UAV Actuator Fault Detection Through Artificial Intelligent Technique

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ABSTRACT

The design of Fault Detection and Diagnosis (FDD) is a tedious and challenging task. It is due to the changes and uncertainties associated with the aircraft dynamics following an occurrence of a fault. It was believed that until recently, the control reallocation following a system fault was too complex and computationally intensive for real world flight control cases. However, the recent, a dramatic improvement in computer speed and the development of more efficient algorithms have changed the situation considerably. This paper presents an artificial intelligent, in specific using Fuzzy Inference System method to detect an actuator fault. Three ground simulations were performed to validate the performances of the fault detection technique proposed. The residuals were evaluated by using three membership functions of the Fuzzy Inference System. The results show that the proposed technique was able to detect the actuator fault.

Keywords: *Fault Detection; actuator fault; fuzzy inference system.*

Introduction

One of the efforts to improve the reliability of UAVs is to detect a fault prior to or during flight. However, the faults which are intermittent and gradual are not easily being detected. One of the available techniques for fault detection

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is by using a residual detection filter. The difference between the measurements in the real system and the system models – known as residuals are a good estimation on whether the system operates normally or not [1]. Unfortunately, perfect modeling of the system might not be achieved, thus, there might be some errors in the residual generation. This error is unsatisfactory for dynamic system as found out by Gladysz and Wang [2] and Hu and Seiler [3]. The key to improve system reliability is to design a system that is able to:

a) Automatically detect a fault;
b) Find the fault location;
c) Evaluate the severity of the fault.

A simple and effective fault detection method implemented onboard of the UAV must be particularly robust and implemented in real-time [4]. The fault detection is given a special attention recently especially in an unmanned aerial vehicle application. This is due to numerous accidents which occurred in relation to the usage of UAV. Thus, a research conducted by [5] and [6] uses multiple model residual generator which compares the input requires to perform attitude changes (i.e rolling, pitching). Other research work that utilized the residual filter method to detect UAV fault can be found in [7], [8] and [9]. The residual filter usually accompanied by a threshold method as its fault detecting mechanism. The threshold method works by using a pre-set value representing faulty or non-faulty condition. The threshold value is selected in such a way that it would maximize the fault detection while minimizing the false alarm rate. Once a fault has been detected, a decision logic will trigger a Control Allocation (CA) [5], [10], [11].

However, according to Kobayashi and Takahashi [12] and Castanedo [13], there are some drawbacks in using the threshold method because it depends on the designer’s thought, and inevitably the design work gets into trial and error. There are many examples of research works that utilized threshold method for fault detection can be found in [7], [5], [14], [15], [16].

This paper presents the use of Fuzzy Logic in a fixed wing UAV with a wingspan of 1.2 meter to detect an actuator fault. The fuzzy logic has been used not only for flight controller such as implemented by [17], [18], [19] but it has also being used in fault diagnosis by [20]–[22]. Apart from residual generator and analysis for fault diagnosis, the fuzzy logic has also being used for trend monitoring of a UAV system [23]. The result from research conducted by [24] indicates that multiple-model FIS approximates the real process very accurately. The fuzzy logic was also used for a fault classification by Noor [25], which could indicate a specific action that must be taken from a reported fault.

Fault Detection Strategy

The non-faulty condition needs to be identified by the controller in advance for the purpose of implementing the fault detection. Deviation from the healthy state will trigger an alarm indicating the system is not within its normal operating range. The entire fault detection is divided into two functional blocks, which are:

a) Fault detection & decision maker;
b) Control input.

The control input block receives signals from the autopilot controller and passed these signals to the fault simulation controller block and fault detection block. The fault detection block receives the inputs from the actuator position sensor and elevator position sensor. Whereas the fault simulation block sends a command to the servo actuator depending on the fault mode selected by the pilot.

