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Altitude Identification and Intelligent Control of a Flapping Wing Micro Aerial Vehicle using Modified Generalized Regression Neural Networks

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***Abstract*—The design of an intelligent controller for the Flapping Wing Micro Aerial Vehicle (FWMAV) is addressed in this paper. Generalized Regression Neural Network (GRNN) is used for the identification and control. One of the main issues associated with the GRNN is the growth in the size of the hidden layer with the data size increase is addressed in this research. The superiority of the GRNN controller is shown using numerical simulations in the presence of disturbances and the performance is compared with a classical Proportional Integral Derivative (PID) controller.**

I. Introduction

Autonomous systems have recently become popular due to their various applications in different aspects of the life. These applications range from robot vacuums to more advanced systems such as the autonomous cars or aircraft. A substantial research interest in the development of Unmanned Aerial Vehicles (UAVs) is evident nowadays since UAVs have many useful applications in imaging, surveying, monitoring, rescue, agriculture, military, and many more applications in science and research. UAVs can be categorized into fixed-wing, rotary wing, and flapping wing. Most commercial drones such as quadcopters are rotatory wing UAVs. Flapping wing UAVs are challenging due to non-linear dynamics, over-actuated systems, and due to the size of these models, they are also highly susceptible to atmospheric disturbances. In this paper, the FWMAV under consideration has four actuators with a total weight of only 80 grams.

There are mainly two approaches to model the FWMAV; either using the non-linear flapping flight models or using the quasi-steady modeling. Quasi-steady modeling is more popular than non-linear models, and it is mainly used to estimate the instantaneous forces generated by a flapping wing motion. The instantaneous force is a summation of the forces due to inertia, translation, rotation, and wake capture. Further details of the quasi-steady modeling can be found in [1]–[3]. For non-linear systems such as FWMAV, it is hard to obtain an accurate model of the system dynamics from the basic principles of physics. Hence, one of the most common solutions is using system identification techniques. System identification can be classified as either gray-box or black-box techniques. In the gray-box methods, combinations of equations and data-driven models are used to find the system model while in the black-box approach the modeling is only based on the input-output data. Based on the nature of the input-output data, either time domain or frequency domain identification methods can be employed. Some of the methods employed for the identification of flapping wing UAVs are the subspace algorithm [4], combination of linear modeling of forces and momentum using Newton- Euler equations and the least square parameter estimation [5], stepwise regression in time domain to find a linear model [2], and other studies which are based on parameters estimation [6].

Artificial Neural Networks (ANNs) are one of the black-box system identification techniques. They can be used to identify non-linear systems [7]–[9]. ANNs have several applications not only in control systems but also in industry [10], agriculture and food engineering [11], medicine [12], finance [13], and many more. Fuzzy logic-based identification is another black-box method which also has a good potential in identification of UAVs dynamics [14].

This research proposes to use the ANN-based identification for the FWMAV. GRNN has been used successfully before [15] for identification of quadcopter dynamics.

Designing a control system that can handle the complexities in the FWMAV and attain a degree of performance and stability is an arduous task for many control system techniques. FWMAV follows the same control methodology as those which are used for UAVs by controlling the Euler angles (θ, ϕ and γ) and the position in the 3D plane (X, Y, and Z). However, for FWMAV the control mechanism is based on the flapping parameters and not on the thrust of the motor as in rotary wing UAVs. Some of the control methods that have been used to control the flapping wing UAVs include Linear Quadratic/Gaussian Regulator (LQR/LQG) [16], pseudo-inverse control [17], Proportional Integral Derivative (PID/PD) controller [18], [19], Adaptive Feedforward Cancellation (AFC) [20] and adaptive Lyapunov-based control [21]. In this paper, the intelligent control of FWMAV using neural networks is considered. The research aims to offer an algorithm to optimize the size of GRNN in the training stage, implement the improved GRNN for system

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identification of the FWMAV and design an adaptive control system based on GRNN. The controller results are compared with the conventional PID controller results and the controller disturbances rejection is tested as well.

