Fault Detection, Identification and Accommodation Techniques for Unmanned Airborne Vehicle

Lennon R. Cork[1], Rodney Walker[1], Shane Dunn[2]

[1] Cooperative Research Centre for Satellite Systems, Queensland University of Technology, GPO Box 2434, Brisbane, Queensland, 4011, Australia
[2] Air Vehicles Division, Defence Science and Technology Organisation, PO Box 4331, Melbourne, Victoria, 3001, Australia

Summary: This paper presents a review of fault detection, identification and accommodation (FDIA) techniques, followed by results from an evaluation of a neural network (NN) fault detection scheme for critical failures of an unmanned airborne vehicle's (UAV's) angular rate sensors. Neural networks are used to provide analytical redundancy, from which residuals are generated, enabling the detection of failures on sensor measurements. Upon detection of a failure, the faulty signal is replaced by the neural network based estimate, allowing the flight to continue within specified performance limitations. The performance of this technique is assessed through an evaluation of aircraft stability in the presence of a fault that would normally cause the aircraft to behave unacceptably. This investigation forms part of a year long literature review aimed at identifying approaches suitable for combating the low reliability and high attrition rates of today's UAVs.

Keywords: UAV, fault diagnosis, fault accommodation, neural networks, sensor fault detection, system architecture, parameter estimation.

Introduction

Unmanned Airborne Vehicles (UAVs) are assuming prominent roles in both the commercial and military aerospace industries. The promise of reduced costs and reduced risk to human operators is one of their major attractions, however these low-cost systems are yet to gain acceptance as a safe alternative to manned solutions. The absence of a thinking, observing, reacting and decision making pilot reduces the capability of UAV's to manage adverse situations such as faults and failures.

This paper reports on research currently being undertaken at the Queensland University of Technology (QUT) into fault detection and accommodation techniques for low cost UAV systems. The paper begins by highlighting current fault detection and accommodation approaches for UAVs with a focus on sensor failures. Sensor failures are critically important as they can often lead to unrecoverable flight. As reduced complexity, lower costs, and weight optimization are major design specifications, traditional approaches such as built in tests and multiple redundancies are no longer appropriate. One method employed to combat sensor failures is the use of model-based techniques to produce parameter estimates that can be used for both fault detection and fault accommodation.

The approach presented in this paper uses neural networks to provide analytical redundancy from sensors already existing onboard a UAV. An investigation was undertaken into the neural network based sensor fault detection, isolation and accommodation (SFDIA) process proposed by Napolitano [1] with a particular focus on using UAV specific sensor models and analyzing the closed loop aircraft performance. The objectives of this investigation were to gain an understanding of the difficulties associated with neural network based fault detection and accommodation approaches.

The scope is limited to a selection of sensors and failure modes, with only a limited focus on the application of these techniques to multiple failures. Performance of the approach was measured using altitude and heading tracking errors from a normal set point. Recommendations for improvements are made based upon the limitations of this neural network approach, with the aim of including a broader range of failures, while still maintaining an accurate model in the presence of these failures. The future direction of this research and its objectives are outlined at the conclusion of this paper.

Fault Detection and Accommodation techniques

The aerospace industry has used fault detection for a variety of applications such as detecting structural failures, engine failures and avionics/power system failures, however only small quantities of these applications have been specifically focused towards UAVs [2-4]. Texts written by Patton, Frank and Clark [5], Anderson and Lee [6] and Gertler [7] offer good explanations of fault detection and accommodation techniques. Surveys on fault detection techniques written by Isermann [8], Frank [9] and Wilsky [10] also provide good starting points for fault detection, identification and accommodation (FDIA) research.

Types of Faults and Failures

Faults in closed loop systems are commonly represented as either actuator, plant or sensor failures (refer, Fig. 1). The fault detection and accommodation techniques required will depend on the type of failure experienced. Plant and actuator failures in UAVs generally result from mechanical or structural failures, and often require adaptation of the control system. Providing redundancy or other types of fault accommodation is normally not feasible. Sensor failures can be a major source of error in UAVs, particularly when a UAV uses less reliable components due to design restrictions. To Detect and manage these three types of failures a combination of techniques would be required, however this paper is focused upon sensor failures and sensor fault detection and accommodation (SFDA).

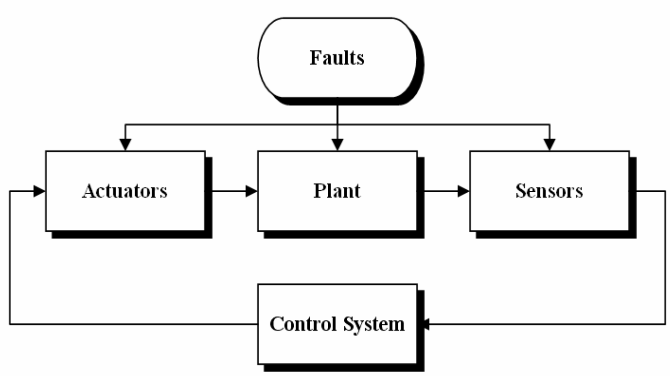

Fig. 1: Representation of fault locations in a closed loop system

Fault Detection Methods

Fault detection procedures can be divided into knowledge, signal processing or model-based approaches. Knowledge based techniques use artificial intelligence approaches, such as neural networks or fuzzy decision logic to detect and classify faults. Papers written by Gupta and Yamakawa [11], Boullart and Krijgsman [12] and Oosterom and Babuška [13-15] use knowledge-based approaches for FDIA. Signal processing techniques use signal features (spectrum information, statistical information etc.) to generate signals that give an indication of the existence of a failure. Examples of signal processing approaches have been published by Zhang and Jiang [16], Mackey [17] and Menon [18, 19]. Model-based techniques are similar to signal processing techniques, except that a model is used to estimate measure the values, from which error signals (residuals) can be used to give an indication of the existence of a failure. Model based techniques form a considerable portion of FDIA research and there exists an abundance of literature on this subject [5-10].

Neural Network approaches to fault detection

Testing has shown that the neural networks approach has proven to be an extremely powerful method for fault detection. Neural network FDIA solutions normally come in two forms; the first is a Knowledge-based approach where neural networks are trained to recognise faults, based on certain criteria/features (Zhang [20] and Johnson [21]); the second approach is a model based approach where neural networks are used to provide analytical redundancy for fault detection purposes.

