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MODEL BASED FUZZY LOGIC SENSOR FAULT ACCOMMODATION

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ABSTRACT
Sensor in-range fault accommodation is a fundamental challenge of dual channel control systems in modern aircraft gas turbine engines. An on-board real-time engine model can be used to provide an analytical third sensor channel which may be used to detect and isolate sensor faults. A fuzzy logic based accommodation approach is proposed which enhances the effectiveness of the analytical third channel in the control system's fault isolation and accommodation scheme. Simulation studies show the fuzzy accommodation scheme to be superior to current accommodation techniques.

INTRODUCTION
Modern aircraft gas turbine engines are often equipped with dual channel (duplex) control systems. This differs greatly from flight control systems which are typically either triplex or quadruplex. There are a number of reasons for this disparity, including:

- Inherent reliability of the engine system is limited by the failure rate of the rotating machinery - driving the control system to zero failures has limited benefits. Duplex provides sufficient fault coverage (typically 95% to 99+%) to balance the control system failure rate with that of the other engine subsystems.
- Cost, weight and space requirements are all significantly less for a duplex system than a triplex or quadruplex system.
- Engine control system failures do not often result in loss of vehicle control, which is often the case for most flight control failures. In single engine aircraft, engine shutdowns can cause loss of the vehicle, but usually not the pilot. In dual engine aircraft, engine shutdowns usually result in loss of mission capability.

With the exception of certain "prime reliable" components, such as fuel pumps and actuator pistons, which have negligible failure rates, the duplex system provides sufficient redundancy such that no single failure can cause loss of system functionality. In order to provide fault coverage, however, the control system must detect and isolate the fault, then perform the appropriate accommodation. For the large majority of faults, detection and isolation are one and the same. Processors can fail memory, check-sum or timer checks. Servo valves can show shorts or opens via current checks. Sensors can fail rate or range checks or have shorts or opens.

One category of faults which provides a significant fault isolation challenge in duplex systems is in-range sensor faults. If both channel's sensors pass range and rate checks, but disagree, the question of which value to use poses a dilemma. If both channels agree within the tolerance of the sensing system's accuracy, then the two sensors can be averaged to get a "good" value. Once the disagreement becomes gross, however, one value must be considered "good", and the other discarded.

One approach for selecting the "good" sensor is to look at failure modes. A thermocouple which is inserted into the engine hot section will read a much cooler temperature if a short occurs in the wires leading to the probe. Failure modes that will cause the thermocouple to read high are rare. Therefore, selecting the high channel for this type of sensor would be a reasonable approach. Since many types of sensors do not have a "most likely" failure direction, another approach is to select "safe". A speed sensor, which counts magnetic pulses, can fail either high if a chafed cable generates spurious pulses, or low if a short-circuit eliminates some of the pulses. The consequences of picking an erroneously low speed signal may

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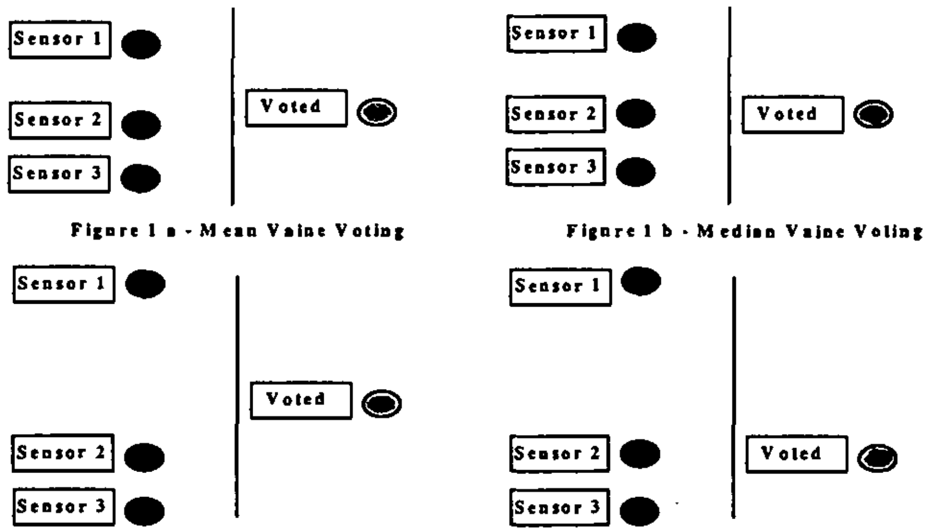

Figure 1 a - Mean Value Voting

Figure 1 b - Median Value Voting

Figure 1 c - Mean Value Voting-Faulted Case

Figure 1 d - Median Value Voting-Faulted Case

Figure 1 - Median Versus Mean Value Voting

include catastrophically overspeeding the engine. The consequences of picking an erroneously high signal are usually limited to a performance loss which results from unnecessarily limiting engine speed. By this logic, the obvious choice for a select "safe" strategy is to choose the high signal. This strategy falls apart however, if the speed error is high enough, since this error drives the engine to shutdown, a highly undesirable result for a single engine aircraft.