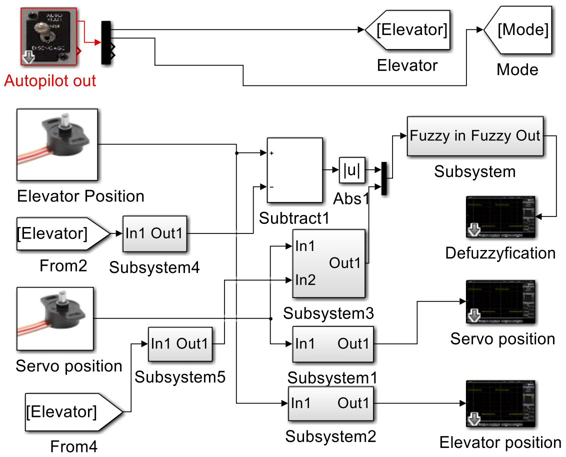

Figure 1: Simulink diagram of control algorithm performing actuator fault detection, fault diagnosis, fault recovery and fault simulation.

The fault detection block produces two residuals as outputs. These residuals represent the response of the actuator and the elevator control surface to the input signal. The values from the residuals are then processed by the decision-making block which utilized a Fuzzy Inference System (FIS) method. The output from the FIS is a value that corresponds to the condition of the actuator. When the FIS detects an elevator servo fault, the recovery block disables the faulty elevator actuator and transfers the pitch control to the healthy stabilator actuator. The fault simulation block enables the actuator fault to be simulated during flight. The overview of the control algorithm, starting from fault detection to fault recovery is shown by a Simulink diagram in Figure 1.

The flow chart for the fault detection and accommodation implementation is shown in Figure 2.

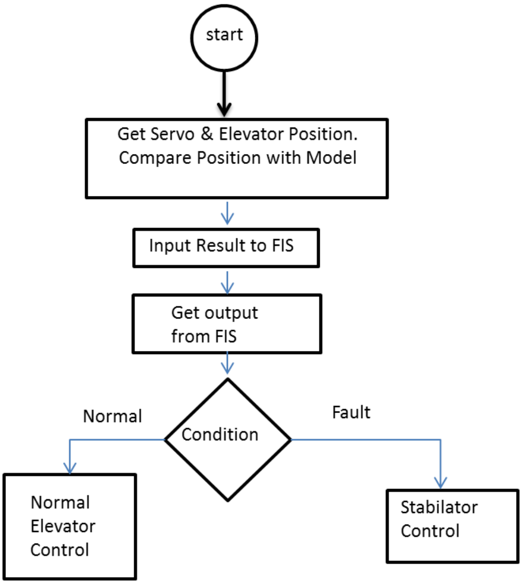

Figure 2: Flow chart for the fault detection and accommodation technique.

The user has two options during flight, which are normal flight and fault detection and identification system enabled. If normal flight is selected, the pitch control is allocated to the elevator control surface. If FDI mode is enabled, the system monitors the current response of the elevator system and compares them to the healthy actuator system. Once a deviation from healthy system is detected, the pitch control will be allocated to the stabilator control surface. The fault detection block consist of the FIS processing block, elevator position sensor, servo position sensor and output to one of the digital I/O pins available on the microcontroller.

Fault Detection Implementation

Intrinsically, the fault detection is designed using known input signal and actual process output signal. Then, the fault is detected by using a residual and a fixed limit (threshold) technique. This research is based on the residual and the threshold methods but it is processed using a Fuzzy Logic Artificial Intelligence (AI) technique. The proposed technique provides advantages as listed below:

a) Overcome rigid threshold method;
b) Able to determine fault condition;
c) Recovery action depends on fault severity.

