Fuzzy Logic Based Integrated Controller for Unmanned Aerial Vehicles

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ABSTRACT
This paper discusses the integration of health monitoring and flight control systems for small Unmanned Aerial Vehicles (UAVs). After briefly reviewing previous fuzzy logic controllers (FLC) of air vehicles, a very low cost integration method is proposed. The proposed fuzzy logic (FL) selects the best gain values for the operation of PD or PID controllers of the autonomous flight system according to the health of the components. Such gain adjustments help the UAV to execute maneuvers in a more conservative manner when the system have structural or proportion system problems.

Keywords
Unmanned Aerial Vehicles, Fuzzy Logic Control, ANFIS, Neural Network

1. INTRODUCTION
The latest flight missions have demonstrated the benefits of small UAVs. They are cheaper, do not risk the lives of the pilots, are more difficult to inflict damage on to than conventional planes because of their size, and can be operated with much smaller fighter teams than what is typically required. As technology progresses, the capabilities and the reliability of the UAVs will improve and they will be used for more demanding tasks. New UAV designs have already been discussed for combat and space applications. In order to assess the condition of the vehicle and to operate the system safely in the event of any component failure, more complex health monitoring systems will be required.

Today, the UAVs employed are operated from remote locations or by programmed waypoints. The ultimate goal is to develop fully independent UAVs, which can conduct specialized and/or covert operations for warfare, weather and disaster surveillance, imaging spectrometry, and reconnaissance [1]. With the implementation of such a control system, the small UAV will not be limited to visual range or short distances for operation nor will it be dependent on human control from an operational base. At present, the forecasted optimal method for such small UAV focuses on a hybrid scheme, which involves the use of neural networks and fuzzy logic control [2]. The neural network could be used to learn the pilot's skill in maneuvering a flight vehicle. FL is very convenient to develop sophisticated hardware that directly implements engineers' knowledge. FL will be used to tune the PD or PID control gains according to the readings of the sensors, which monitors the condition of the structure and the engine.

Since the development of such a hybrid system proves to be time consuming and involves generating many algorithms and models, we focus only on one strand of the hybrid scheme, which is the fuzzy logic control in this paper. This artificial intelligence system is quite favored for automatic control because it avoids complex non-linear equations and can utilize the best pilot expertise available. Fuzzy logic, which is based on the mathematical theory of fuzzy sets [3], circumvents complex differential equations by offering a collection of if-then rules which operates as a linear function even though the function itself is not known. Moreover, this logic does not operate on binary output such as true or false, up or down, left or right, but rather facilitates for the entire intermediate spectrum of outputs to be included. In this paper, previous fuzzy logic controllers (FLC) are reviewed and a simple integration method is proposed. This method correlates the gain and the limits of the actuators for conservative vehicle operation when some of the components have problems.

2. FUZZY LOGIC CONTROL

2.1. Background
Prior to investigating the fuzzy logic cases, we examine the Fuzzy Logic Control (FLC) implementation process and specific modes of implementation. There are two types of fuzzy logic inference systems (FIS) available: Mamdani and Sugeno. Both of these methods essentially contain the same steps, the main difference being that the Sugeno method outputs are usually linear. The following FLC cases mainly utilize the Mamdani method. In terms of the fuzzy logic processes, there are three main processes, shown in Figure 1. In the first main fuzzification process, a crisp value is "fuzzified" which means that it is characterized by a fuzzy set. This is followed by the inference process whereby the fuzzified inputs that are represented in the form of membership functions are combined and used to display the knowledge of the experts in the form of rules. In the final process known as defuzzification, the output

value is “defuzzified” thus allowing obtaining the important crisp value. In the cases studied, the center of area defuzzification method is employed which generates the center of gravity of the output set. The membership functions mentioned earlier are vaguely defined sets, which represent the range of the various inputs. There geometries can be triangular, trapezoidal, singleton or variations of the Gaussian function, etc. Genetic algorithms and neural networks [4] may be used to develop and tune the functions.

