International Journal of Robotics and Automation (IJRA)
Vol. 2, No. 2, June 2013, pp. 73~82
ISSN: 2089-4856

UAV Controller Based on Adaptive Neuro-Fuzzy Inference System and PID

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Article Info

Article history:

Received Dec 7, 2012
Revised Apr 2, 2013
Accepted Apr 21, 2013

Keyword:

ANFIS controller
Neuro-fuzzy controller
Autopilot
Lateral controller
UAV

ABSTRACT

ANFIS is combining a neural network with a fuzzy system results in a hybrid neuro-fuzzy system, capable of reasoning and learning in an uncertain and imprecise environment.In this paper, an adaptive neuro-fuzzy inference system (ANFIS) is employed to control an unmanned aircraft vehicle (UAV). First, autopilots structure is defined, and then ANFIS controller is applied, to control UAVs lateral position. The results of ANFIS and PID lateral controllers are compared, where it shows the two controllers have similar results. ANFIS controller is capable to adaptation in nonlinear conditions, while PID has to be tuned to preserves proper control in some conditions.The simulation results generated by Matlab using Aerosim Aeronautical Simulation Block Set, which provides a complete set of tools for development of six degree-of-freedom. Nonlinear Aerosonde unmanned aerial vehicle model with ANFIS controller is simulated to verify the capability of the system. Moreover, the results are validated by FlightGear flight simulator.

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1. INTRODUCTION

The unmanned aerial vehicles are widely used by military and commercial organizations to perform some missions automatically. Choosing a proper controller is important challenge for UAVdesigners. UAVs employ some different navigationequipment, such as gyroscopes, GPS units, cameras, but what can led to premier UAV is a good controller that has an ability to adapt it with various conditions. Numerous techniques have been proposed to control UAVs, such as PID control [1], fuzzy control [2], [3], [4], genetic fuzzy control [5], neural network control [6], fuzzy classifier system [7], adaptive neuro-fuzzy system control [8].

PID controllers are widely used in UAVs because of their ease of use, but they have linear nature so it needs to tune their coefficients again in some conditions, to get the best performance. Neural networks have nonlinear nature and they can preserve the UAV in best performance when its efficiency is based on the training data [9]. Fuzzy controller proposed by different papers, but this type of controller need an expert to write their rules, and its performance is depended on the rules [10].

ANFIS is combining a neural network with a fuzzy system, results in a hybrid neuro-fuzzy system, capable of reasoning and learning in an uncertain and imprecise environment. Therefore, it is suitable for using in complicated systems such as UAVs. In addition, the art of ANFIS is combining the transparent linguistic reasoning of fuzzy logic by the learning abilities of neural networks to create intelligent self-learning which led to a wide range of applications in the past decades. ANFIS has special architecture based on Sugeno type of inference system that enables the use of hybrid learning algorithms. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs [11].

Generally, in UAV's autopilot, there are two major controllers, longitudinal and lateral controllers. The longitudinal controller, controls height and speed. Similarly, lateral controller,controls heading and yaw angle.Lateral controller has an important role in maneuvers, so ANFIS controller is applied to lateral controller sorely, when PID longitudinal controller has acceptable results in maneuvers.

In this perspective, the aim of this paper is to apply ANFIS to UAVs lateral controller, to enhancing the lateral controller's performance.It will guaranty the best possible controlling in hard situations such as winds, gusts, instead of retuning PID coefficients.In the next section, a typical structure of a PID control system is the PID control structure in both lateral and longitudinal control is introduced. Section 3 is dedicated to explain the ANFIS lateral controller. The performances of PID and ANFIS lateral controller are compared in section 4 and also longitudinal controller results are considered. Finally the performance of ANFIS controlleris is verified by Flight Gear simulator.

2. PID BASED CONTROLLER

Proposed autopilot has three major blocks, consists of UAV aerodynamics model, guidance unit, and controller unit, as shown in Figure 1. The performance of the proposed system is evaluated by Matlab, using Aerosim Aeronautical Simulation Block Set [12] and Aerospace toolbox.