Napolitano, Gampa and Seanor’s work on neural network fault detection and flight control systems provided the inspiration for the work described in this paper. They have produced a good series of papers on neural network fault detection for aircraft systems [1, 22-29]. Patton, Chen and Siew [30] and Alessandri and Parisini [31-34] have also produced papers on model-based neural network-based fault detection techniques.

Fault Detection Performance

The performance of a fault detection procedure is measured by its percentages of successful detections as well as its percentage of false alarms. There are four possible outcomes (two successful, two unsuccessful) for a fault detection system. A successful outcome is one which determines the correct health status. A false alarm is where a fault is declared when no fault exists whereas a missed alarm is where a fault is not detected when a failure occurs. Other terms that are often used in the literature to indicate FDI performance are detectability, isolability and robustness. Detection delay is also an important parameter when determining fault detection performance. Refer to Patton et al [5], Anderson et al [6] and Gertler [7] for a detailed account of there terms.

Fault Accommodation Procedures

Accommodation of a sensor failure is generally achieved through two methods. The first method is system reconfiguration, where the system is altered to minimise the effect of a fault. A reconfigurable controller fits into this type of solution. The other method of accommodating faulty measurements is by modifying or replacing the faulty signal. This requires a form redundancy (either hardware or analytical) that can be used to accurately estimate the faulty sensor measurement.

System performance

The ultimate goal of a fault detection system for an unmanned airborne vehicle is to allow the aircraft to continue flying with an acceptable level of performance, for an adequate time span to either complete it's mission or for recovery from the failure. Providing UAVs with FDIA capabilities will improve their reliability and safety, however there will always be a limit to the level of faults that can be detected and accommodated. As more components fail, the system becomes less capable and reliable. For this reason any fault detection scheme and accommodation process must be backed up by suitable maintenance procedures and realistic expectations.

In the remainder of this paper, a neural network (NN) FDIA approach will be described and demonstrated using simulated aircraft data.

Neural network-based SFDA

In order to examine the performance capabilities of a fault detection scheme using neural network approximations, a model for simulating a variety of UAV avionics systems was required. Fig. 1 gives an overview of the simulation model developed in Matlab/simulink™ for investigating the neural network FDIA scheme.

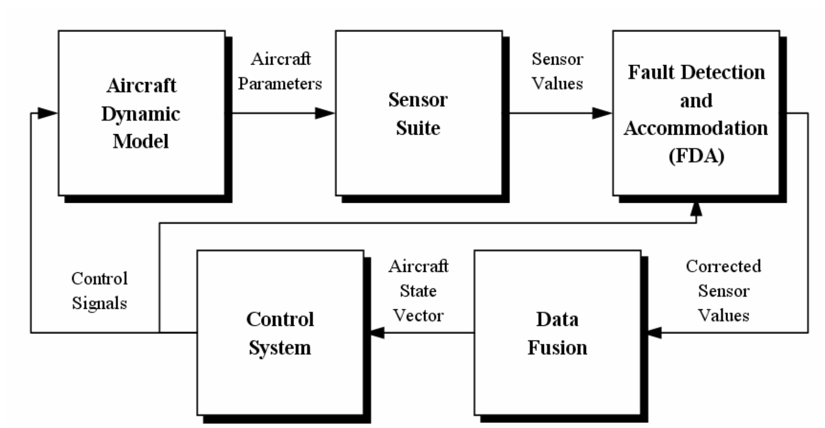

Fig. 2: System Architecture Overview

Aircraft Dynamic Model

The aircraft dynamic model is a six degree of freedom, nonlinear model of a General Aviation North American Navion. The model was developed by Unmanned Dynamics LLC, as part of the Aerosim blockset, for Matlab/simulink™. The model outputs state vector information such as position, velocity, acceleration, Euler angles and angular rates as well as atmospheric data (temperature, density, pressure) and earth parameters (magnetic field, gravity). These values are then passed to the sensor suite for the modelling of sensor measurements.

Control System

The control system in this investigation uses angle and rate feedback to control the aircraft in both the lateral and longitudinal motions (Fig. 3 and Fig. 4). Table 1 shows the closed loop altitude and heading control system errors. These errors are for straight and level commands of 0 degrees (heading) and 1000 meters (altitude). A number of identical simulations were conducted to assess the variation of the results. All simulations performed for this paper were conducted for the same series of command values forming a standard flight profile from which this approach is assessed.

Table 1: Normal lateral and longitudinal controller characteristics

Controlled parameter	**Maximum steady state error**	**Simulation repeatability**	
		Max difference	Standard deviation
Heading	2.4 degrees	9.1 degrees	1.7 degrees
Altitude	13.5 meters	35.0 meters	8.7 meters

The maximum steady state error is the largest, instantaneous error between the controlled parameters and the straight and level set points (heading = 0º, altitude = 1000m). These values represent the ability of the aircraft to track the commanded headings and altitude. The variation (repeatability) is due to uncertainty on the sensor measurements and the values listed in Table 1 indicate how these uncertainties affect the aircraft's closed loop tracking capabilities.

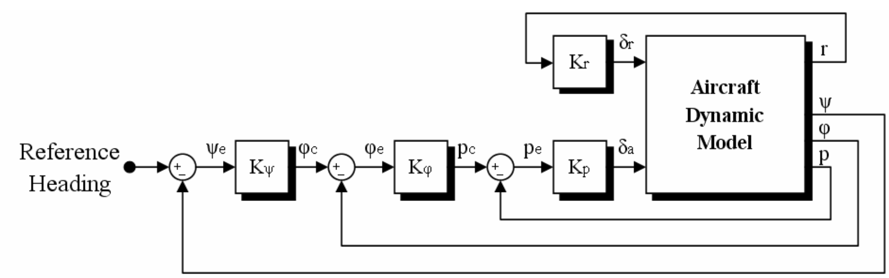

Fig. 3: Lateral controller architecture

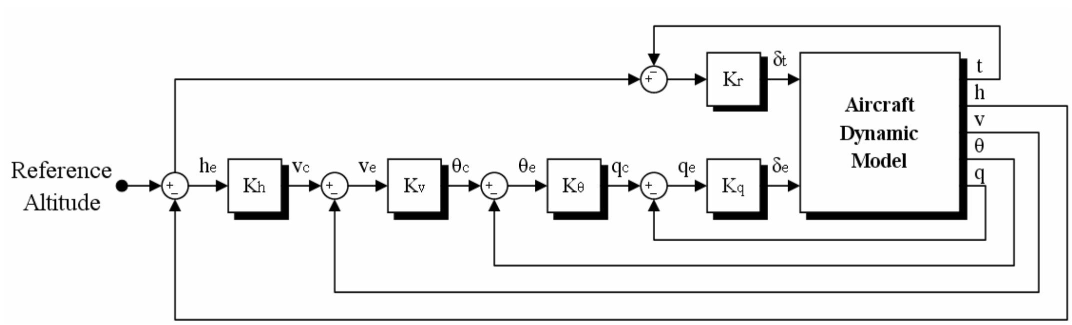

Fig. 4: Longitudinal controller architecture

Sensor Suite

The sensor suite is responsible for modelling the impact of a variety of failures as well as generating realistic measurements. An analysis of the normal performance of the system using these measurements was performed and criteria for faults requiring detection were made based on the closed loop behaviour of the aircraft.