The proposed GRNN-based controller can adapt to aggressive variations in the desired reference within a brief time and can provide a practical solution to reject disturbances which are very common in UAVs systems. The rest of the paper is organized as follows. The tools and methods section II explains the GRNN optimization and the control system. The simulation results for identification and control are discussed in section III and comparison with the conventional PID controller is also provided. Section IV provides some useful conclusions and recommendations regarding the work.

II. Tools and Methods

GRNN [22] is a single-pass learning ANN. It is a variation of Radial Basis Functions Networks (RBFNN). It has proven abilities in regression, approximation, and forecast problems. GRNN is composed of input, pattern, summation, and output layers or the summation and output layers can be combined as one output layer. The pattern or the hidden layer uses a normalized radial basis activation function as given by equation (1).

The output of the GRNN can be calculated using equations (2) and (3). When the GRNN is trained in batch mode, it stores every distinct input/target pattern. After enough number of training patterns, it can generalize easily when new patterns appear in the input. The major advantage of this training approach over the backpropagation training is the quick learning process. Also, GRNN has a high accuracy in estimation of the output provided it has been trained with enough input samples. The other substantial advantage of GRNN is that the only free parameter for tuning in GRNN is the width of the radial basis function or the smoothing parameter σ. On the other hand, GRNN has some disadvantages including the growth of the hidden layer size in the training phase and sometimes modifying σ does not lead to the required results especially when using GRNN as a controller. In this paper, the first issue will be addressed by suggesting a method to optimize the size of GRNN.

$$F(z) = \frac{exp-(z^2)}{\sum_{i=1}^{N} exp-(z^2)} \tag{1}$$

$$di(x) = (X - X_i)(X - X_i)^T \tag{2}$$

$$\hat{Y}(x) = \frac{\sum_{i=1}^{N} Target(i)\ exp-(\frac{d_i(x)^2}{2\sigma^2})}{\sum_{i=1}^{N} exp-(\frac{d_i(x)^2}{2\sigma^2})} \tag{3}$$

GRNN is a robust tool for prediction and approximation; however, since it is associative memory neural network, it saves every distinct training pattern in the hidden layer by assigning a neuron in the hidden layer for every input/output pattern which can lead to a large size network and long computation time. Because of this issue, a new method based

TABLE I
GRNN optimization

Tolerance (MSE)	Neurons number
Original	1001
$1e^{-1}$	195
$1e^{-2}$	554
$1e^{-3}$	834

on incremental evolution is employed here to keep the size of GRNN optimized during its training. The incremental evolution initializes GRNN with the first 100 training inputs. Then for every new training input, the Mean Squared Error (MSE) will be calculated to decide whether we need to train the network with this input or it already has something similar. If MSE is more than the tolerance or the threshold, as set by the user which indicates the level of the required accuracy, the hidden layer will be updated to accommodate for the new pattern. Otherwise, the network will not be changed. Using this algorithm which is described in (Fig. 1), the size of the hidden layer is optimized as shown by (TABLE I) for our FWMAV. The original size of the hidden layer before applying the algorithm is 1001 neurons, and after applying the algorithm, there is a substantial decrease in the hidden layer size, up to 195 neurons for $1e^{-1}$ tolerance.

Input: Input/target pair
Output: Identified output
Initialisation :
Initialize GRNN with the first 100 data points
LOOP Process
for $i = l$ to N **do**
  statements..
  if (MSE(net(input(i)),target(i))> Threshold **then**
    ADD neuron to the hidden layer
  else
    Identified output=net(input(i))
  end if
end for
return Identified output=net(input(i))