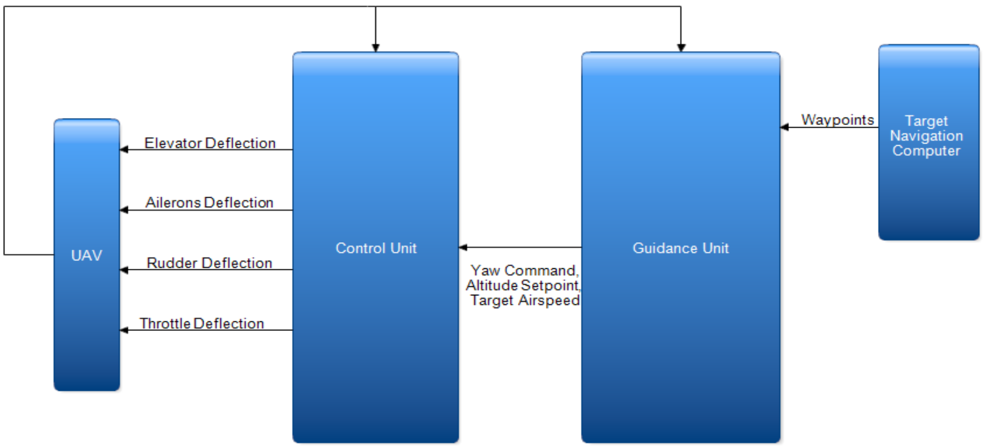

Figure 1. Proposed autopilot algorithm implemented in Simulink environment

In the control unit, two main controllers is applied, they are longitudinal and lateral controller. The longitudinal controller, based on guidance units command, produces a proper value for elevator deflection (δ_e) and throttle deflection (δ_t). Height and speed is controlledbytheseparameters, respectively. Similarly, lateral controller produces a proper value for rudder deflection (δ_r) and ailerons deflection (δ_a). Similar to longitudinal controller, heading and yaw damping is controlledby δ_r and δ_a.

For longitudinal controller, Niculescuin [13] have proposed a good working longitude controller, where the altitude-holdautopilot converts altitude error into a commanded pitchangle. The velocity-hold autopilot converts velocity error to throttle command. The structure of longitudinal PID controller is shown in Figure 3.

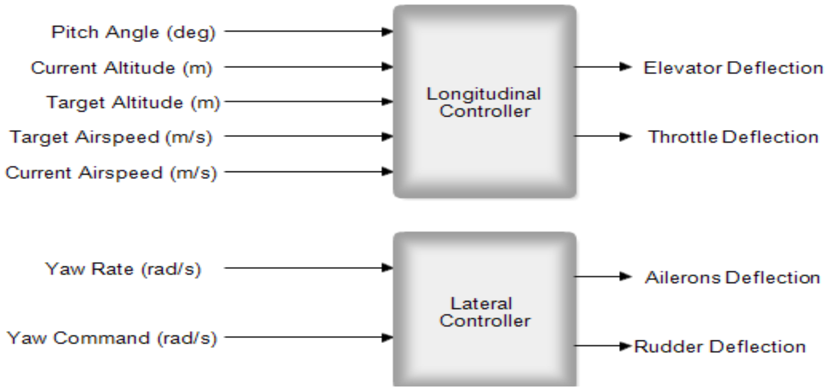

Figure 2. Structure of control unit.

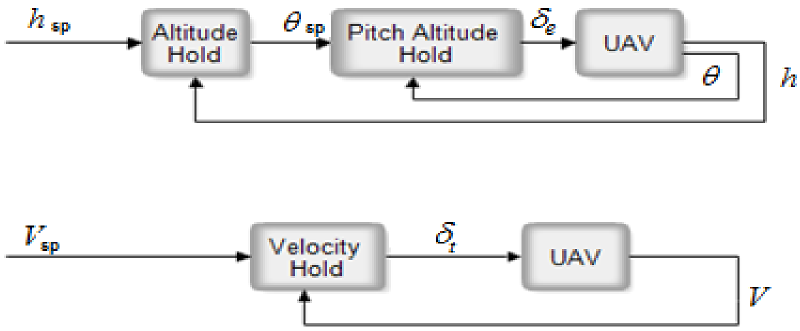

Figure 3. Longitudinal PID controller main structure.