Sensor Measurements

Raw sensor measurements are generated from the dynamic model outputs by restricting the signals with transportation delays (computation lag), resolution and range limits. Sensor noise is added to the delayed signals and the resulting measurements are sampled at realistic sample rates. Table 2 shows the sensor suite specifications used to model sensor values in this simulation.

Table 2: Sensor suite specifications

Sensor values	**Modelled on**	**Performance / Specifications**			
		Rate	Resolution	Range	Noise Level[1]
Position	Garmin Ltd. 15H/L GPS engines	1Hz	0.0001 º (lat, long) 0.1 m (alt)	-	< ±15m
NED Velocities		1Hz	0.1 knots	< ±999.9 knots	< ±0.1 knot
Angular rates	XBow, Inc. AHRS400C C-100 unit.	50Hz	0.025 º /sec	< ±100 º /sec	< ±0.05 º/sec
Accelerations		50Hz	0.25 mg	< ±2 g	< ±8.5 mg
Magnetic Field	PNI Corp TCM2 Unit	25Hz	0.01 μT	< ±80 μT	< ±1 μT
Air Data Information	Sensors with ADC.	50Hz	0.1 knot (Vel) 0.05 º (α, β)	< ±22.5 º	< ±0.75 º

Sensor Fault Performance Criteria

To limit the fault modes requiring detection to those which are the most critical, an analysis on the effects of a variety of faults was performed. The decision criteria for fault modes requiring detection (Table 3) are based on the performance capabilities of the control system (Table 1). Fig. 5 and Fig. 6 show the simulation repeatability and the limits specified by the criteria of maximum variation (Table 3). These figures give an idea of the standard flight profile as well as the limits to which the simulation is repeatable and the limits where a fault will cause the aircraft to exceed the detection criteria.

For this investigation we have specified that the altitude error should be no more than 100 meters and that a maximum instantaneous heading error greater than 20 degrees is unacceptable. We have also specified that the straight and level altitude error should be no more than 15 meters and the heading error should be no more than 5 degrees. The decision criteria listed in Table 3 are absolute maximums and are considerably greater than the average heading and altitude error that would be experienced during normal flight (Table 1). The reason for the use of large decision criteria is that distinguishing between normal flight and faulty flight becomes difficult if the decision criteria are too close to the normal operation of the aircraft.

[1] 3σ value, using normally distributed noise models. We acknowledged that this may not be representative of "real-world" noise models, however they provide an appropriate starting point for this research.

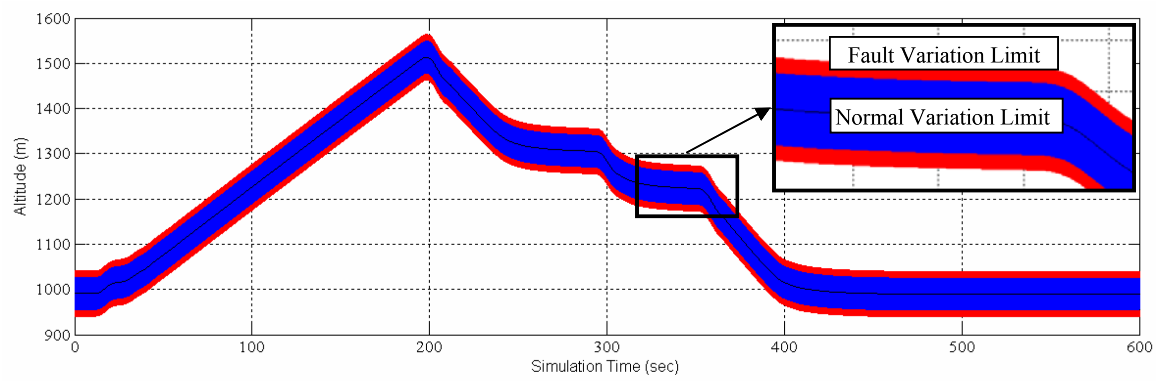

Fig. 5: Altitude variation limits for normal and faulty sensors

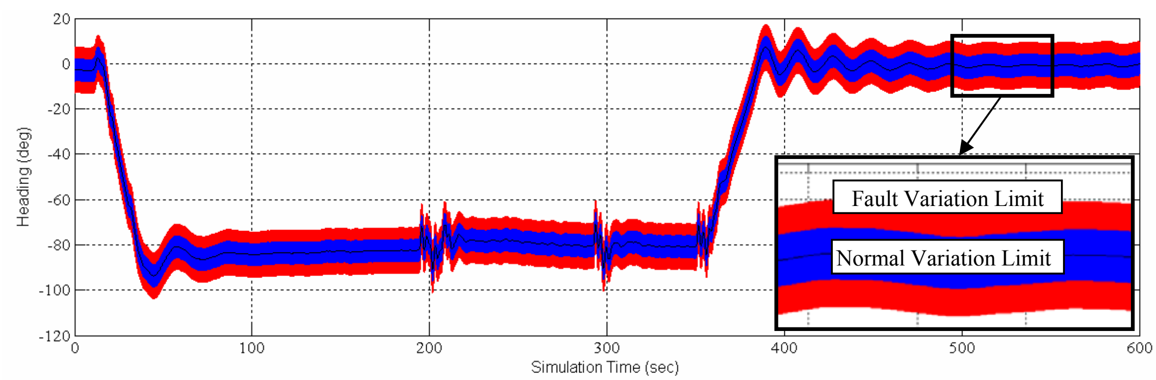

Fig. 6: Heading variation limits for normal and faulty sensors

Faults are applied to a sensor signal for the entire duration of the simulation and the resulting errors in heading and altitude are generated. If these errors are greater than the decision criteria in Table 3 then the fault is of a magnitude that requires detection. These criteria offer a threshold for acceptable performance of the closed loop system and do not impact on the aircraft flight; rather, they are a tool for determining the level of fault that should be detected.