It is a challenging task to achieve a precise detection of an actuator fault due to their non-linear behavior and measurement noise outside of a controlled laboratory test. To facilitate the fault detection, there are two position sensors installed to detect the current position of the elevator control system. The actuator position sensor is an internal potentiometer within the servo actuator while the elevator position transducer is a MagnePot 6120 series, a non-contacting hall-effect rotary position sensor produced by TT Electronics. The elevator position sensor was mounted on the upper surface of the horizontal stabilizer and connected through a connecting rod from the elevator control surface. Then, the polynomial input and output transfer function of both the position sensors are constructed. Based on the mathematical model, the servo actuator failure is simulated on the ground and the response from the model is monitored.

The actuator residual is composed of an actuator model and the actual measurement. The actuator model is a transfer function of the actuator and it has the information of the healthy relationship between the elevator input command and the servo position. The input to the actuator polynomial model is from the elevator control signal while its output is an estimate of the current position of the servo actuator. A difference between the actual output and the polynomial estimation is an indication of the servo actuator condition. A value called residual is the result of the difference between the polynomial model and the position sensor. A zero difference reflects that the servo position is exactly as the estimated output position, while the bigger difference shows a divergence from a healthy condition. Then, based on the value of the residual, the fault decision block evaluates the current condition of the system.

Actuator and Control Surface Modeling

System identification for the elevator system is performed on the elevator system. The goal of the system identification is to choose a model that yields the best possible fit between the system responses to a PWM input. The input signal to the servo actuator drives the actuator output shaft and then deflected the elevator control surface to the_upward or downward position. The servo shaft position and the control surface position are measured by the microcontroller's build-in Analog Digital Converter (ADC). A repetitive PWM input signal is used to rotate the servo shaft in the interest of performing the system identification. The input signal used is shown in Equation (1).

$$u(t) = A\sin(\omega t + \varphi) \tag{1}$$

where A= 70, ω = 0.2 and φ = 90.

This signal excites the servo to its normal operating condition. The value of A was chosen as 70 so that the servo is rotated from +20 degree to +160 degree. The value of ω is chosen as 0.2 to rotate the servo once every 5 seconds. Finally, the φ is chosen as 90 to ensure the servo starts at center position. The outputs from both the servo position sensor and elevator position sensor with input from the sinusoidal signal are plotted against time.

The servo shaft position is commanded to move from minimum of 20 degrees to the maximum of 160 degrees. The servo position output signal is a 10-bit ADC value (0-1023) corresponds to the DC voltage output from the position transducer within the servo. A polynomial fitting was performed and the result is shown in Figure 3. The polynomial fitting is the result of the time domain transfer function obtained from the ground test.

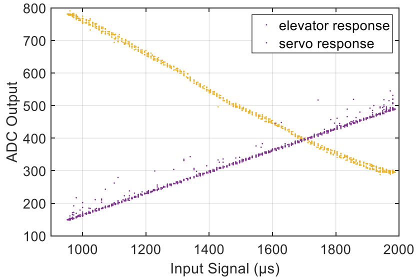

Figure 3: A linear regression fitting for the servo actuator and elevator control surface.

Through MATLAB curve fitting toolbox, the distributed points resulted in linear regression line. Equation (2) indicates that the best fit of the servo output signal responding to an input signal has a linear relationship with the input signal.

$$y(ADC_{Servo}) = 0.33133x - 165.35 \tag{2}$$

Residual Generation

A single model residual is created from single input and single output system. The input to the residual generator is an elevator control signal from the autopilot controller and the output is from the servo position. From the autopilot control signal, the actuator polynomial model estimates the position of the servo actuator. The output from the actuator polynomial model and the actual servo position is compared and the difference between them is the residual values. The absolute value of the difference between the estimator block and the actual servo response is called the residual. In normal condition, the residual is zero or close to zero depending on the modeling accuracy.

Fuzzy Inference System

To get a crisp output values, Mamdani inference technique was used as to perform the defuzzification. The most commonly used defuzzification method is the centroid or Centre-of-Area (COA) which was used as the fault severity indication. Figure 4 shows the design of the membership function as proposed by Dalton [20].