Recent advances in the technology of modeling Gas Turbine engines has produced accurate, real-time engine models which are suitable for incorporation in the engine control system's embedded software (Kerr, 1992). The real time models are constructed using a simplified analytical model of the engine to minimize on-board computing requirements and allow for real-time execution. In order to provide accurate predictions, a state observer is employed which causes the model to "track" the sensors and thereby provide more accurate predictions for synthesized engine variables.

An on-board model provides an alternative approach to the in-range sensor fault isolation problem, since it can effectively provide an analytical third channel of a sensor. This third channel can referee the disputes between the duplex channels and greatly improve the chances of selecting the sensor which is providing the most correct value to the control system. The state observer feature of the model complicates the implementation of the third channel approach, since the model tends to "track" the voted sensor value, and can thereby lose its ability to provide a discriminator between the two sensors.

Triplex redundancy management

Several viable options exist for handling triplex sensors. Either the mean of the three channels or the median value can be used by the control system as the "voted" value. Using the mean has the advantage that it is statistically the closest approximation to the "true" value of the sensed parameter when all three sensors are functioning properly. The mean, however is corrupted when a sensor is faulty, but has not yet been detected and isolated. The median is normally quite close to the mean and has the advantage that it is not corrupted when one sensor drifts or provides erratic readings. Figure 1 illustrates these two approaches.

Fault detection and isolation is usually accomplished by a parity space approach (Patton, 1992) Parity is examined by comparing the relative errors between each of the three sensors. If two of the errors become large relative to the third, the parity vector becomes large and points to the erroneous sensor. Figure 2 illustrates this approach. These approaches assume that the three sensors are essentially identical, and that their values should all be given equal weight in "voting" the value to be used by the control system. With an analytical third channel, the model value may need to be considered differently than the values given by the sensors.

For most sensors, the sensed value would be given precedence over the model predictions. Under this scenario, the voted value could be the average of the two sensors, providing they agree with each other. If a disagreement occurs, the model would be consulted to pick the correct sensor (the one which agrees most closely to the model), and the voted value would then become that sensor. The disadvantage of this approach is that the control system must abide the corrupted average until the faulted sensor exceeds a tolerance limit which must be sufficiently wide to preclude false alarms.

This paper will offer a simple, fuzzy logic based approach which weights the sensor average based on the sensors agreement with the other channel and the model. This approach attempts to use the relative agreement of the three inputs to provide a robust dual channel / analytical triplex voting scheme.