3. ANFIS STRUCTURE

In fuzzy reasoning, fuzzy rules obtained from experts in special field, but it suffers from lack of an effective learning mechanism. Neuro-fuzzy control system is introduced in [14], which is used neural network to implement fuzzy inference control system.

Fuzzy inference system itself does not have their own learning, its application has been greatly restricted. Artificial neural network cannot express fuzzy language, in fact, similar to a black box, the lack of transparency, cannot express the reasoning of the human brain functions. ANFIS uses the advantages of both, they can to be combined for their short comings. However, ANFIS has some limitations, specifically, it only supports Sugeno-type systems, the all membership functions has to be linear combination of each other or to be constant, and the number of output membership functions must be equal to the number of rules.

Considering the special structure first-order Sugeno fuzzy inference system, the system has multiple inputs and single output. For first order Sugeno fuzzy model with fuzzy if-then rules, the general rule set is as follows:

Rule 1:

If x_1 is A_{11} and x_2 is A_{12} and… x_n is A_{1n}, then $f_1=p_{11}x_1+p_{12}x_2+....+p_{1n}x_n+q_1$

Rule 2:

If x_1 is A_{21} and x_2 is A_{22} and… x_n is A_{2n}, then $f_2=p_{21}x_1+p_{22}x_2+....+p_{2n}x_n+q_2$

. . . .

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Rule m:

If x_1 is A_{m1} and x_2 is A_{m2} and… x_n is A_{mn}, then $f_m=p_{m1}x_1+p_{m2}x_2+...+p_{mn}x_n+q_m$

Where, m is multiplication of a number of membership functions in each inputs to each other. The corresponding equivalent ANFIS structure of the model is shown in Figure 4. According to this Figure, there are five layers described as follows:

Layer l: Each nodeinthis layer, introduce a membership function in universal of discourse of each input variable. i.e.

$$O_{1,i} = \mu_{A_i}(x) \tag{1}$$

Where x is the input variable, A_i isith fuzzy set that related to linguistic variable (for example in 2 rules system, it is "small" or "large"). In the other words, the output of this layer is a membership value.

Layer 2: each node in this layer named by$\pi$and its function is:

$$O_{2,i} = \mu_{A_i}(x_1).\mu_{B_i}(x_2) \;\ldots\; \mu_{P_i}(x_n) \tag{2}$$

Each nodes output represents the strength of the incentive of a rule. The function of this node can use to performs fuzzy"and"operator.