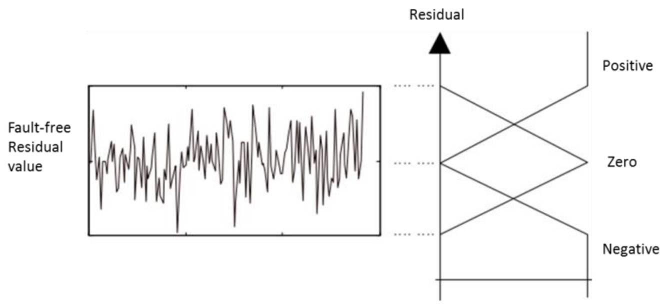

Figure 4: Evaluation of the membership function as proposed by Dalton [20].

According to the figure 4the membership function, a FIS rules is designed for the output function. A total of nine rules were used for the output as indicated in Table 1.

Table 1: FIS rules for the fault detection system.

Rules	Servo Residual	Elevator Residual	Fault
1	Normal	Normal	Normal
2	Normal	Medium	Medium
3	Normal	High	High
4	Medium	Normal	Medium
5	Medium	Medium	Medium
6	Medium	High	High
7	High	Normal	High
8	High	Medium	High
9	High	High	High

Results and Discussion

A series of simulations were performed to validate the performance of the designed fault detection system. A software triggered fault and a physical fault were introduced and the response from the FIS is evaluated. Three simulations were performed to test the effectiveness of the FIS, they are:

a) Case 1 - Fault detection from random fault;
b) Case 2 - Fault detection from simulated fault;
c) Case 3 - Fault detection from mechanical fault.

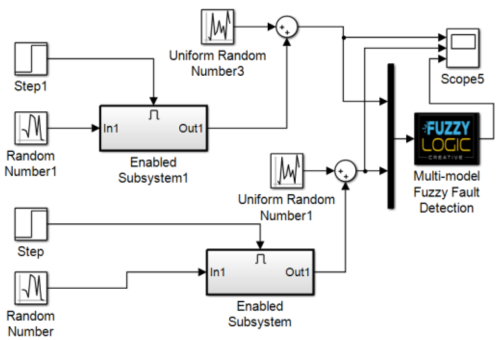

Figure 5: Simulation of the fuzzy fault detection.

Case 1 - Fault Detection from Random Fault

The performance of the multiple-model fuzzy fault detection system was tested using a Simulink simulation. Figure 5 shows the Simulink block for the simulation.

For simulation purposes, the residual generators were replaced by randomly generated numbers. The simulation was performed for the duration of 20 seconds. For the first 10 seconds, the input to the fuzzy logic was a small residual from Uniform Random Number1 block and Uniform Random Number3 block with a value of less than 120 which corresponded to a healthy system. After 10 seconds, a fault was triggered by adding higher values to the residual generators (Random Number block and Random Number1 block) which corresponded to the faulty elevator system. Figure 6 shows the results of this simulation.

Prior to the fault injection, at a time less than 10 seconds, the fuzzy output values were lower than 1. When the fault was triggered, the fuzzy output rose to values of 5. Since random values are injected into the residual generators, it can be observed that at certain times the ranges of the FIS were from 4 to 6. In actual flight, the similar condition might occur where the fault is intermittent.

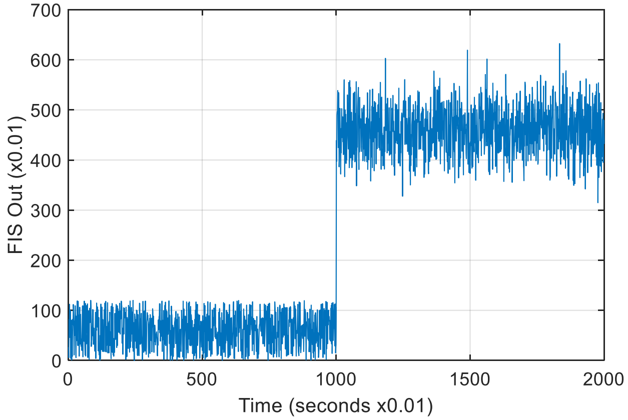

Figure 6: Results of fault detection from the random simulated input.