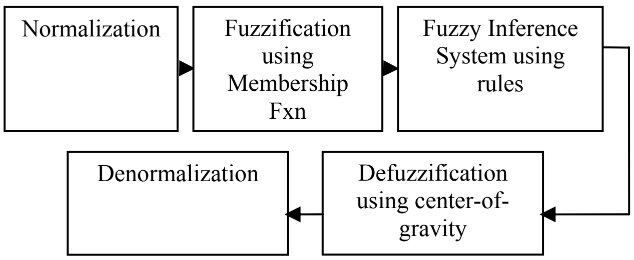


Figure 1. Main processes of fuzzy logic method

2.2. Previous Applications

With the fuzzy logic methodology kept in mind, we examined a few cases of fuzzy logic implementation in flight control. The first fuzzy system analyzed was taken from Mengali’s paper. This simulation involved a two loop system (see Figure 2) which made use of a reference model plane (an ideal model whereby the airplane dynamics have been linearized about a point in the flight envelope and driven by a reference input r) versus a real plane whose dynamics are nonlinear. Thus in this system, the inner loop involved the application of the reference signal R to both systems. This generated an error as the performance of the realistic model did not match the optimized performance of the ideal model (due to model uncertainties, nonlinearities etc) [4]. Applying this error signal to the fuzzy knowledge based controller, the supervisory expert control system (SECS) was employed. This proportional derivative controller’s responsibility was to drive the error of the real model to zero. Its output U was added to the real model to obtain the performance of the outer loop.

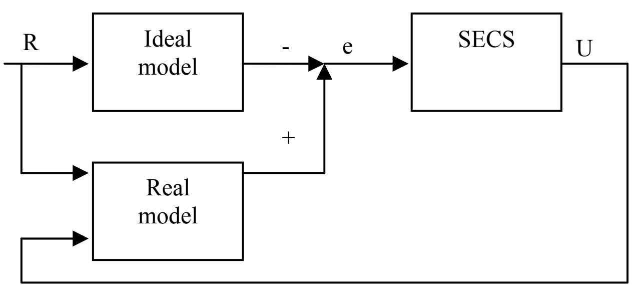


Figure 2. Loop arrangement of the aircraft control system

In the second case study, the controller of a 1m small-size UAV was developed using fuzzy logic and its integration was then tested [1]. Two control methods were used. The first approach collected information about the inputs of the pilot using a learning algorithm. The plane used a PD controller and two fuzzy logic combinations to allow the plane to maintain its altitude. The PD selected the most appropriate control surface displacements. The two separate fuzzy logics adjusted the proportional and derivative gains by considering the pitch and change angle errors. Seven levels were used with the fuzzy logic. The flight tests demonstrated that the fuzzy logic closed-loop control worked better than the opened-loop control.

According to Rajasekhar and Sreenatha’s [5], fuzzy logic can be used to study missile guidance control. The FLC system was developed using the PNG law $\eta_c=NV_c\lambda'$ where η_c is the achievable control, V_c is the line of sight rate (LOS), λ' is the closing velocity and N is a navigation constant. Hence, the goal of the controller was to zero the LOS rate by making the missile turn rate be directly proportional to the LOS rate [2]. Figure 3 represents how the variables were utilized in this FLC system.