Fig. 1. GRNN Optimization Algorithm

In the identification part, the quasi-steady mathematical model [1]–[3] of the FWMAV is used to generate the input/output data. Since the FWMAV has 4 actuators and each actuator has 8 flapping parameters, flapping parameters analysis is conducted to determine the dominant flapping parameters. A single actuator is isolated to reduce the number of parameters, and then each parameter is separately varied to determine its effect on the output translational and rotational velocities. The flapping amplitude is found to be the dominant parameter which can be used to control the system. Based on this, the flapping amplitude is varied to identify the system outputs; the translational velocities of the body (vb_x,vb_y, and vb_z) and the rotational velocity of the body (ω_{bx}, ω_{by}, and

ω_{bz}) in the 3D plane.
The data used for identification is based on 100 seconds simulation in Simulink with a time step of 0.1 seconds. The Simulink model is based on numerical quasi-steady flapping wing motion analysis. More details of how the model estimates the aerodynamic forces and then solve the rigid body dynamics can be found in [23]. After collecting the data, all the simulation has been conducted in Matlab environment. The identification of the FWMAV is conducted using the optimized GRNN algorithm. Since our FWMAV model can change its actuators flapping amplitude from $-90°$ to $90°$ and since we are interested in altitude dynamics and control; the input flapping amplitude is changed for all the four actuators in a sinusoidal form according to (Fig. 2). The reason for choosing a sinusoidal input wave is to present GRNN with the maximum possible values of the input. The second reason is the nature of the smooth changes in the input which can be captured by the GRNN.

The parameters of GRNN are adjusted in response to the tracking error between the actual altitude of the FWMAV and the desired altitude. This adjustment is considered as the base of the adaptive GRNN controller.
The parameters of GRNN include the hidden and the output layers weights, and the smoothing parameter σ are adapted. However, after modifying each of these parameters separately, changing the output weights is found to have the dominant effect on the output value. The weights update rule is shown in equation (4). The learning rate (α) controls the speed of network learning. However, relatively large learning rate might cause poor controller adaptation since the GRNN controller is a learning-based controller. For learning based controllers to perform well, they need to be represented with a substantial amount of data so they can detect the inputs patterns and predict the future changes.

$$W(i+1) = W(i) - \alpha * e_t(i) \tag{4}$$

where α is the learning rate and should be chosen between 0 and 1, e_t the output tracking error ($y_{desired}$-y_{output}).

III. Results and Discussion

Since we are mainly interested in the body coordinate, the linear and the rotational velocities are the best dynamics representation of FWMAV. The identification includes the translational velocity of the body in the X-direction V_{bx}(Fig. 3) which can be used to control the pitching and the translational velocity in the X-direction and to estimate the X position of the body. The velocity of the body in the Y-direction Vby (Fig. 4) can be used to control the rolling and the translational velocity of the body in the Y-direction and to estimate the position of the body in the Y-direction. The velocity of the body in the Z-direction Vbz (Fig. 5) can be employed to control the translational velocity of the body in the Z-direction and to approximate the altitude of the body (the height from the ground level).

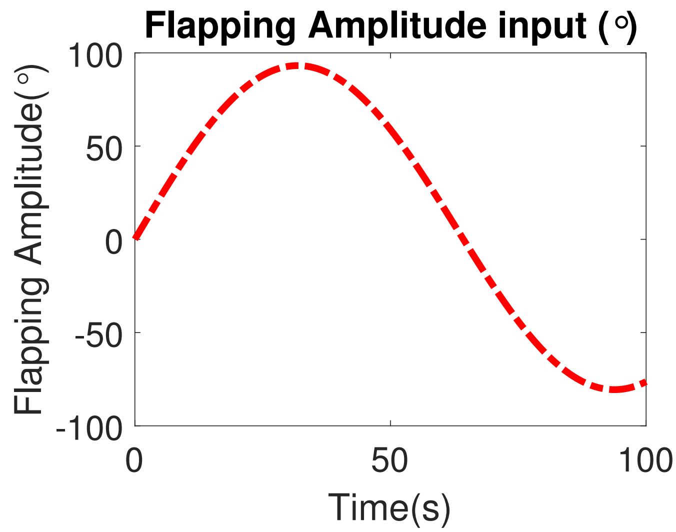

Fig. 2. Flapping Amplitude input

Also the rotational velocities of the body ω_{bx} (Fig. 6) ω_{by} (Fig. 7), and ω_{bz} (Fig. 8) might be utilized to control the orientation of the body (rolling, pitching and yawing) in the 3D plane.