Table 3: Decision criteria for acceptable lateral and longitudinal controlled characteristics

Parameter	**Maximum steady state error**	**Simulation repeatability** (maximum difference)
Heading	5 degrees	20 degrees
Altitude	15 meters	100 degrees

Sensor Faults Exceeding Decision Criteria

A total of four failure modes were selected for simulation, all of which can be modeled by either applying additional and/or multiple components to the original signal (before the sensor models). The first failure mode investigated is a failure to zero, representing a complete failure of the sensor that is undetectable through normal built in tests (noise is still present). The second failure mode is simulated by an additional step, representing a sudden jump or constant bias on the sensor. The third failure is simulated by an additional ramp, representing a slowly degenerating sensor and the fourth failure is an additional noise source.

The last three failure modes have varying severity depending on the size of the additional components. Failures were only considered for the body angular rate sensors p, q and r to limit the complexity of the fault detection and accommodation process. These sensors were chosen because they are present both directly and indirectly (Euler calculations) in the control system feedback for both lateral and longitudinal control. This generates a total of 12 failure modes that were investigated.

Table 4: Faults that cause aircraft to exceed detection criteria during flight

Fault Mode	**Body Angular Rates**		
	p - Failures	q - Failures	r - Failures
Failure to Zero *(Entire simulation duration)*	Aircraft exceeds decision criteria	Aircraft meets decision criteria. No FDIA required	Aircraft meets decision criteria. No FDIA necessary.
Step Failure *Constant bias (entire simulation duration)*	Exceeds decision criteria with a step failure greater than 0.5 degrees/sec	Exceeds decision criteria with a step failure greater than 0.2 degrees/sec	Exceeds decision criteria with a step failure. greater than 5 degrees/sec
Ramp Failure *Constant slope (value limited by simulation time)*	Exceeds decision criteria with a ramp slope greater than 0.005 degrees/sec	Exceeds decision criteria with a ramp slope greater than 0.006 degrees/sec	Exceeds decision criteria with a ramp slope greater than 1 degrees/sec
Additional Noise *Maximum noise value (~3σ). Normally distrib.*	Exceeds decision criteria with noise failure greater than 5 degrees/sec	Exceeds decision criteria with noise failure greater than 2 degrees/sec	Exceeds decision criteria with noise failure greater than 50 degrees/sec

The numbers listed in Table 4 are only of any value when the model for each failure mode and the significance of the feedback path is understood. For example, failure to zero of the p – rate sensor creates errors in the Euler angle calculation, causing the aircraft to roll heavily, causing the aircraft to loose altitude. The important thing to note from Table 4 is that with the current control system architecture and data fusion process, step and ramp failures have the most effect on the closed loop stability and failures on the r – angular rate sensor are less significant than failures on the p and q angular rate sensors. Fig. 7 and Fig. 8 show the variation from the standard flight path that occurs when we use the faults specified in Table 4.

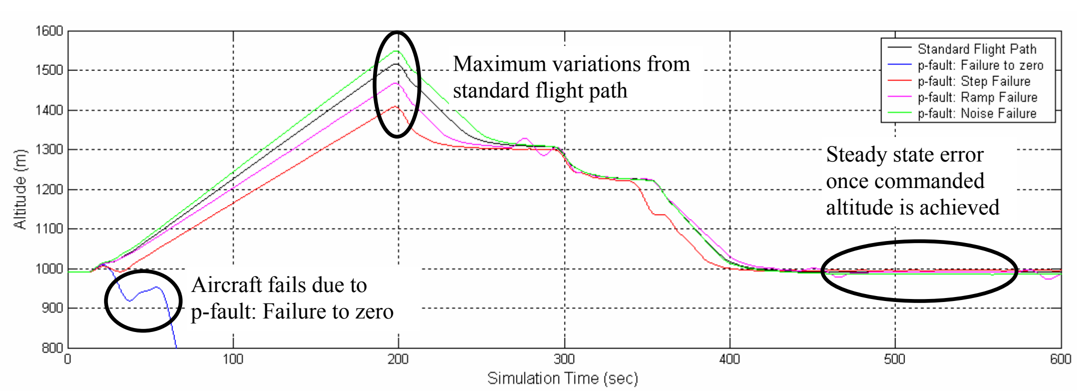

Fig. 7: Altitude variation for normal and faulty sensors: Effect of each fault mode

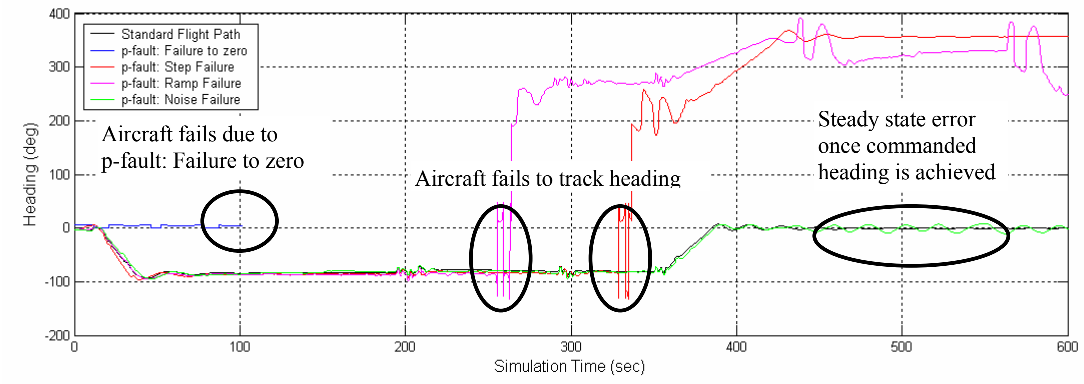

Fig. 8: Heading variation for normal and faulty sensors: Effect of each fault mode

Data Fusion

The data fusion process uses low-pass filtering to reduce the effects of noise on the sensor measurements. The filtered measurements are then used to compute Euler angles. The data fusion process is aimed at providing stable and accurate estimates of the control system parameters. The performance of the fusion process could be improved by implementing a Kalman Filter. This may also improve the stability of the aircraft when a fault occurs due to the tightly coupled nature of closed loop systems. A change in stability would in turn change the fault modes that meet the criteria in Table 4.

Fault Detection and Accommodation

The first step in the fault detection and accommodation process is the estimation of sensor values using neural networks. The error between the estimates and the measurements are then used to generate residuals for fault detection. Once a fault is detected the measured values are replaced with the NN estimate. The architecture used to achieve this is shown in Fig. 9.