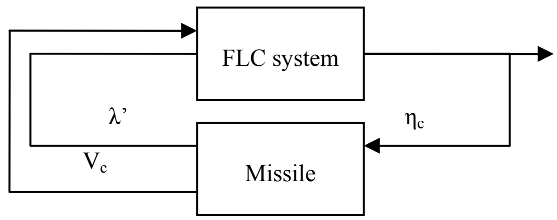


Figure 3. Missile Guidance arrangement using a fuzzy logic controller

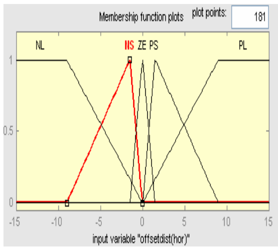
Finally, we examined the application of unmanned landing of an aircraft [3]. This study focused on the nonlinear control actions of a fuzzy controller (FC) operating effectively in the automated landing of unmanned aircrafts. A fuzzy inference system was set up with two inputs and one output. Seven triangular membership functions were used for the inputs to be converted into linguistics variables. Seven triangular membership functions were also used for the output functions and forty-nine fuzzy logic rules were established. The fuzzy controller successfully controlled three-dimensional flight path, sink rate, and angular altitudes to allow safe landing of the unmanned aircraft. A High SIQ (System Intelligent Quotient) mechanism was created which combined elements of human pilot intelligence with landing knowledge. The system was tested with simulations as well as in "real-life" landings in which operations demonstrated definite potential of fuzzy logic usage as a controller.

3. FUZZY LOGIC IMPLEMENTATION

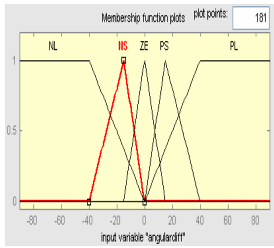
After studying the fuzzy logic implementations for aircraft modeling, projectile guidance, altitude maintenance and unmanned landing, we now put forth our strategy for a flight control system. For a small UAV, basic navigation (in horizontal and vertical planes) utilizing FLC will be attempted. In terms of optimizing parameters, as we mentioned before neural networks are good at learning and recognizing patterns however, their training and learning processes require a lot of time. Furthermore, it is difficult to analyze the trained network and explain how neural networks get their decisions. In order to acquire our control rules and tuned membership functions we relied on Shiori and Ueno’s approach [6]. Input and output elements are selected based on PD control. The two input variables utilized are the offset distance and the difference of the directional angle, both whose membership functions are triangular. Thus, based on the difference of the coordinates and the directional angle, the expert controller’s responsibility will be to drive these errors to zero accordingly by altering the throttle as well as the aileron, rudder and elevator positions. Additionally the control output will also employ a triangular membership function. As rule bases are given for course maintenance in both the horizontal and vertical direction from Shiori and Ueno’s paper, we generate two different fuzzy logic systems shown in Tables 1 and 2, each of them containing their own separate rules.

Table 1. Horizontal direction

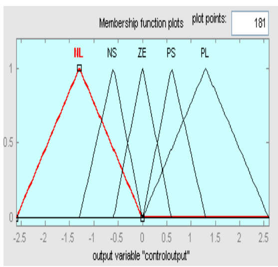
MF of Closing offset dist (hor)