The GRNN identifier is very accurate in detecting the changes in the translational and rotational velocity profiles. The mean squared error (MSE) in the identification of the GRNN is shown in (Fig. 9). The identification error starts very low at $3.7e^{-4}$ then it grows to 5e-4 since new training patterns appear. When the network learning improves, the identification error almost completely vanishes.

Next, separate GRNN is used as a controller of the altitude of FWMAV. For a block diagram of the GRNN controller of the FWMAV altitude see (Fig. 10). The flapping amplitude either will be increased or decreased to track the altitude, based on the controller output.

A simplified square input is given for both the PID and the GRNN controller, and the output is recorded as shown in (Fig. 11). The performance of the PID controller quickly degrades with input changes while the GRNN controller can easily adapt to the input changes.

A variable squared input is fed to the GRNN controller to test its ability as shown in (Fig. 12). The closed-loop response is very accurate and robust to the input changes.

Random disturbances in the intervals[1.5-1.55] seconds and [3.5-3.55] seconds are added to the system output to test the ability of the GRNN controller to reject the disturbances. The controller shows quick and efficient disturbance rejection behavior as seen in (Fig. 13).

The performance of the GRNN-based controller improves with time since the neural network parameters approach to the optimal parameters.

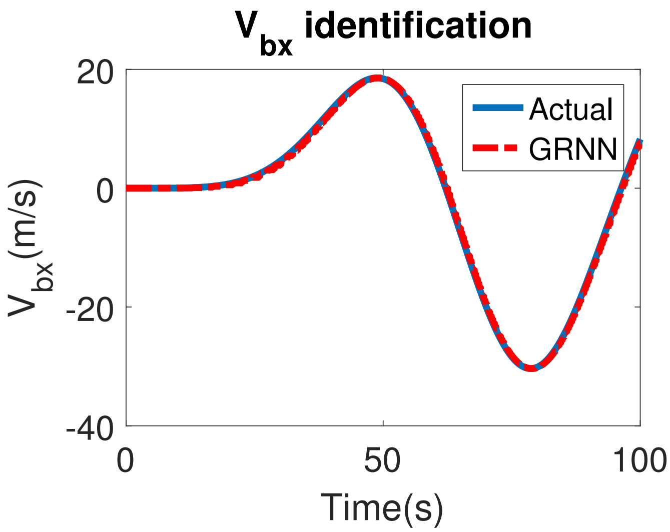

Fig. 3. v_{bx} identified

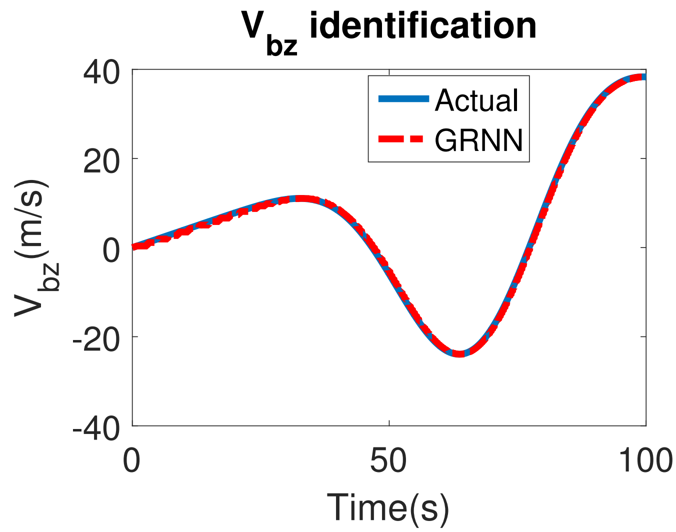