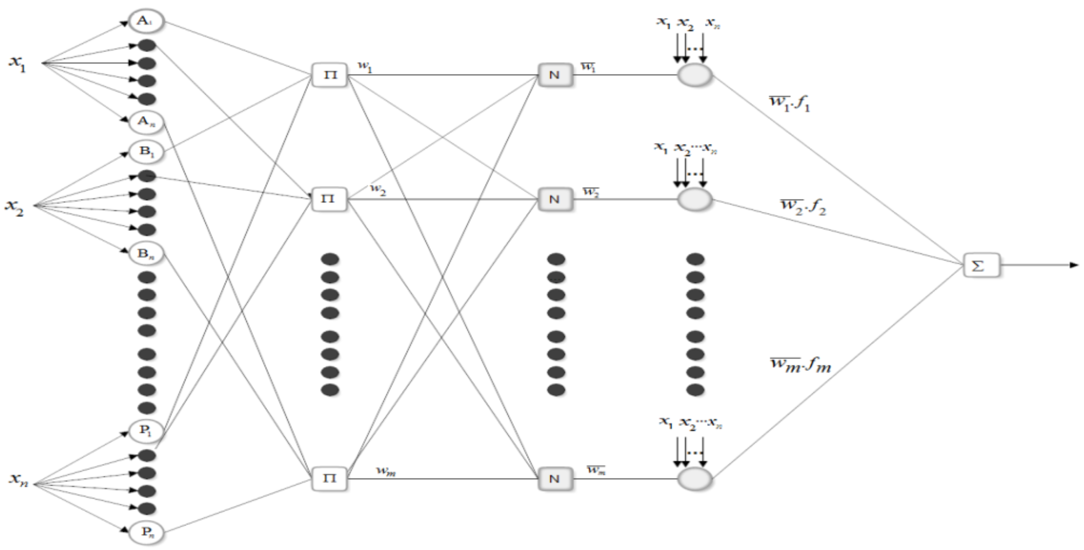

Figure 4. ANFIS general structure

Layer 3: Each node in this layer is named by N, each node calculates the normalized output of each rule.

$$O_{3,i} = \frac{\overline{w_i}}{\sum_i w_i}, i = 1,2,\ldots,m \tag{3}$$

Layer 4: each node of this layer is an adaptive node of the node function, p_i , q_i , r_i is parameters of this layer which is called the conclusion parameters.

$$\begin{aligned} &O_{4i} = O_{3i}.f_i \quad i = 1,2,\ldots,m \\ &where: \quad f_i = p_{i1}x_1 + p_{i2}x_2 + \ldots + p_{in}x_n + q_i \end{aligned} \tag{4}$$

Layer 5: Single node in this layer is a node “Σ”, it calculates all received signals. And as the total output it is:

$$O_{5,i} = \sum \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1, 2, \ldots, m \qquad (5)$$

There are two major learning algorithms that are used in ANFIS, they are back propagation and Hybrid learning algorithm. In this work, Hybrid learning algorithm is used, it is faster and more efficient than back propagation. Hybrid learning algorithm combines the method of least squares and the gradient decent method. The total output of $O_{5,i}$ can be expressed as follows:

$$O_{5,i} = \overline{w_1} f_1 + \overline{w_2} f_2 + \ldots + \overline{w_m} f_m \qquad (6)$$

From the above equations, one can be stated that the output is a linear combination of parameters. So when the default parameters are fixed, total output is a linear combination of output parameters.

ANFIS algorithm is the most obvious advantage of eliminating a large number of mathematical calculations, Matlab encapsulates the complete algorithm of the function and automatically generates rules, and depends on the training data, ANFIS performance can be measured. However, to best performance of AFNIS system, internal parameters of the system, such as the membership function, the number of membership functions, number of training data, verify the number of data and also training times have to be carefully adjusted.

Matlab Fuzzy Toolbox is used to training ANFIS controller. PID controller with best results is used to train ANFIS. Training method of ANFIS is shown in Figure 5, where data that used to train ANFIS consists of yaw error and yaw error rate, and the output of the PI controller.

Figure 5 reveals the procedure of training ANFIS using PI controllers data. Data consists of yaw error which is subtract of current yaw rate and yaw command (yaw error), yaw error rate which is subtract of current yaw error and previous yaw error (which is named yaw error rate) and also PI controllers output.