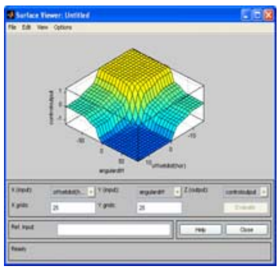
MF of Error angular diff



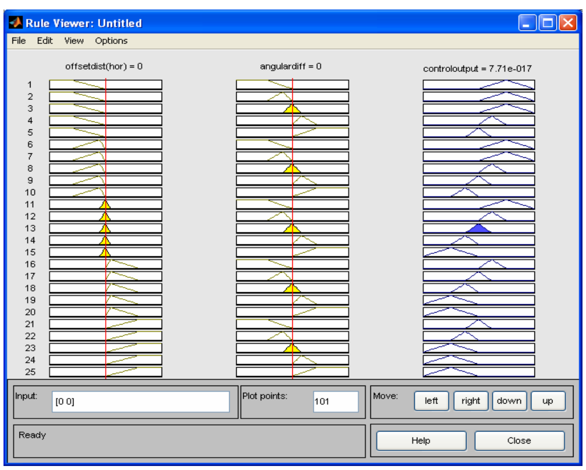
MF of control output



3D Surface



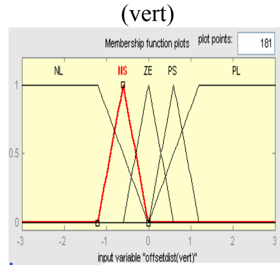
View of Rules



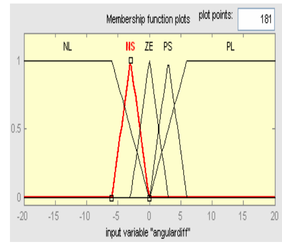
In terms of flight guidance, the control systems of UAVs usually follow the instructions of the pilots at remote location. The more sophisticated systems follow the programmed waypoints with the help of their GPS to reach to their targets. However, in order to maximize the performance of the UAVs’ tasks, adjustment of the sophisticated systems’ flight characteristics according to the operating and structural condition would be quite beneficial. Hence, an ideal Integrated Structural Health Monitoring and Autonomous Guidance and Control (ISHM + AG&C) integration is presented in the Figure 4. It evaluates the flight path, flight condition, and structural health information simultaneously. It processes the gathered information and determines the proper flight characteristics. It may report the abnormalities to the ground crew. The architecture of a simple integrated system is presented in Figure 5.

Table 2. Vertical direction

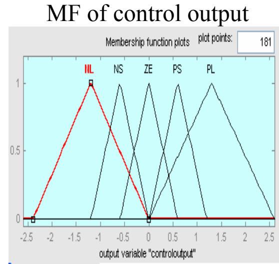
MF of Closing offset dist (vert)