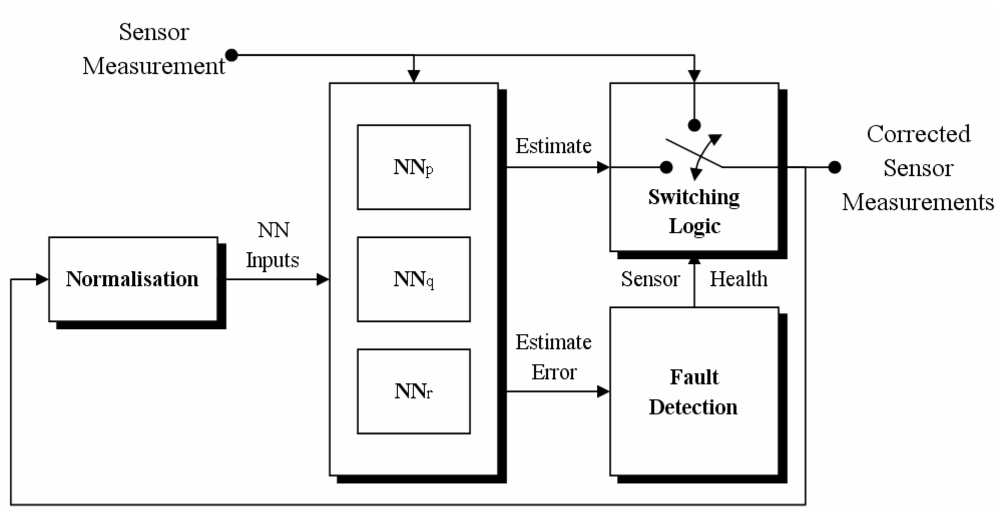

Fig. 9: Neural Network Estimation and Fault Detection Architecture

Estimation of Sensor Measurements using Neural Networks

The neural networks used to estimate the sensor measurements were Multi Layer Perception (MLP) NN trained with the Extended Back Propagation algorithm (EBPA) [1]. Each network was trained over a number of simulations before being used in the simulation model and each network uses all available sensors as inputs into the input layer of the NN (except for the sensor measurement being estimated). There are a number of neural networks and training architectures that promise better performance [22, 23], however this research is less focused on the neural network specifics and more on the results of their applications. Fig. 10 shows the actual measurements and the estimated signal and Fig. 11 shows the error in the estimate of the p – angular rate sensor. The results are based on the standard flight path. The neural network has been trained over a number of simulations and maintains a small learning rate.

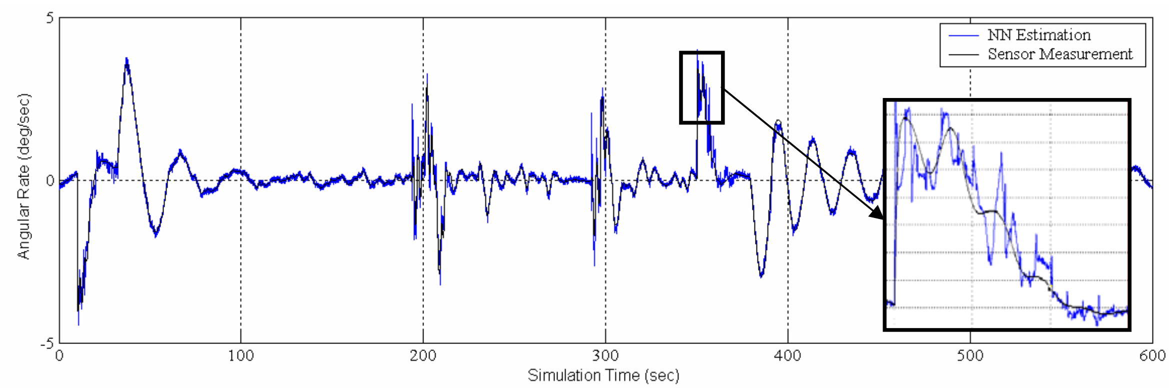

Fig. 10: p – Angular Rate Neural Network Estimation

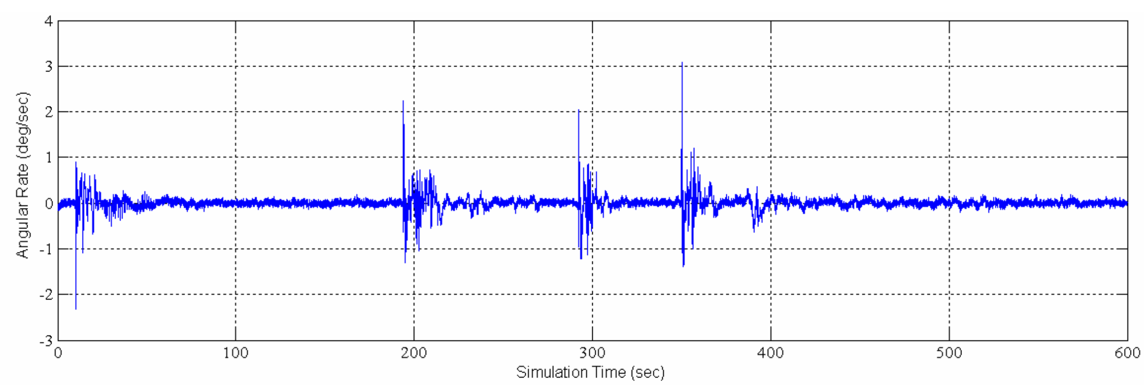

Fig. 11: p – Angular Rate Neural Network Estimation Error

Inspection of the neural network estimates highlights that the peak errors are caused by small delays between the NN estimates and the actual values. The estimates contain more noise than the original sensor measurements as the NN are to some degree, compounding the noise from the sensors it uses for its estimation procedure. See Table 5 for values on the estimation performance of the neural networks.

Performance of Neural Network Estimations with and without On-Line Learning

The estimation performance of the neural network when on-line learning is enabled, is important when first detecting failures. However, once a fault is detected, on-line learning is disabled to avoid the NN learning the fault. This causes an increase in estimation error as shown in Fig. 12 and Fig. 13.