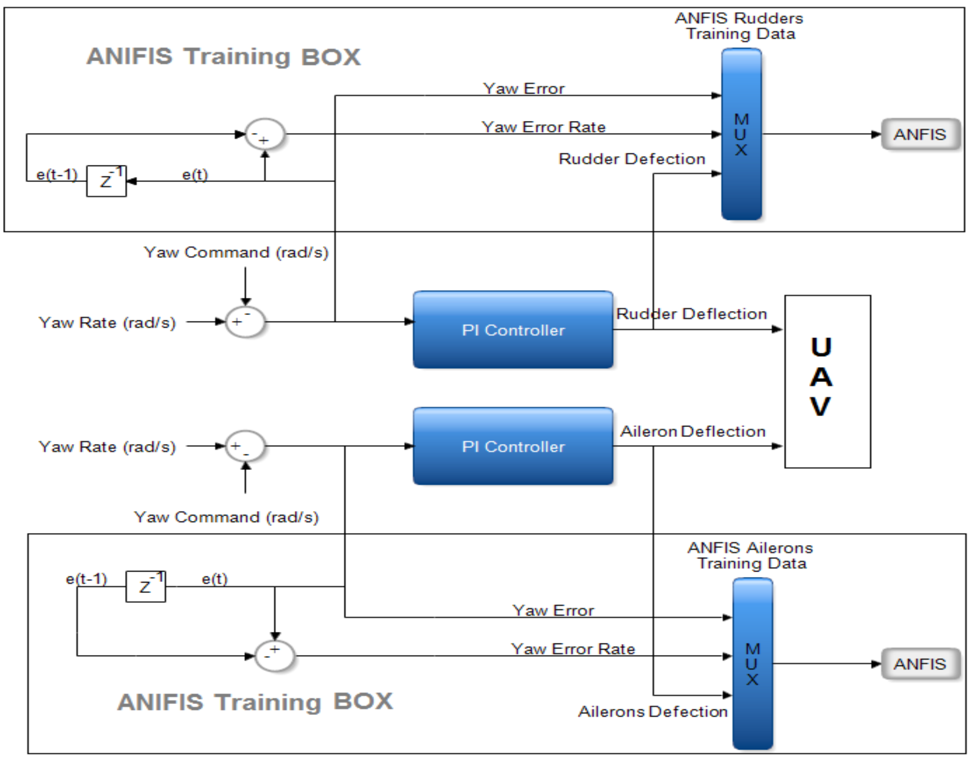

Figure 5. Lateral controllersPI controllers which used to generate ANFIS training data

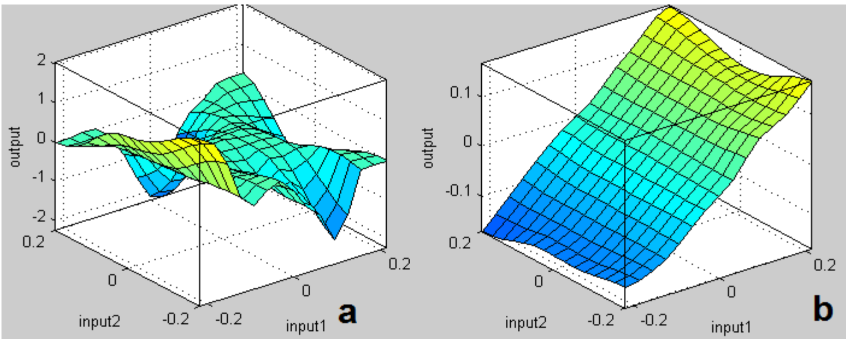

Figure 6. Inputs-output surface (a) ailerons, (b) rudder

After ANFIS training, the input-output surface of trained ANFIS controllers is shown in Figure 6.

The input membership functions of fuzzy controller are shown in Figure 7. According to this figure, five and three membership functions for the yaw error (7) and yawerror rate (8) are used, respectively. Positive large, positive small, zero, negative small, and negative large are linguistic functions of yaw error. Three membership functions are enough to make distinct status of yaw error rate. Positive, zero, and negative are yaw error rates linguistic functions. In addition, grid partitioning is used to generate fuzzy interface system (FIS). Fuzzy C-Means Clustering is used in grid partitioning method. Fuzzy c-means (FCM) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade [15]. This technique was originally introduced by Jim Bezdek in 1981 [16] as an improvement on earlier clustering methods [16]. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. According to Figure 5, yaw error and yaw error rate is defined as follows:

$$error(t) = yawcmd(t) - yaw(t) \tag{7}$$

$$errorrate(t) = error(t) - error(t-1) \tag{8}$$

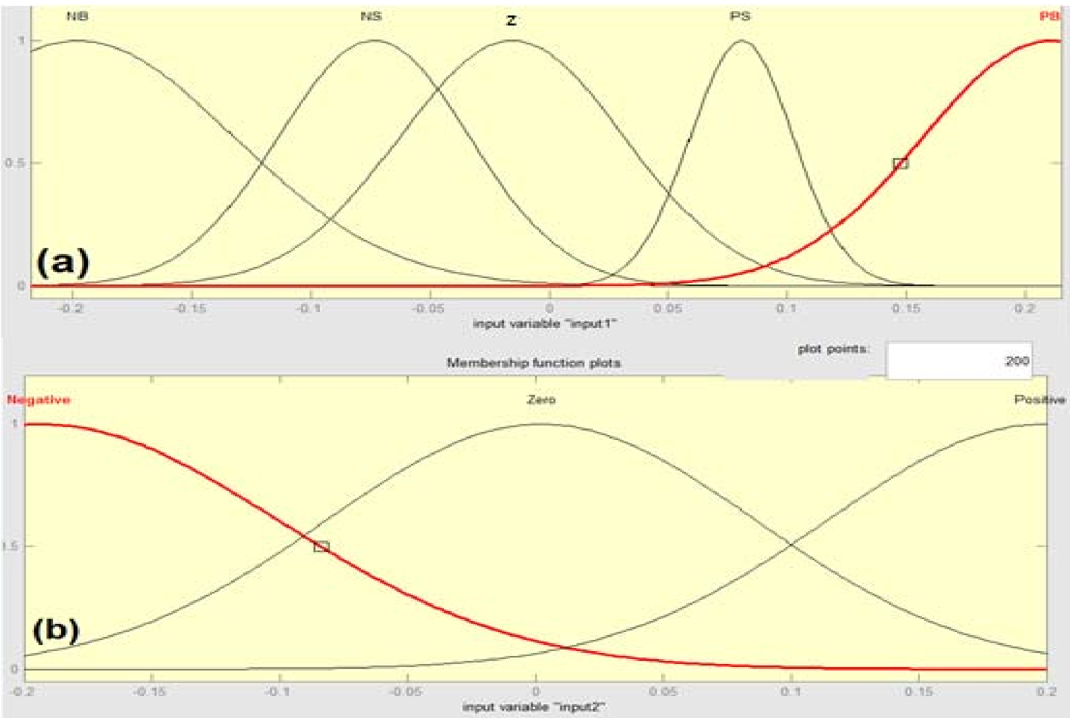

Figure 7. The trained membership functions for the ailerons (a) yaw error (b) yaw error rate

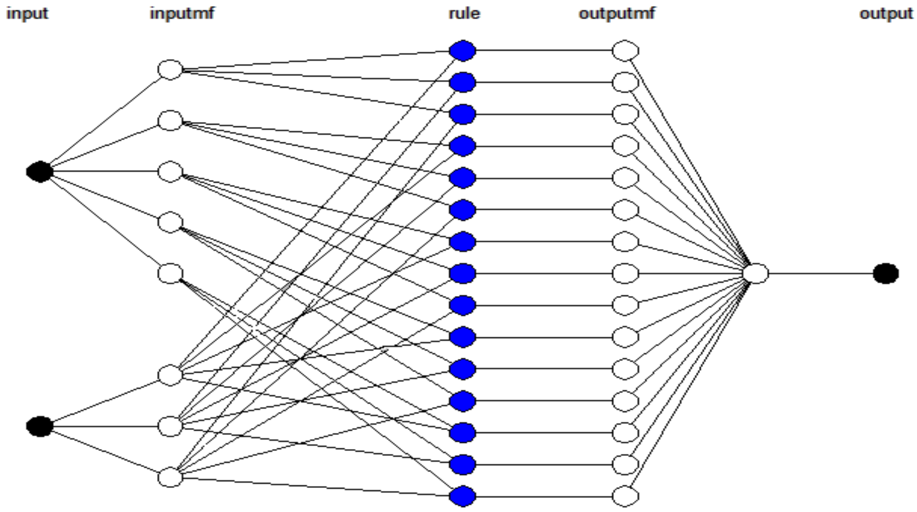

Figure 8. Proposed ANFIS controller structure, there are single output and two inputs by five and three membership functions related to yaw error and yaw error rate respectively

4. SIMULATION RESULTS

Provide a statement that what is expected, as stated in the "Introduction" chapter can ultimately result in "Results and Discussion" chapter, so there is compatibility. Moreover, it can also be added the prospect of the development of research results and application prospects of further studies into the next (based on result and discussion).