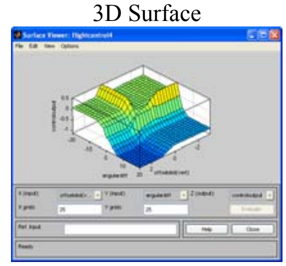
MF of Error angular diff



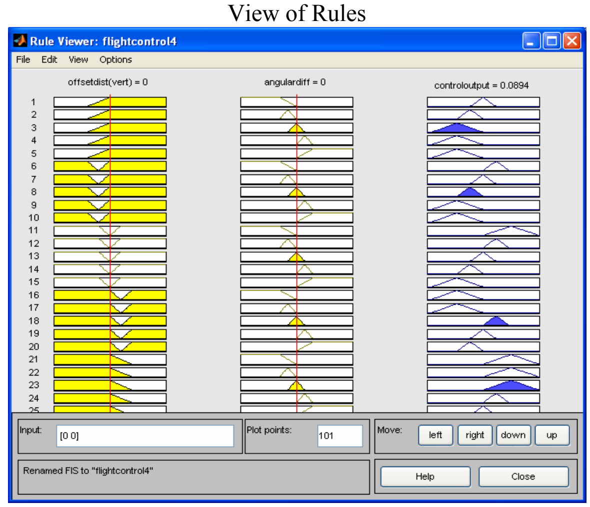
MF of control output



3D Surface



View of Rules



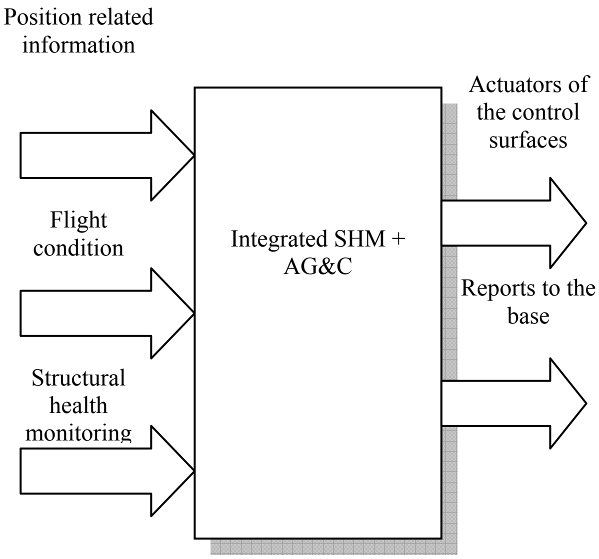


Figure 4. The integrated ISHM and AG&C

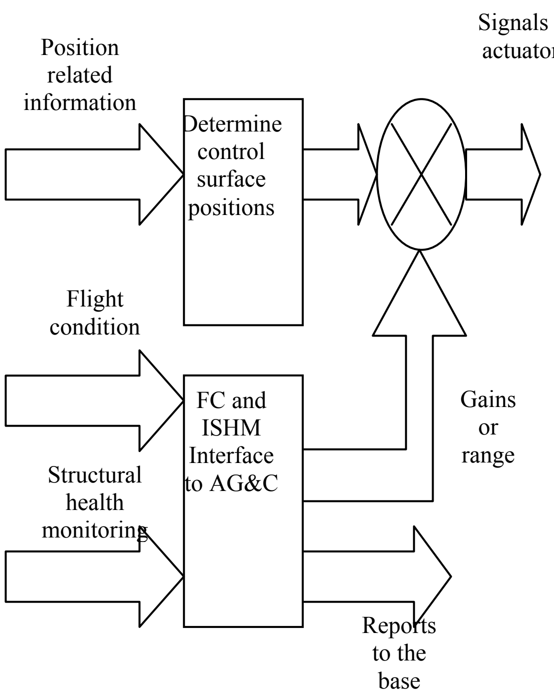


Figure 5. The simplest approach for the integrated ISHM and AG&C system

A fuzzy, fuzzy-neural, or a neural network based “FC and SHM Interface to AG&C” unit (Figure 6) can be used to evaluate flight condition and structural health data. Flight condition data is primarily the engine performance information including the vibratory signature, emission, and temperature of the engine(s). The structural health data is the location, size and severity of structural problems. The signal-processing unit may determine the gain to control the severity of the control surface actions. Ideally, the gain should have a nonlinear relationship with the inputs. Fuzzy logic is a fine choice if the developers want to provide rules. If the developers want to implement an accurate and sophisticated IO relationship, the membership functions and rules can be established using genetic algorithm.

The information coming from the ISHM is processed using fuzzy logic. The gains and the ranges of the AG&C are controlled based on the condition of the structure, control surfaces and engine. A simple implementation of the FC and SHM interface is presented in the Figure 6. The corresponding FL system is presented in the Table 3.

Table 3. A simple fuzzy logic controller to adjust the agility of UAVs according to flight and structural conditions