Fig. 5. v_{bz} identified

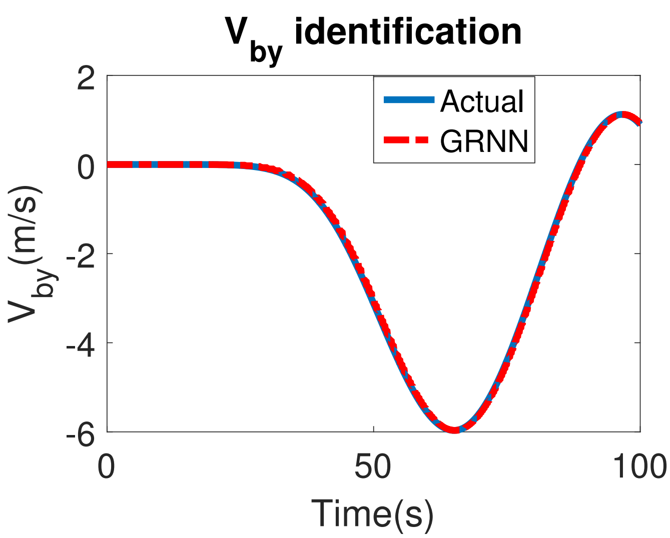

Fig. 4. v_{by} identified

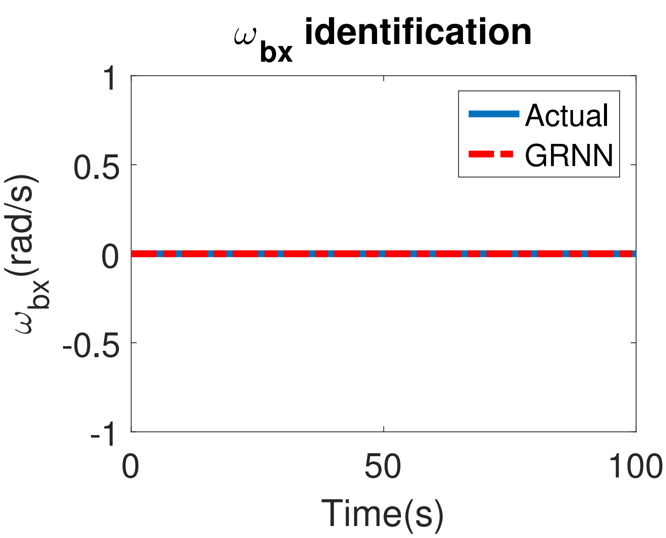

Fig. 6. ω_{bx} identified

IV. Conclusions and Recommendation

This paper presents the identification and control of FWMAV using the GRNN. GRNN is an efficient tool for identification of complex non-linear plants; however, it has some limitations which should be addressed to improve its performance and its efficiency. These issues are the hidden layer size growth and the failure of tuning σ to generate a significant impact on the output. On the other hand, GRNN has unique features including the reduced training time since it is single pass and memory-based network which qualifies it to be deployed in the dynamic systems which require lesser computational times and higher accuracy. This research addresses the problem of the hidden layer growth by implementing a novel algorithm which decides whether a neuron is needed in the hidden layer or not based on the identification error.

Since GRNN learning is controlled by the learning rate $(alpha)$, it could be convenient to use a special algorithm to find and select the optimal learning rate. This issue will be addressed in future research papers.

PID controllers offer robust control systems around the operating points of the systems but not adaptive controllers such as those provided by neural networks. The results of the GRNN clearly show the inadequacies of the PID controller when controlling a complex plant such as FWMAV. Further research is required on the effects of the adaptation mechanism on the GRNN.