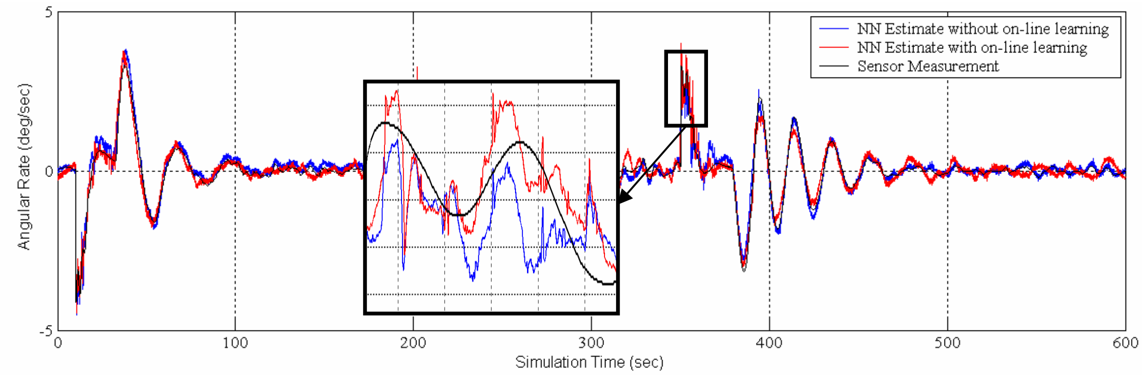

Fig. 12: Neural Network Estimation with and without On-Line learning

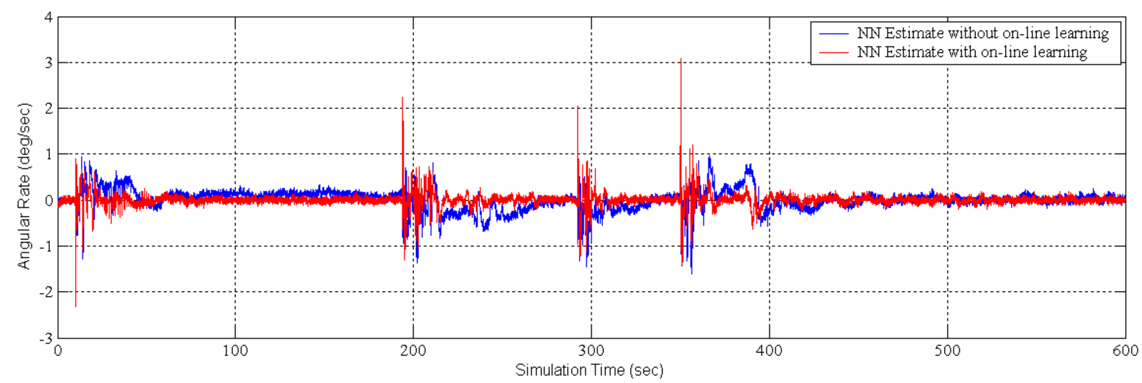

Fig. 13: Neural Network Estimation error with and without on-line learning

The errors are considerably less when on-line learning is enabled. Table 5 shows the typical errors associated with the two estimates for each of the angular rate sensors. Each entry gives an indication of how accurate the NN estimations are. Note the increase in mean and standard deviation between outputs with learning enabled and leaning disabled.

Table 5: Typical estimation errors with and without on-line learning

Parameter		**Neural Network Estimation Error**		
		Maximum	Mean	Standard Dev.
Learning Enable	p	3.2 deg/sec	0.0007 deg/sec	0.14 deg/sec
	q	5.0 deg/sec	0.0010 deg/sec	0.25 deg/sec
	r	3.6 deg/sec	0.0011 deg/sec	0.18 deg/sec
Learning Disabled	p	2.8 deg/sec	0.1723 deg/sec	0.18 deg/sec
	q	4.4 deg/sec	0.0956 deg/sec	0.38 deg/sec
	r	4.2 deg/sec	0.1551 deg/sec	0.36 deg/sec

Fault Accommodation Performance

The major concern with using these estimations as redundant signals is that the estimation error compiled with the sensor suites existing uncertainty will create closed loop instabilities. With enough error it is to be expected that the accommodation process will fail, so it is important to determine what accommodation processes can be achieved with the given estimations before this instability occurs. This determines the fault modes that can be accommodated by this neural network approach. Table 6 shows the performance of the closed loop system when a fault mode is being accommodated for the entire simulation duration. Acceptability is once again based on the criteria in Table 3. The values in Table 6 are given in percent, representing the percentage of times the aircraft recovers given the specified accommodation signals.

Table 6: System Performance when using Accommodated Signals

Accommodated Signals	**Post failure Aircraft Recovered**		**Post failure Aircraft Failed**	
	With acceptable heading error	With acceptable altitude error	Due to detection criteria	Due to complete failure (crash)
p only	100%	100%	0%	0%
q only	100%	70%	30%	0%
r only	100%	100%	0%	0%
p and q	10%	0%	100%	0%
p and r	0%	0%	100%	0%
q and r	100%	100%	0%	0%
p, q and r	0%	0%	100%	100%

We can now say that this approach will be successful when accommodating single failures in p and r and most of the time. The estimation error is too large for the accommodation process to include multiple failures of p and r and p and q however the combination of failures in q and r results in acceptable performance. This is due to the feedback nature of the estimation process in the neural networks as well as the structure of the longitudinal and lateral controllers. For example, a failure in the p-angular rate sensor would cause additional error on the q and r-angular rate sensor estimates. The only combination of accommodated signals that caused the aircraft to become completely unstable was using the combination of p, q and r. For this investigation only single failures were considered in the detection procedure.

Fault Detection Performance

For fault detection the estimate error is filtered and a threshold is used to determine if the error is beyond normal limits. Detection logic is applied over a number of samples to limit the possibility of a false alarm. Once a sensor is declared faulty it remains that way for the entire simulation duration.