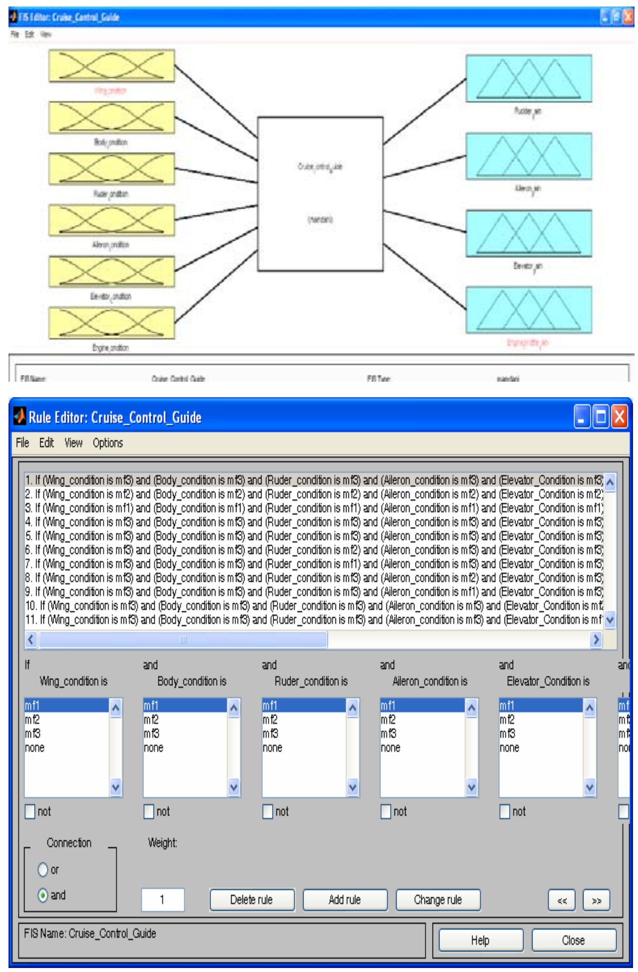
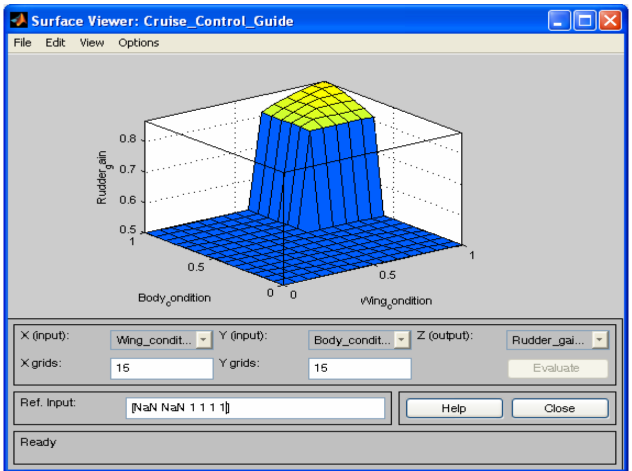


Table 3. A simple fuzzy logic controller to adjust the agility of UAVs according to flight and structural conditions (continued)



Rules and typical surface

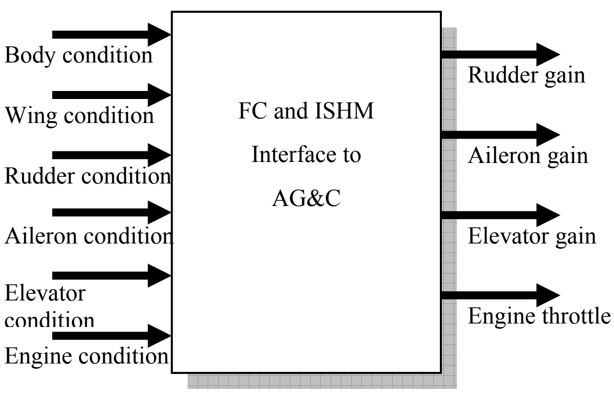


Figure 6. An integrated flight control and integrated system health monitoring system concept

4. RESULTS AND DISCUSSIONS

The input and output relationship of the FL were presented with 3-D plots in the Tables 1and 2. The smoothness, consistency and representation of desired characteristics strongly suggest the feasibility of the FL applications for control of UAVs and integration of FC and SHM. Program size was very reasonable. Pentium microprocessor of our microcomputers calculated the input output relationship and created the corresponding plots in a fraction of second for a 25X25 grid. The computations were completed in two to three seconds when the grid size was increased to 200X200. FL has been implemented using microprocessors and digital signal processors (DSP) in many engineering applications. All these observations indicated that FL could be effectively used for integration of FC and SHM systems. The integrated system could control the agility of the plane by changing the gains of the PD and PID controllers.

Another option for implementation of the desired characteristics to the integrated system is to use the adaptive neuro-fuzzy inference system (ANFIS). Performance of ANFIS was evaluated by following Yingjie's approach in his paper on Auto-landing [7]. In his study, two inputs including the altitude and velocity and one output (force) were utilized. As the ANFIS system only supports Sugeno type fuzzy system, the Mamdani data first had to be imported and an initial FIS had to be generated. ANFIS then attempts to learn from the data set to get the membership function and rules according to the characteristics of the initial FIS (see Table 4). The architecture of the ANFIS is presented in Table 4. There are three layers with multiple nodes between the two inputs and one output.