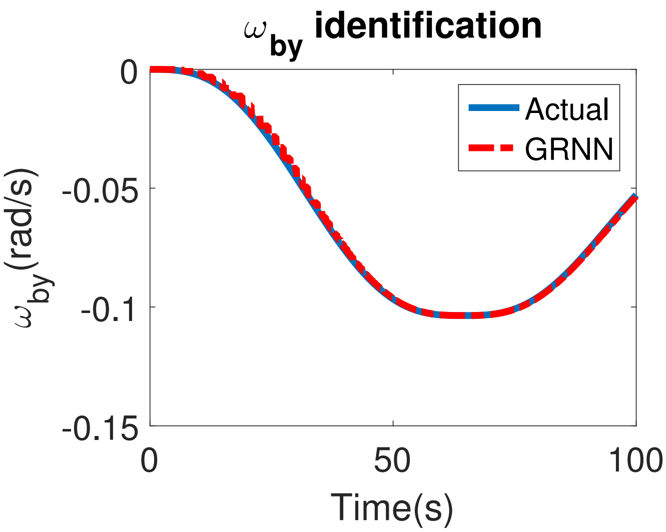

Fig. 7. ω_{by} identified

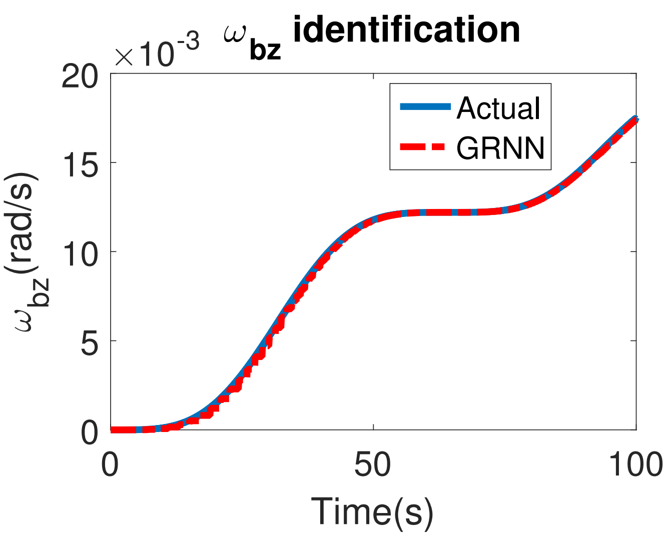

Fig. 8. ω_{bz} identified

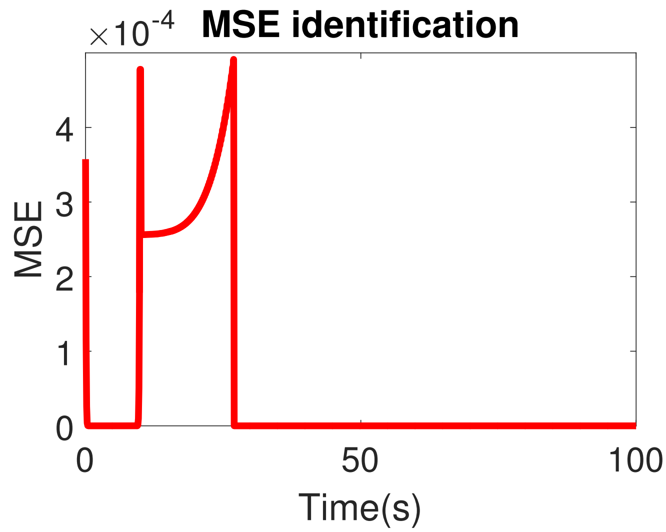

Fig. 9. Mean Squared Error (MSE) change with time

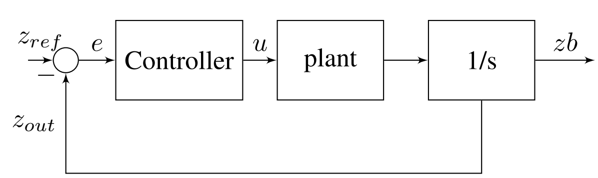

Fig. 10. Closed loop block diagram

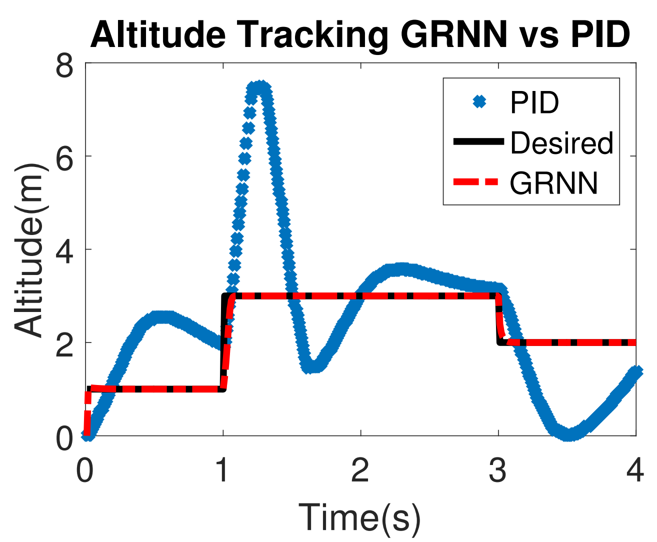