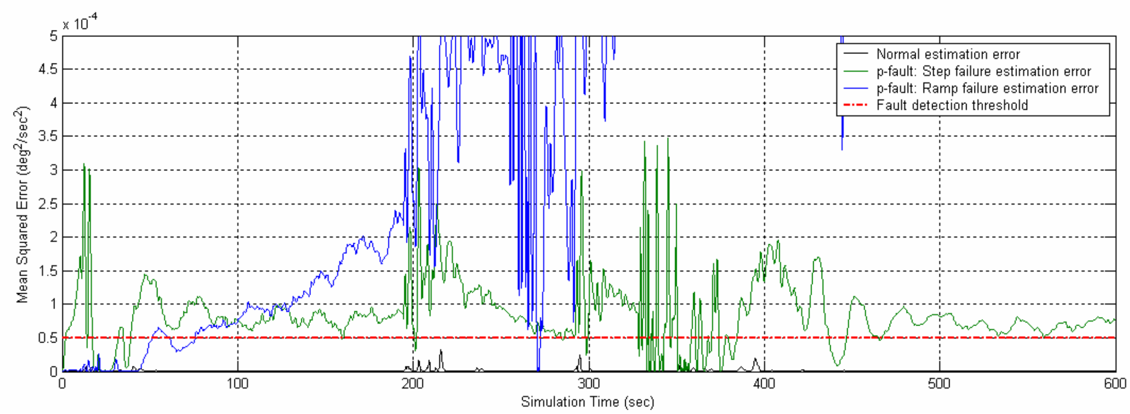

Fig. 14: Neural network errors and detection threshold

Performance of the fault detection process is given in terms of the percentage of time that successful detections are made and the percentage of time that false alarms are generated. The ultimate goal of any fault detection process is to bring successful detections to 100%, whilst lowering false detections (false alarms) to 0%. If a fault detection process is too sensitive it will often result in a high percentage of false detections without any significant improvement in the percentage in successful detections. Table 7 shows the performance of the fault detection process performed in these simulations. The percentages are taken from a small population of simulations and some more analysis is required to produce more accurate results.

Table 7: Performance of Fault Detection Process

Failure mode		Successful Detection	False Alarms	Detection Delay
No actual failures		N/A	10 %	N/A
Failure to Zero	p Sensor	90 %	40 %	< 20 sec
	q Sensor	80 %	30 %	< 30 sec
	r Sensor	100 %	10 %	< 15 sec
Step Failure	p Sensor	70 %	30 %	< 15 sec
	q Sensor	80 %	30 %	< 25 sec
	r Sensor	100 %	10 %	< 20 sec
Ramp Failure	p Sensor	70 %	30 %	< 80 sec
	q Sensor	60 %	20 %	< 120 sec
	r Sensor	100 %	10 %	< 50 sec
Noise Failure	p Sensor	80 %	40 %	< 30 sec
	q Sensor	80 %	30 %	< 25 sec
	r Sensor	100 %	10%	< 15 sec

The percentage of false alarms is not a major concern as we have already shown that the accommodation process performs adequately. The major problem with the fault detection procedure implemented is the detection delays. The greater the detection delay becomes, the more the neural network learns the fault. If the neural network learns a fault, then the performance of the accommodation process is reduced.

Switching Logic

The logic used to switch between faulty signals and their NN estimation is a simple hard switching method. Once a fault is declared, the sensor is treated as faulty for the remainder of the simulation. There are a number of alternatives to hard switching between the two signals, however this runs the risk in the fault developing to a level at which the aircraft cannot recover. Detection delay plays an important part in the switching transients that occur in hard switching systems. If a detection delay is too big the transients caused by the switching logic may in fact cause the aircraft to become unstable. The only way to know this for sure is to test the neural network fault detection and accommodation process and see how the overall system performs.

Overall System Performance

The final test for this neural network fault detection and accommodation technique is to simulate a set of faults and determine the percentage of times the aircraft recovers from faults that can be accommodated by the neural network architecture. The preliminary results are presented in Table 8.

Table 8: Overall Performance

Failure mode with accommodation techniques		**Aircraft Recovered**		**Aircraft Failed**	
		With acceptable heading error	With acceptable altitude error	Due to detection criteria	Due to complete failure (crash)
Failure to Zero	p Sensor	100%	30%	70%	0%
	q Sensor	100%	50%	50%	0%
	r Sensor	100%	100%	0%	0%
Step Failure	p Sensor	80%	100%	20%	0%
	q Sensor	100%	40%	60%	0%
	r Sensor	100%	100%	0%	0%
Ramp Failure	p Sensor	100%	100%	0%	0%
	q Sensor	100%	50%	50%	0%
	r Sensor	100%	100%	0%	0%
Noise Failure	p Sensor	70%	100%	30%	0%
	q Sensor	100%	70%	30%	0%
	r Sensor	100%	100%	0%	0%

The results shown indicate that the aircraft is able to maintain flight regardless of the fault that is generated; however the performance of the fully integrated system is sometimes less than desirable. This is due to the tightly coupled nature of the closed loop aircraft systems. A small improvement in the data fusion process or the control system can have a dramatic effect on the performance of the fault detection and accommodation process. Detection delays also play an important role in the performance of this accommodation scheme, as the weights of the neural networks are being updated and partially learn the fault that exists on the sensor. For example, the results show that for a failure to zero of the p-rate sensor, the aircraft exceed the specified altitude error (refer, Table 3). The reason for this is the detection delay is sufficient enough for the aircraft to loose altitude while the fault sensor measurements are present in the control loop.

Conclusion

The neural network fault detection and accommodation process investigated shows promising results for minimising the effects of sensor faults in UAV avionics systems, however there is always room for improvement. The biggest difficulty with any model-based fault detection and accommodation process is the interaction between systems in the control loop. The tightly coupled nature of UAV systems makes achieving an optimal and robust solution difficult. There are a variety of adaptation techniques that could be used to increase the recovery rate of the aircraft; however this adds complexity and cost. Including neural network estimates for each sensor would increase the complexity of this approach significantly.

Based on the findings and experience gained from this investigation the future direction of this project will be focused on developing fault detection and accommodation techniques that are tightly coupled with the data fusion and control systems. The intended outcomes of this project are to develop an optimal procedure that can deal with a variety of sensor faults by using all available aircraft data. Once this is achieved, actuator and plant failures will be investigated and integrated into the solution. Achieving this will hopefully aid the development of more robust and reliable UAV systems without relying on expensive avionics grade components.

Acknowledgments

This research is supported by the Cooperative Research Centre for Satellite Systems and the Queensland University of Technology. Unmanned Dynamics provided the Aerosim blockset used for the nonlinear aircraft model and Mr Giampiero Campa from the West Virginia University provided the Adaptive Neural Network Library. This research was supported in part by a grant of computer software from QNX Software Systems Ltd.

References

[1] M. R. Napolitano, Y. An, and B. A. Seanor, "A fault tolerant flight control system for sensor and actuator failures using neural networks," *Aircraft Design*, vol. 3, pp. 103-128, 2000.

[2] C. Rago, R. Prasanth, R. K. Mehra, and R. Fortenbaugh, "Failure detection and identification and fault tolerant control using the IMM-KF with applications to the Eagle-Eye UAV," presented at Decision and Control, 1998. Proceedings of the 37th IEEE Conference on, 1998.