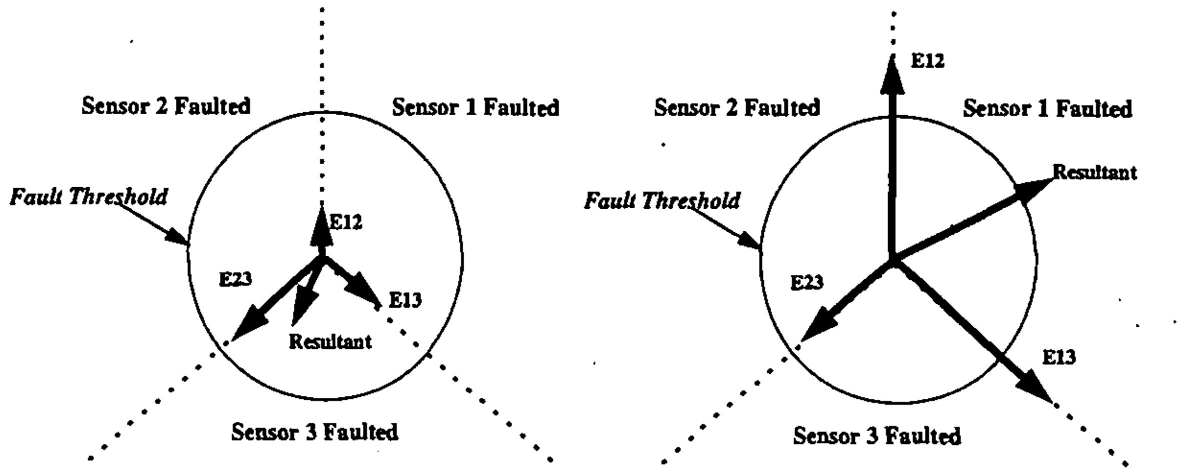

Figure 2a - Normal Case **Figure 2b - Sensor 1 Faulted**

Figure 2- Parity Space Approach

APPLICATION OF FUZZY LOGIC TO REDUNDANT SENSOR SELECTION

The problem of redundant sensor selection is particularly suited to the calculus of fuzzy if/then rules as described by Zadeh (1992) for several reasons. First, the fuzzy if/then paradigm along with the concept of linguistic variables (a variable whose values are linguistic terms rather than numbers) (Zadeh, 1973) provides a structure with which to capture human intuition and experience in the form of if/then rules. As we (humans) look at the data of various redundant sensor failure scenarios it is very easy for us to choose an appropriate voted value at any time during and after the failure. It is this ability we wish to capture in the sensor selection algorithm. Second, the use of fuzzy sets to represent our input/output variables (through fuzzification / defuzzification) provides precision at the set level which allows us to write fuzzy rules at a very high level of abstraction. This makes populating the fuzzy rulebase a very simple and straight forward process. Third, the structure of the fuzzy system allows for any number of antecedents in each of the rules which make up the fuzzy rulebase. This allows us to simply generate multidimensional non-linear relationships between inputs and output(s). These relationships make up a response surface referred to as a fuzzy associative memory or FAM (Kosko, 1992) which would otherwise be very difficult to visualize or create.

The operation of any fuzzy logic if/then system can be broken down into three primary functions as follows.

- Fuzzification of inputs: Conversion of the "crisp" (or real) inputs into fuzzy variables.
- Fuzzy inferencing: Evaluation of the fuzzy if/then rules.
- Defuzzification: Conversion of the output fuzzy variable(s) to "crisp" output(s).

The specifics of a fuzzy system for redundant sensor selection are detailed below.

Fuzzification (Fuzzy Membership Functions)

Our fuzzy system will be based on a series of if/then rules in which the antecedent and consequent parts are linguistic variables which are fuzzy rather than crisp. The meaning of these linguistic variables is defined by their membership functions. As mentioned previously we have chosen to use a parity space approach in which the "crisp" inputs to our system will be the relative errors between each of the three sensors:

$$E12 = ABS(S1-S2)$$
$$E1M = ABS(S1-SM)$$
$$E2M = ABS(S2-SM)$$

where S1 is the value from sensor #1, S2 is the value from sensor #2, and SM is the model predicted value. A conscious decision was made to consider the absolute values of these errors since the goal of the Fault Detection and Accommodation (FDA) system is to isolate the faulted sensor, not determine if it is faulted high or low. The inclusion of the sign of the error adds complexity to the algorithm, with no benefit to its effectiveness. Figure 3 shows a typical triangular membership function which could be used to fuzzify the crisp inputs. The scale of the abscissa axis is dependent upon the particular sensor in question and is influenced by experience / knowledge of that sensor's most likely failure mode. A logical choice for a scale factor is the expected variability of the sensor. The granularity of the linguistic variables was chosen as shown to be three (small, medium, large).

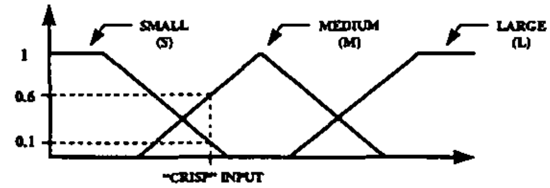

Figure 3 - Typical Membership Functions

In this example the crisp input shown is considered 'small' to the degree 0.1 and 'medium' to the degree 0.6. For the fuzzy sensor selection system each of the sensor errors (E12, E1M, E2M) are fuzzified using the same set of membership functions. Some investigation was done into the effect of using differently shaped membership functions (such as sinusoidal) with no discernible effect on the outcome. The overlap of the membership functions can be used to tune the overall input/output response surface while the granularity or number of membership functions can be used to provide more flexibility in the accommodation of particular combinations of sensor values.

Fuzzy Inferencing (Fuzzy Rulebase)

Once the inputs are fuzzified they can be used to evaluate the fuzzy if/then rulebase. Again it is the precision of the fuzzy membership function which defines the linguistic variable that allows the use of highly abstract if/then rules. Since the order of our input (n) is three and the granularity of our membership functions (m) was chosen to be three there are exactly $n^m = (3)^3 = 27$ possible combinations of inputs which make up the fuzzy "possibility space" (Kang, 1993). Therefore we must come up with n^m rules to completely fill the fuzzy if/then rulebase. It should be recognized that depending upon the membership functions not all of these combinations are physically possible and therefore require no rule to be generated yet are included for completeness. Figure 4 shows a sample fuzzy if/then rulebase for the redundant sensor selection system. The antecedent portions of the rules depicted in figure 4 are the fuzzy representations of the three input sensor errors.