4.1. Lateral Controller Results

To compare thePID and ANFIS lateral controllers performance precisely, a small square pulse is applied to both systems, as shownin Figure 9. As it is shown, ANFIS has a better pulse response to the yaw rate command.

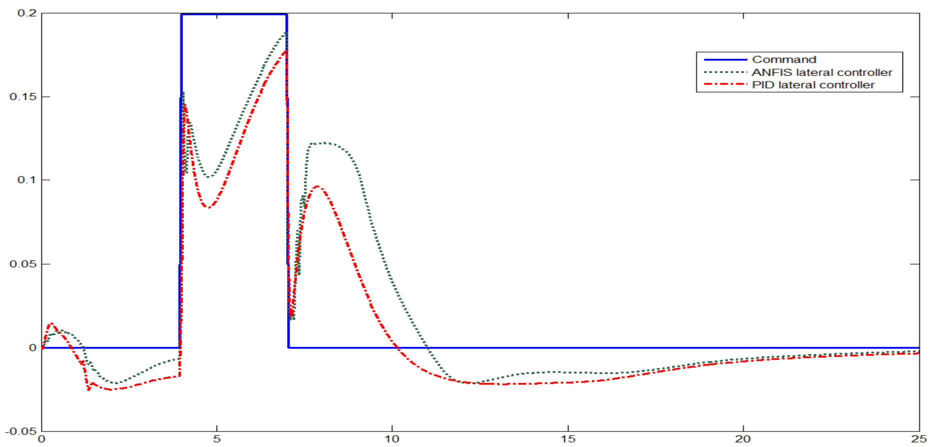

Figure 9. Yaw rate over time, output of PID and ANFIS to yaw command

4.2. Longitudinal Simulation Results

In longitudinal controller, a typical command is set to longitudinal controller, by decreasing the altitude, airspeed is decreased in proportion to altitude decreasing rate. Decrease the both of altitude and airspeed led to faster response to the command. Longitudinal Simulation Results is as follows, consists of airspeed and altitude to typical command.

