the pitch torque, U_4 is the yaw torque, ω_n is the propeller speed, b is the thrust factor, d is the drag factor, and l is the distance between the hexacopter's centre spot and the centre spot of its propeller.

The six degrees of freedom (DOF) of the hexacopter is reflected by the six translational and rotational positions X, Y, Z, ϕ, θ, ψ as in equation (6). These positions are controlled by four inputs or control signals, *i.e.* U_1, U_2, U_3, U_4, as in equation (7). Since the output signals outnumbered the input signals, this system can be categorized as an under-actuated system. Thus, the control system of the heavy-lift hexacopter is designed in to be divided into two parts, i.e. inner loop and outer loop, as can be seen in Figure 2. The inner loop control is used to control the hexacopter attitude and altitude, which consist of roll, pitch, yaw, and z movement. Meanwhile, the outer loop control is used to control the x and y movement which directly depicts the real position of the hexacopter.

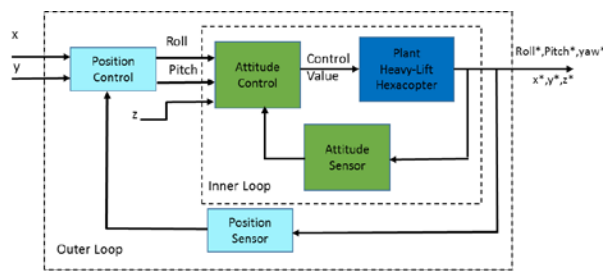

Figure 2. Block Diagram of Hexacopter Control System

2.2 Data Acquisition

This study utilizes the same heavy-lift hexacopter that was developed in the University of Indonesia as already described in [9]. The data utilized for both training and testing are the data obtained from real heavy-lift hexacopter flight experiment. To obtain the data, the hexacopter was controlled by a remote control to fly with helix trajectory to a certain height (26.04 meters) and then back down again, also with helix trajectory. This helix up-and-down motion was chosen by considering the numerous movements involved, so that the characteristics of the obtained data can be significantly enriched. The flight data were stored on the on-board memory on the flight controller and the data acquisitions were performed two times, one for the training data (Figure 3 and 4) and the other for the test data (Figure 5 and 6). Figure 3 and 5 shows that the roll and pitch data ranged from -15° to 15°, whereas the yaw data ranged between 258° to 302°. Meanwhile, Figure 4 and 6 shows the control inputs, e.g. the motor rotational speeds, which were represented by the motors Pulse Width Modulation (PWM).