Another important difference of the ANFIS system from the conventional fuzzy logic is having only one output function that has to be linear or constant. There is no sharing of rules for the output membership functions [8]. The membership function of the output of our case study is presented in the Table 5. However, after ANFIS completed all the training and the generation of rules, the 3-D plots, which show the relationship between the inputs and the output, was very similar to the desired characteristics in Table 6. In the event that the network was unable to represent all the features of the system then another set of testing data would be required to help model validation. As a result, an overall important note about using the neural network is that initial data still has to be given to the system and it must be capable of developing an acceptable algorithm within a reasonable time. Once this is successfully established, we will be one-step closer to achieving a completely self-sufficient UAV.

Table 4. Fuzzy Interface System (FIS) and nodal network

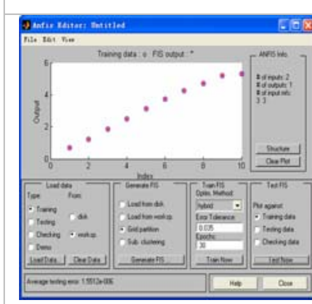
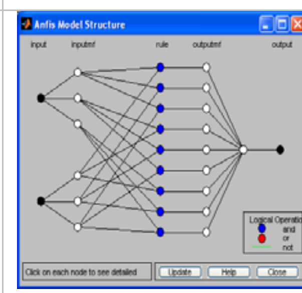
Training Data	Nodal Network
	

Table 5. Membership Functions

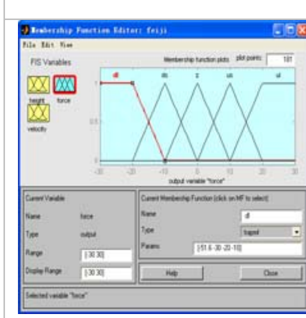
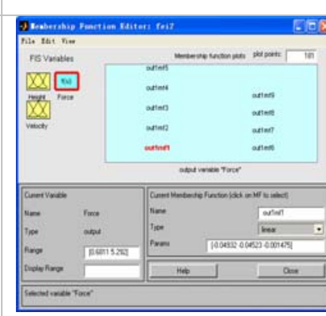
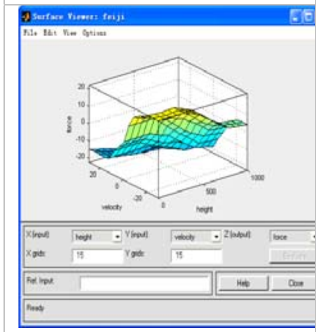
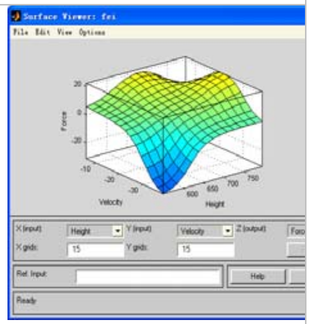
Membership Function of Force FIS	Membership Function of Force for ANFIS
	

Table 6. Control Surfaces

Control Surface for FIS	Control Surface for ANFIS
	

5. CONCLUSION

In this paper, we reviewed some of the well-known studies on the use of fuzzy logic (FL) for the flight control path of UAVs. The study indicated that FL is very suitable for the task and can be easily implemented using even simple microprocessors and DSPs. Small program size and computational speed was very convenient for miniaturization. The desired input and output relationships were generally obtained with little compromise in our case studies when we used FL. ANFIS was found more convenient to obtain the desired relationship between the inputs and the output.

We proposed the use of FL for development of an integrated system that reduces the agility of the plane when any component of the plane has problems. For small UAVs, an easy approach was to evaluate the condition of all the considered components and to adjust the gains of the PDs and PIDs that control the autonomous flight system. We easily implemented the desired input and output relationships using conventional FL and ANFIS.

6. ACKNOWLEDGEMENTS

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