The consequent portion of the rules are any of a number of sensor/model average values {A12=AVE(S1,S2), A1M=AVE(S1,SM), A2M=AVE(S2,SM), A12M=AVE(S1,S2,SM)}. In this example we have chosen to ignore the model predicted value when the two sensor inputs agree (E12 small). As the error between sensor #1 and #2 increases (E12 medium) we begin to use the model predicted value to influence the selected value. And as the error grows even larger (E12 large) we use the model predicted value and our knowledge of the relative errors to choose an appropriate average. For example, one of the rules states:

IF (E12 is medium) AND (E1M is small) AND (E2M is large) THEN use A1M

The rule selection allows incorporation of experiential knowledge of the particular sensor and it's typical failure modes. The rulebase may vary significantly depending on the expected accuracy of the particular model estimated parameter, the most likely failure mode of the sensor, or the relative consequences of an erroneously selected value.

Each antecedent of each rule in the rulebase is evaluated using the fuzzified inputs and will result in a degree of fulfillment between 0.0 and 1.0. The antecedents are then combined using the logical product or minimum function (the fuzzy equivalent to the logical AND) (Schwartz, 1994) to produce a resultant degree of fulfillment for each rule. Consider the previously mentioned rule and suppose the values

E12 = L	E2M: S	E2M: M	E2M: L
E1M: S	M	A1M	A1M
E1M: M	A2M	M	A1M
E1M: L	A2M	A2M	M

E12 = M	E2M: S	E2M: M	E2M: L
E1M: S	A12	A12M	A1M
E1M: M	A12M	A12M	A12M
E1M: L	A2M	A12M	A12

E12 = S	E2M: S	E2M: M	E2M: L
E1M: S	A12	A12	A12
E1M: M	A12	A12	A12
E1M: L	A12	A12	A12

Figure 4 - Sample Fuzzy If/Then Rulebase

of the errors are such that E12 is considered medium to the degree 0.7 while E1M is considered small to the degree 0.3 and E2M is considered large to the degree 0.4. The resultant degree of fulfillment of this rule will be MIN(0.7,0.3,0.4) = 0.3.

Defuzzification

Once the degree of fulfillment of each rule in the rulebase has been determined all that remains is to defuzzify the output value. The result of the rulebase evaluation is a fuzzy set which must be converted into an appropriate crisp value (a voted sensor value). A simple defuzzification method is to use the degree of fulfillment weighted average of the rulebase consequent blocks. We define

$$\text{Voted value} = (\Sigma\, c_i{*}dof_i) \;/\; \Sigma dof_i$$

where c_i is the consequent part of the ith rule and dof_i is the degree of fulfillment of the i^{th} rule. This method of defuzzification is equivalent to the "mean of maxima" method summarized by Filev (1991) with the consequent part of the i^{th} rule corresponding to the maxima of a fuzzy membership function. The boundedness of this defuzzification method (and most methods) is guaranteed since the output can only be weighted averages of the inputs.

Response Surface

The overall relationship between inputs and output(s) can be mapped as an 'n+1' dimensional response surface referred to as a fuzzy associative memory or FAM. For the fuzzy sensor selection system this 4-dimensional surface can only be visualized in part. Figure 5 represents a portion of this surface that was generated by holding E12 constant and large while varying E1M and E2M over their respective ranges of possibility and holding the consequent averages constant. The ultimate implementation of the fuzzy sensor selection system would be in the form of a trivariate look-up table representing the entire response surface.

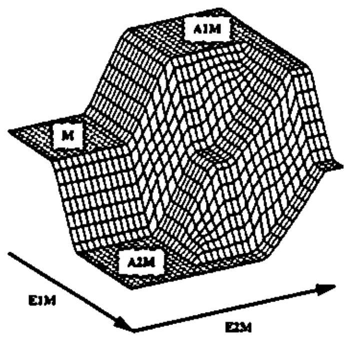

Figure 5 - A Portion of the Response Surface

EXPERIMENTAL RESULTS

The fuzzy logic approach to redundant sensor selection was demonstrated using the simulation of an advanced gas turbine engine control system. This control system features an on-board, real-time engine model which is utilized for parameter synthesis as well as FDA.

Figure 6 shows the Test Configuration for this study. For convenience the model and FDA logic were implemented as a piece of software separate from the rest of the control system. This allowed for easy fault implementation and minimized the computing time required to conduct the tests.