[3] P. Schaefer, R. D. Colgren, R. J. Abbott, H. Park, A. Fijany, F. Fisher, M. L. James, S. Chien, R. Mackey, M. Zak, T. L. Johnson, and S. F. Bush, "Technologies for reliable autonomous control (TRAC) of UAVs," presented at Digital Avionics Systems Conferences, 2000. Proceedings. DASC. The 19th, 2000.

[4] S. M. Magrabi and P. W. Gibbens, "Decentralised fault detection and diagnosis in navigation systems for unmanned aerial vehicles," presented at Position Location and Navigation Symposium, IEEE 2000, 2000.

[5] R. J. Patton, P. M. Frank, and R. N. Clark, *Issues of fault diagnosis for dynamic systems*. London: Springer, 2000.

[6] T. Anderson and P. A. Lee, *Fault Tolerant Principles and Practice*: Prentice-Hall, 1981.

[7] J. J. Gertler, *Fault Detection and Diagnosis in Engineering Systems*: Marcel Dekker Inc, 1998.

[8] R. Isermann, "Process fault detection based on modelling and estimation methods, A survey," *Automatica*, pp. 387-404, 1984.

[9] P. M. Frank, "Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy. A survey and some new results," *Automatica*, pp. 459-474, 1987.

[10] A. S. Willsky, "A survey of design methods for failure detection systems," *Automatica*, pp. 601-611, 1976.

[11] M. M. Gupta and T. Yamakawa, *Fuzzy Logic in Knowledge Based Systems Decision and Control*: Elsevier Science Publishers B.V., 1998.

[12] L. Boullart, A. Krijgsman, and R. A. Vingerhoeds, *Application of Artificial Intelligence in Process Control*. Oxford: Pergamon Press, 1992.

[13] M. Oosterom, R. Babuska, and H. B. Verbruggen, "Soft computing applications in aircraft sensor management and flight control law reconfiguration," *Systems, Man and Cybernetics, Part C, IEEE Transactions on*, vol. 32, pp. 125-139, 2002.

[14] A. Ichtev, J. Hellendoorn, and R. Babuska, "Fault detection and isolation using multiple Takagi-Sugeno fuzzy models," presented at Fuzzy Systems, 2001. The 10th IEEE International Conference on, 2001.

[15] M. Oosterom and R. Babuska, "Virtual sensor for fault detection and isolation in flight control systems - fuzzy modeling approach," presented at Decision and Control, 2000. Proceedings of the 39th IEEE Conference on, 2000.

[16] Y. Zhang, J. Jiang, M. Flatley, and B. Hill, "Condition monitoring and fault detection of a compressor using signal processing techniques," presented at American Control Conference, 2001. Proceedings of the 2001, 2001.

[17] R. Mackey, "Generalized cross-signal anomaly detection on aircraft hydraulic system," presented at Aerospace Conference, 2001, IEEE Proceedings., 2001.

[18] S. Menon, O. Uluyol, K. Kini, and E. O. Nwadiogbu, "Startup fault detection and diagnosis in turbine engines," presented at Aerospace Conference, 2003. Proceedings. 2003 IEEE, 2003.

[19] O. Uluyol, K. Kim, S. Menon, and E. O. Nwadiogbu, "Synergistic use of soft computing technologies for fault detection in gas turbine engines," presented at Soft Computing in Industrial Applications, 2003. SMCia/03. Proceedings of the 2003 IEEE International Workshop on, 2003.

[20] Q. Zhang and Y. Zhang, "A method for fault detection and isolation using neural networks," presented at Neural Networks, 1996., IEEE International Conference on, 1996.

[21] T. Brotherton and T. Johnson, "Anomaly detection for advanced military aircraft using neural networks," presented at Aerospace Conference, 2001, IEEE Proceedings., 2001.

[22] F. E. Nasuti and M. R. Napolitano, "A learning approach to the SFDIA problem using radial basis function networks," presented at Intelligent Control, 2000. Proceedings of the 2000 IEEE International Symposium on, 2000.

[23] G. Campa, M. L. Fravolini, M. Napolitano, and B. Seanor, "Neural networks-based sensor validation for the flight control system of a B777 research model," presented at American Control Conference, 2002. Proceedings of the 2002, 2002.

[24] M. G. Perhinschi, M. Lando, L. Massotti, G. Campa, M. R. Napolitano, and M. L. Fravolini, "Online parameter estimation issues for the NASA IFCS F-15 fault tolerant systems," presented at American Control Conference, 2002. Proceedings of the 2002, 2002.

[25] G. Silvestri, F. B. Verona, M. Innocenti, and M. Napolitano, "Fault detection using neural networks," presented at Neural Networks, 1994. IEEE World Congress on Computational Intelligence., 1994 IEEE International Conference on, 1994.

[26] D. Del Gobbo and M. R. Napolitano, "Issues in fault detectability for dynamic systems," presented at American Control Conference, 2000. Proceedings of the 2000, 2000.

[27] M. R. Napolitano, G. Molinaro, M. Innocenti, B. Seanor, and D. Martinelli, "A complete hardware package for a fault tolerant flight control system using online learning neural networks," presented at American Control Conference, 1999. Proceedings of the 1999, 1999.

[28] D. Del Gobbo, M. Napolitano, J. Callahan, and B. Cukic, "Experience in developing system requirements specification for a sensor failure detection and identification scheme," presented at High-Assurance Systems Engineering Symposium, 1998. Proceedings. Third IEEE International, 1998.

[29] M. R. Napolitano, G. Silvestri, D. A. Windon, II, J. L. Casanova, and M. Innocenti, "Sensor validation using hardware-based on-line learning neural networks," *Aerospace and Electronic Systems, IEEE Transactions on*, vol. 34, pp. 456-468, 1998.

[30] R. J. Patton, J. Chen, and T. M. Siew, "Fault diagnosis in nonlinear dynamic systems via neural networks," presented at Control, 1994. Control '94. Volume 2., International Conference on, 1994.

[31] A. Alessandri and T. Parisini, "Model-based fault diagnosis using nonlinear estimators: a neural approach," presented at American Control Conference, 1997. Proceedings of the 1997, 1997.

[32] A. Alessandri, M. Baglietto, and T. Parisini, "Robust model-based fault diagnosis using neural nonlinear estimators," presented at Decision and Control, 1998. Proceedings of the 37th IEEE Conference on, 1998.

[33] A. Alessandri and T. Parisini, "Neural state estimators for direct model-based fault diagnosis," presented at American Control Conference, 1998. Proceedings of the 1998, 1998.

[34] A. Alessandri, "Fault diagnosis for nonlinear systems using a bank of neural estimators*1," *Computers in Industry*, vol. 52, pp. 271-289, 2003.