Case 2 - Fault Detection from Simulated Fault

This time, the fault simulates a locked elevator at a minimum position. The fault simulation controller is able to provide three flight conditions to the system which are:

a) Normal elevator operation, stabilator remained at neutral position;
b) Elevator locked at neutral position, stabilator function normally;
c) Elevator locked at minimum position, stabilator function normally.

If a normal elevator operation is selected, the elevator signal from the autopilot controller is routed to the elevator actuator while the stabilator actuator received a command to remain at the neutral position from the Constant2 block. Once the pilot switched to the second mode, the Switch and switch2 blocks move to the normally-open position. This action causes the elevator to move to the neutral position while the stabilator has the pitch control of the UAV. Whilst in this mode, the actual servo position output is still enables, which should indicate a non-faulty condition. The above fault conditions and their operation were designed in Simulink and shown in Figure 7.

Switch1 block has another fault trigger option available for a different fault condition. The signals to both of the inputs to Switch1 are a similar value which moves the servo to a neutral position. If flight tests were being performed, the normally-open switch will be set a different value to simulate an actuator fault. The third mode if selected by the pilot, the system should indicate any failure condition immediately. The pitch control was still maintained by the stabilator while the elevator remains locked at the neutral position. The servo position output however (from Figure 7), was replaced by an artificial value of 10. While in this mode, a properly designed FIS should be able to indicate a faulty condition.

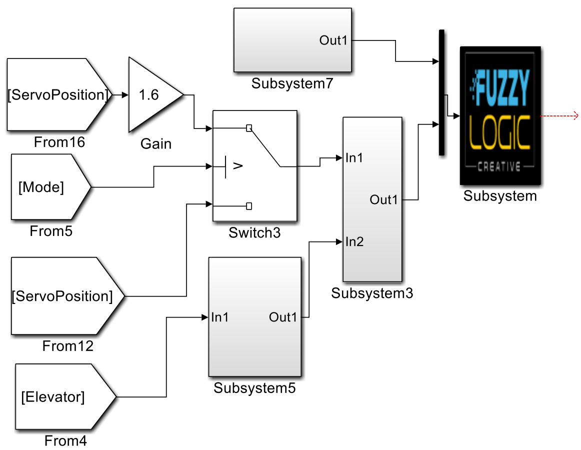

Figure 7: Simulink block diagram of fault simulation for conduction ground assessment.

Result from Fault Detection of Simulated Fault

The ground fault simulation began with a fault triggered t = 2 seconds. The fault behavior was set as locked elevator at the neutral position. The input and output signal plot were shown in Figure 8.

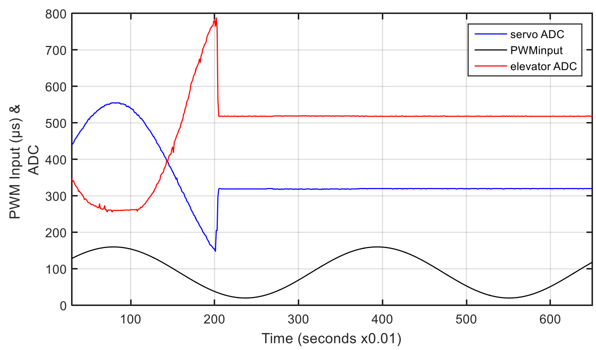

Figure 8: Elevator input signal and corresponding output signals from servo position and elevator position.