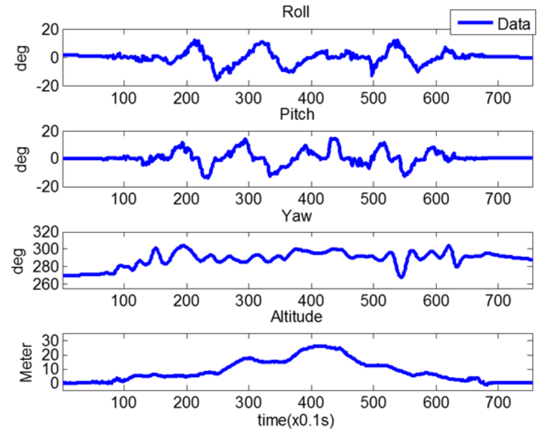

Figure 3. Heavy-Lift Hexacopter Movement for Training

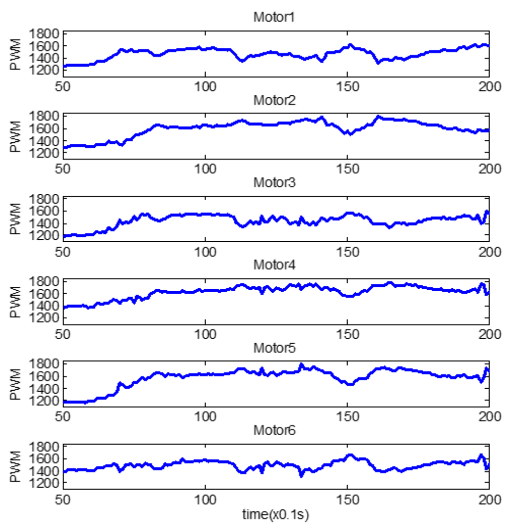

Figure 4. Motor Speed (PWM) of the Heavy-Lift Hexacopter for Training

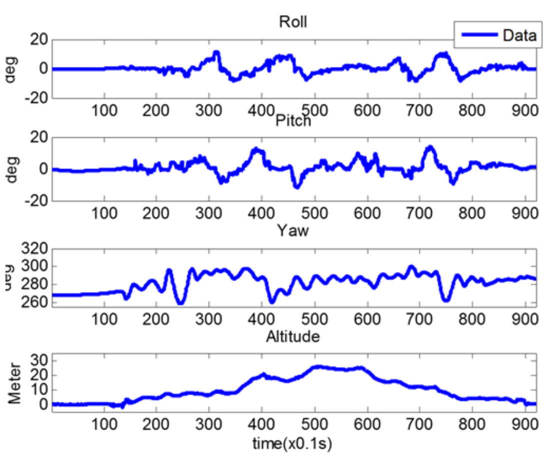

Figure 5. Heavy-Lift Hexacopter Movement for Testing

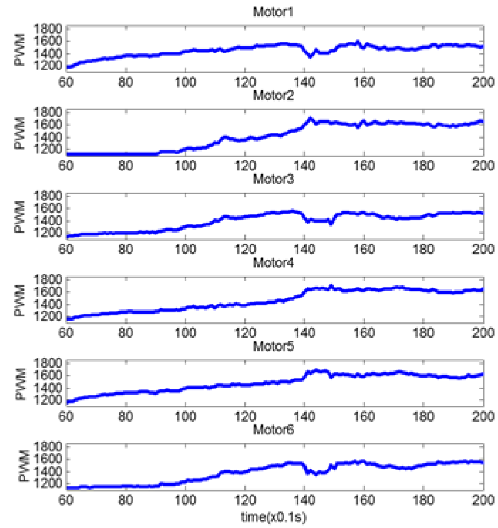

Figure 6. Motor Speed (PWM) of the Heavy-Lift Hexacopter for Testing

3. DIRECT INVERSE CONTROL BASED ON ELMAN RECURRENT NEURAL NETWORK

Neural Network Direct Inverse Control (DIC) is one of the control methods that has the ability to control a nonlinear plant by conducting training on the prevailing inverse model as opposed to the plant to eliminate the dynamic properties [11-13]. It is desired that the output of the inverse model is the same as the required/desired plant input so that the plant can be correctly controlled and perform a similar response to the given reference signal. By directly cascading the inverse model (NN INV) and the plant model (NN ID) as in Figure 7, it is desired that the resulted plant output $y(k)$ is the same as the input of the DIC system or the reference signal $r(k)$. In other words, the DIC system transfer function is expected to be as near as possible to 1 [11].

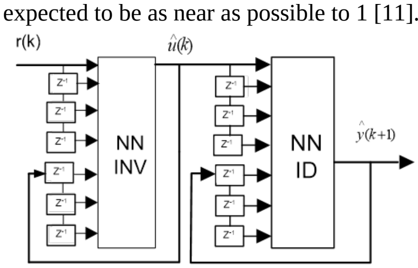

Figure 7. Direct Inverse Control (DIC) scheme

3.1 IDENTIFICATION SYSTEM

In this study, the identification system of a heavy-lift hexacopter is obtained by using neural networks with backpropagation learning algorithm. The neural network configuration for this identification system as the plant model consist of an input layer with 26 neurons, a hidden layer with 35 neurons and an output layer with 4 neurons. The training was conducted by using the training data set, following the training mechanism as depicted in Figure 8a. The result of this training mechanism is described in the next section.

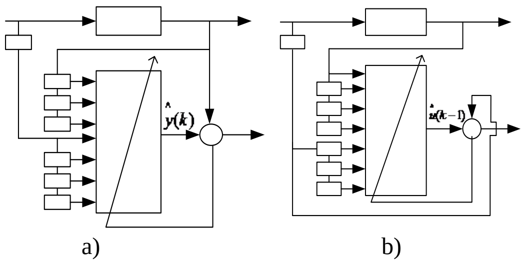

Figure 8. Training configuration scheme a) system identification, b) Inverse model

3.2 INVERSE MODEL USING ELMAN RECURRENT NEURAL NETWORK

The structure of the inverse model training for the DIC system is depicted in Figure 8b. The neural network configuration for the inverse model consists of a single input layer, a single hidden layer, and a single output layer with 24, 35, and 6 neurons, respectively.