Fig. 11. Altitude Tracking GRNN controller

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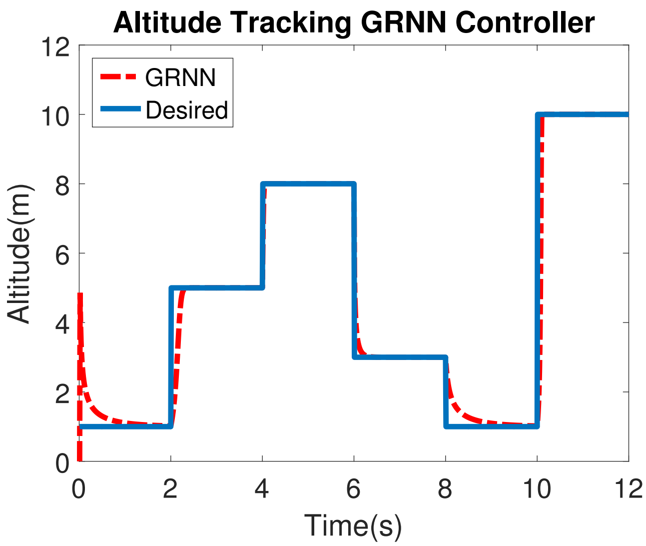

Fig. 12. Altitude Tracking GRNN controller

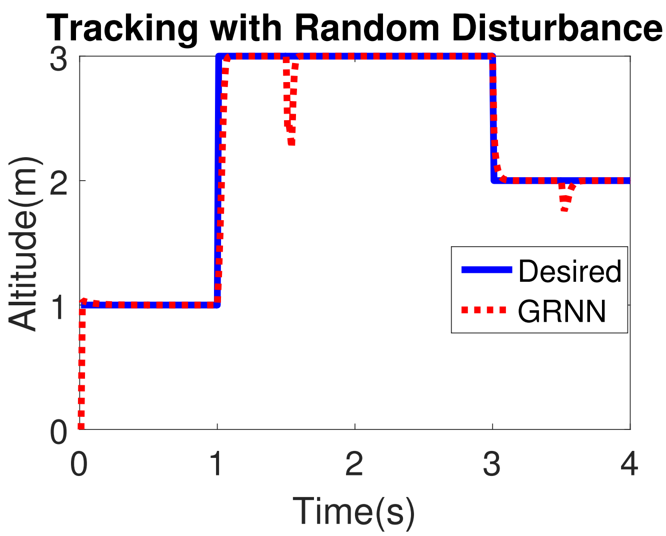

Fig. 13. Altitude Tracking GRNN controller with disturbance

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