The input signal was represented by the black line, which continuously turned the servo actuator from 20 degree to 160 degree back and forth. At t = 2 seconds, the actual input to the servo actuator was replaced by a constant value of 90 which caused the servo to remain at the neutral position while the input signal to the system still continuously is being sent. After t > 2, it can be observed that output from the servo actuator position and elevator position sensor were static. This behavior represented an actuator locked at the neutral position.

Thereafter, the performance of the fault detection algorithm was analyzed. The three of the important fault detection parameters to analyze were the servo actuator position residual, elevator position residual and output from the FIS.

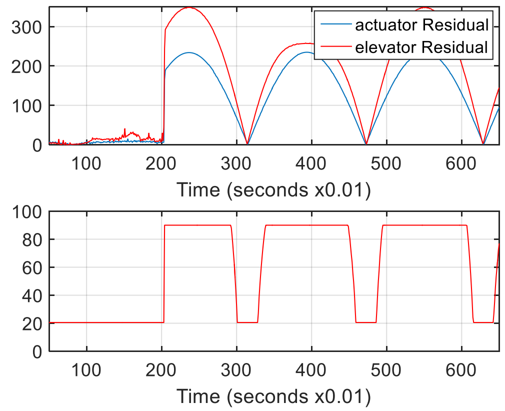

Figure 9: Fault detection algorithm performance.

The elevator models develop by Equation 2 and Equation 3 performed fairly consistent to track input and output data by producing a small residual. These residuals were processed by the FIS block and report a healthy elevator system which had an output value of 20. When the fault is injected at t = 2 seconds, both the residuals were having an abnormally high value. This abnormality was being detected by the FIS block and it output a value of 90. The FIS output has repeatedly given a zero value throughout the fault simulation. This is due to the nature of the sinusoidal input signal which, at every cycle of the sinewave input signal will be similar to the position of the servo actuator position and elevator position.

From the ground simulation test, the fault detection system has shown that it was capable of detecting an actuator fault.

Case 3 - Fault Detection from Mechanical Fault

Next, an actual physical fault was introduced to the elevator system. The fault was introduced by loosening the retaining bolt of the elevator pushrod. The pushrod is a mechanical linkage between the servo actuator and the elevator control surface. To simulate an actual flight environment, an actual flight data is used as input to the FIS.

The result from the mechanical fault is shown in Figure 10. Initially, a normal elevator operation is performed with a small fault was introduced approximately at t = 3.2 seconds. It can be observed that the fuzzy output has increased to a value of 4. When a bigger fault is initiated at t = 10 second, the fuzzy output saturates at a value of 5. It is worth noting that the fault is only triggered at the elevator residual while the servo actuator residual remains healthy. If both the servo actuator and the elevator were damaged, the fuzzy output will increase to a maximum value of 10. From the above fault simulation using an actual elevator output during flight, it can be concluded that the designed fault detection system can effectively detect a fault occurs to the UAV actuator.

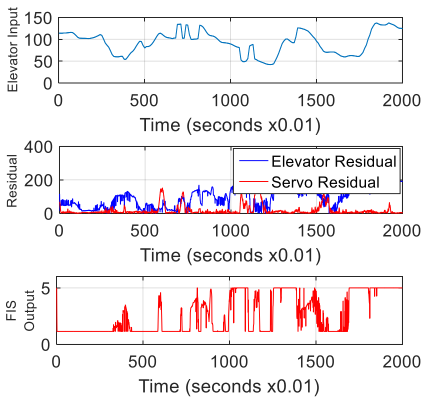

Figure 10: Results from simulated mechanical fault.

Conclusion

FIS is used as a method to detect a fault occurring to the elevator system. The inputs to the FIS are polynomial models from servo actuator position and the elevator position. The developments of these models have been explained in details. Once the models have been developed, a detection system employing fuzzy inference system is used. The validation of the detection system was made by artificially injecting a fault into the system. The developed system shows that it can detect faulty actuation system of the UAV control surface. Once the detection system has been successfully developed, a test bed UAV is designed and fabricated.

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