Elman Recurrent Neural Network (ERNN) learning algorithm was utilized to obtain the most optimal weight of neurons of the inverse model. Compared to the original backpropagation algorithm, ERNN algorithm has the advantage of being able to eliminate the local minimum and also capable of working at higher order dynamical system [10]. As shown in Figure 9, ERNN algorithm has one additional layer namely a context layer that acts as the memory in the inner state to map the dynamic attitude so that the system has the ability to adapt over time. The uniqueness of ERNN is the existence of feedback connection that carries interference information (noise) during the previous entries which will be accommodated for the next input. Due to the nature of this feedback, the unit can continue to recycle information through the network to the next steps and time, and thus an abstract representation of time is produced. ERNN has been widely researched for the purpose of identification, predicting, fault diagnosis and forecasting, identification of spectral signal of music [10-14]. ERNN requires longer training period and has low convergence speed so that the algorithm is less suited to an application that is critical [15].

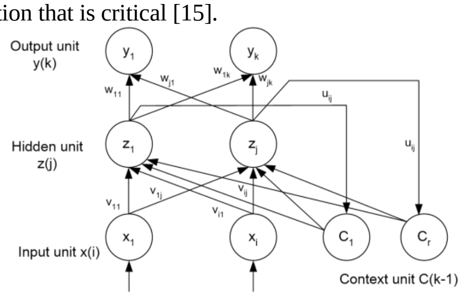

Figure 9. Elman Recurrent Neural Network Architecture

Figure 9 shows the basic architecture of ERNN algorithm that consists not only input layer, hidden layer and output layer but also an additional layer called a context layer ($C(k$-1)). Given that the input is $x(k)$, the output is $y_{ink}(k)$ and the total input to the hidden layer j is $z_{inj}(k)$, then the equations of the architecture are:

$$z_{inj}(k) = \sum u_{ij}(k-1)C_i(k) + v_{ij}(k-1)x(k) \quad (8)$$

$$z_j(k) = f(z_{inj}) \quad (9)$$

$$C_j(k) = z_i(k-1) \quad (10)$$

$$y_{ink}(k) = \sum w_{ij}(k-1)z_j(k) \quad (11)$$

where w_{ij} is the weights of the hidden layer to the output layer, u_{ij} is the weights of the context layer to the hidden layer, v_{ij} is the weights of the input layer to the hidden layer and f is the activation function of the hidden layer. In general, the ERNN training is similar to the well-known backpropagation training, but with adaptive learning rate. This mechanism can prevent the system from the local minimum trap. Like backpropagation learning algorithm, the training was done iteratively by minimizing the resulting error E_k or the difference between the actual output $y_d(k)$ and the output generated by the network $y_{ink}(k)$ expressed as:

$$E_k = \frac{1}{2}(y_d(k) - y_{ink}(k))^2 \quad (12)$$

Based on the error value in equation (12), the weights of each layer can be modified by the following equations:

$$\Delta w_{ij}(k) = \eta(y_d(k) - y_{ink}(k))z_j(k) \quad (13)$$

$$\Delta v_{ij}(k) = \eta\left(y_d(k) - y_{ink}(k)\right)w_i(k-1)\, f'\, z_{inj}\, x(k) \quad (14)$$

$$\Delta u_{i,j}(k) = \eta(y_d(k) - y_{ink}(k))w_i\,(k-1)\, f z_{inj}\, z_j(k-1) \quad (15)$$

where η is the learning rate value.

4. EXPERIMENTAL RESULT

The test result of identification training is depicted in Figure 10. The training reached its convergence in *35,000* epoch and the obtained Mean Sum Square Error (MSSE) for this training was 6.4×10^{-4}. On the testing stage, the obtained MSSE was *0.0122.* This low error value shows that the neural network identification system can represent the heavy-lift hexacopter plant.