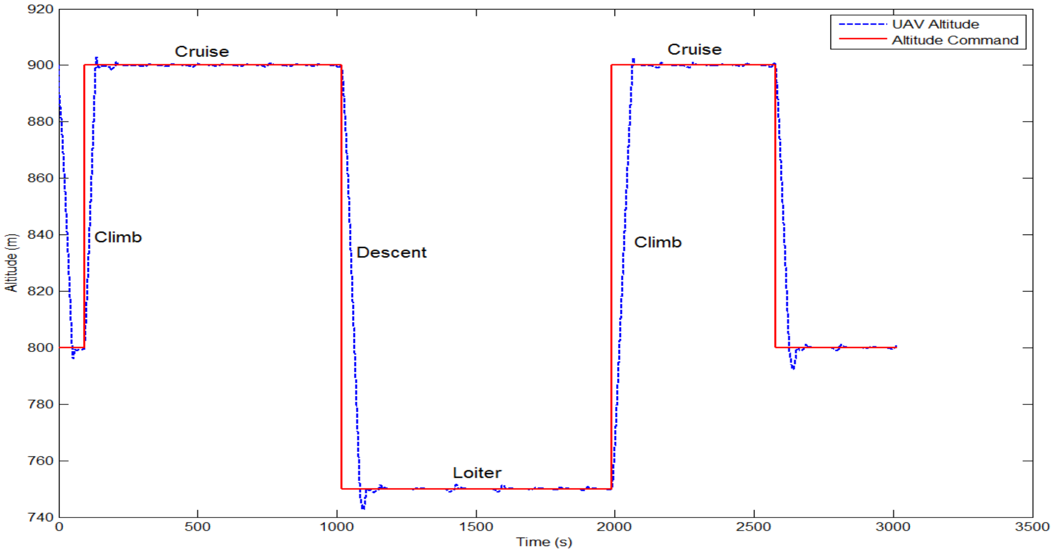

Figure 10. UAVs response to altitude command, in climb, cruise, loiter

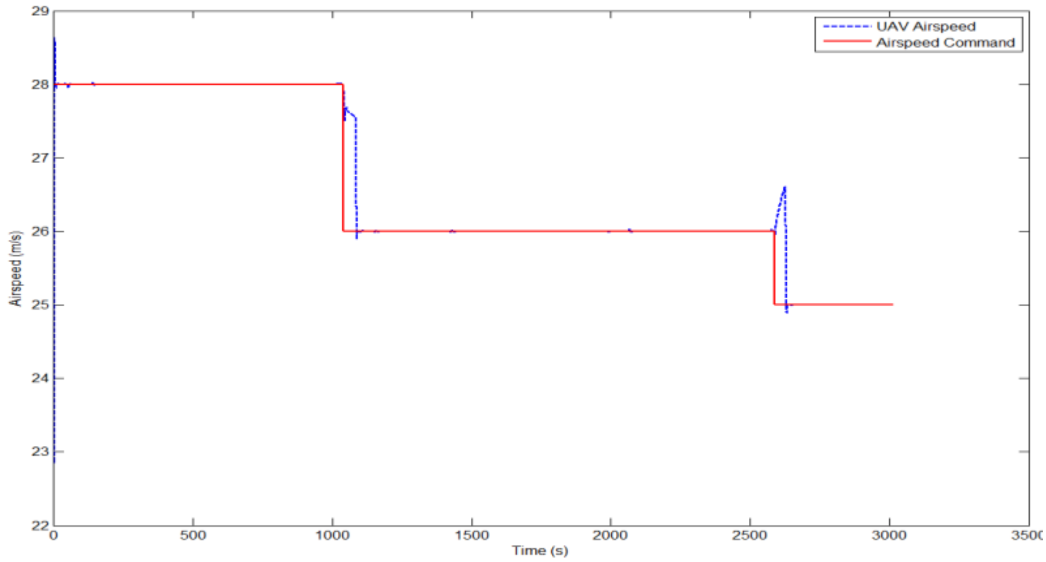

Figure 11. UAV Airspeed, to faster response,when altitude descent occurred, airspeed decreased by autopilot

4.3. Flight Simulation

To evaluate the stability of the proposed UAVs, it is essential to use flight simulator software. There are two common-known flight simulators: FlightGear and Microsoft Flight Simulator. Both have an ability to simulate airplane conditions during flight that can help designers to check their design to resolve the possible errors. In this study, FlightGear flight simulator is used, because it is freeware, open source software, and it can deploy on both Aerosim and Aerospace toolboxes.

There are many parameters are related to UAVs condition such as phy, psi, theta, roll rate, pitch rate and yaw rate, FlightGear is used to check the whole parameters by 6DOF simulation blockset of Aerospace toolbox. Using this toolbox, data is sent to the flight simulator software.

According to Figure 12 and Figure 13, the UAV is in stable condition that it verifies the after mentioned simulation results.

To using FlightGear by Simulink, the exchange protocol is set to Native FDM, the type of Medium is set to the socket and destination port is set to 5500, where UDPmode is selected.

Figure 12. FlightGear simulation environment

Figure 13. UAVs stable condition during flight simulation by FlightGear

5. CONCLUSION

PID control structure is simple, easy to implement, but this traditional controllers designers need to repeatedly selecta large number of design parameters, and need the help of a large number of visual experience to select the structure and parameters of the control system.

Moreover, for more loops, the design process will become increasingly difficult, and in the case of the dynamic characteristics of rapid change, such as UAV systems, it cannot guarantee a successful control. Also PID method relies on accurate nonlinear model, whereas ANFIS has the ability to approximate nonlinear function and it don't need to accurate nonlinear model.

This paper shows that, the lateral ANFIS controller can control UAVs latitude better than conventional PID lateral controller. ANFIS is nonlinear controller, no needs to be tuned after training, while PID is linear and have to be tuned again in some conditions. Simulation results in Matlab/Simulink and in flight simulator reveals the ability of proposed ANFIS lateral controller in compare with PID lateral controller.

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