Simulated faults were implanted into engine temperature, pressure and rotor speed sensors. The faults were implemented as either slow drifts (no fault to threshold in 5 seconds) or sudden shifts (no fault to threshold in 0.15 seconds). The sudden shift time was chosen to implement the fault in a small number of algorithm compute cycles, minimizing the ability of the model to track the faulted input. The slow drift allows ample time for the model to track the signal. The faults were implanted singly and in combinations of sensors. Each test case was started with the values from each of the two simulated sensors being set equal. One channel's value was drifted beyond the in-range threshold value. The test cases were presented to both the baseline FDA scheme and the fuzzy FDA scheme.

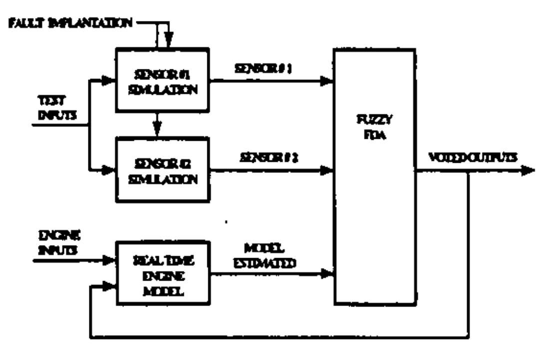

Figure 6 - Fuzzy FDA Test Configuration

Figure 7 shows a representative test case in which one of the sensor values is forced to drift out of range (high). It can be seen that with the baseline FDA approach, the "voted" sensor value follows the average of the two sensors until the fault threshold is reached. At this level, the sensor in closest agreement with the model is selected, and the "voted" value becomes that sensor's output. The disadvantage of this approach is evident in the large error that the system must tolerate prior to failure declaration, and the rapid transient which occurs when the fault declaration is declared. By comparison, the fuzzy logic based FDA approach minimizes the error and gently returns the voted value to it's final level.

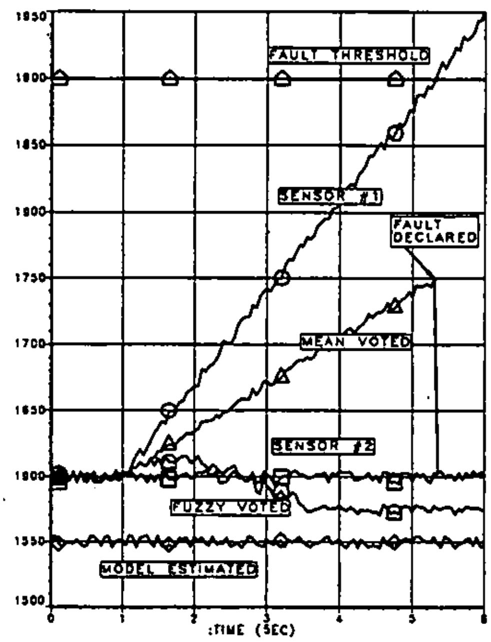

Figure 7 - Fuzzy Versus Mean Value Voting

Twenty two (22) fault cases were tested. In cases where the faults were implanted into pressure or temperature signals, the fuzzy approach reduced the error of the voted signal by up to 5%. In all cases, the performance of the fuzzy FDA was superior to the baseline approach. When faults were implanted into rotor speed signals, there was no difference between the fuzzy FDA and baseline FDA scheme. Analysis showed that the real-time engine model's filter tunes so closely to the Low Rotor Speed and High Rotor Speed sensors that the model does not generate an "independent" value for these parameters. Expected "sensor noise" values for the speed signals used in designing the Kalman Filter gains for the state observer were extremely low. As a result, the model output tracks the voted sensor value extremely well, and the model does not provide an independent estimate. Experience has shown that tight tracking of the rotor speed signals has a beneficial effect on model accuracy, and therefore this problem is inherent in this type of model.

CONCLUSION

This paper has presented a simple and robust fuzzy logic based approach for redundant sensor selection. The methodology enhances the capability of self-tuning, on-board, real-time engine models to provide an analytical third channel for dual channel electronic control systems.

The simulation test results show that the technique minimizes sensor fault effects when compared to a conventional approach based on averaging the dual sensor values until a fault is declared. The reduction in corruption of the voted value enhances the effectiveness of the FDA system, since the model has less tendency to track the faulted sensor. Reduced errors in the voted sensor values has obvious benefits to the control system.

One area where the fuzzy approach showed no improvement over the baseline was in accommodating speed sensor faults. This resulted from the tight tracking of the state observer to the speed signal. One possible approach for overcoming this problem could be to have an "untuned" version of the model running which would be dedicated to providing inputs to the FDA.

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