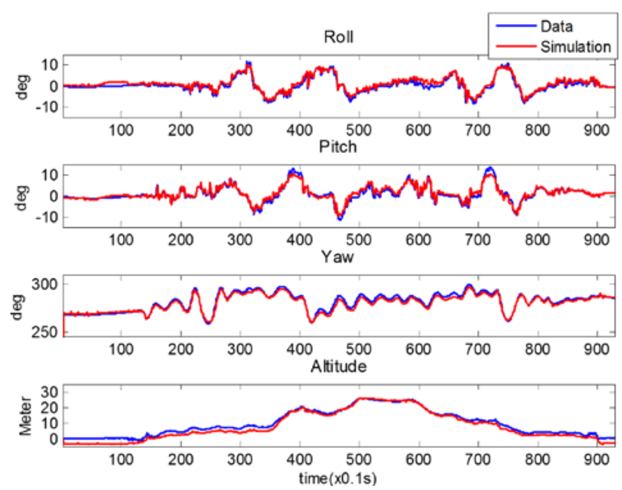

Figure 10. System Identification Test Responses

The test result for the inverse model is shown in Figure 11. The training required *18,000* epoch to produce a training MSSE of 0.0112.

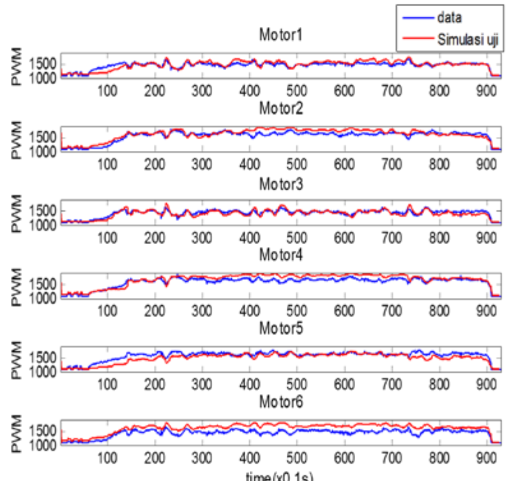

Figure 11. Inverse model Test Responses

After training and subsequent testing, the weights obtained for the NN ID and NN INV configurations were then utilized in the Neural Network DIC system. This DIC system was then tested using the test data as already shown in Figure 5 and 6.
The result of this test is depicted in Figure 12. The figure reflects that the outputs of the simulated Neural Network DIC shown in red curves are in good agreement with the real test data shown in blue curves. The corresponding MSSE which represents roll, pitch, yaw and altitude for this Neural Network DIC test result is *0.0256*.

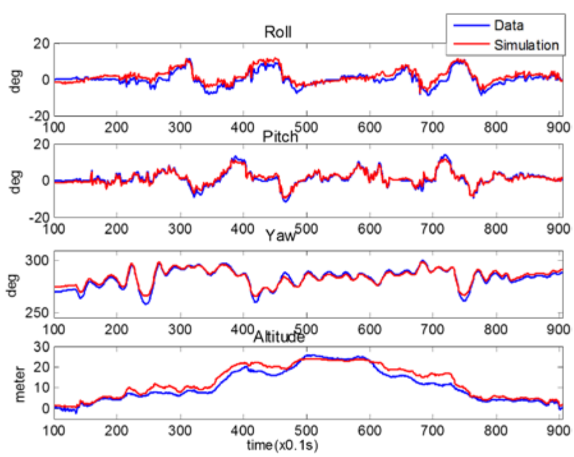

Figure 12. Neural Network based DIC Test Responses

The main focus of the study is the altitude control, and its result can be seen on the most bottom graph in Figure 12. The graph revealed that the altitude of the simulated Neural Network DIC had been able to match the real altitude of the hexacopter, although small discrepancies are still observed at certain heights.

5. CONCLUSIONS

This paper has shown that Elman Recurrent Neural Network can be utilized to control the altitude of a heavy-lift hexacopter with low error and good system response. Furthermore, the proposed Elman Recurrent Neural Network based Direct Inverse Control (ERNN-DIC) also revealed good performance in controlling the attitude of heavy-lift hexacopter, e.g. roll, pitch and yaw. In the future, the proposed ERNN-DIC can also be used to control the real position of the heavy-lift hexacopter. The required investigations for this purpose are still on-going.

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