PLENARY SPEECH FROM 1994 IEEE INTERNATIONAL SYMPOSIUM ON INTELLIGENT CONTROL

Intelligent Fault Diagnosis and Control Reconfiguration

Herbert E. Rauch

Lockheed/Kent Ohlund

Modern technology is leading to increasingly complex systems with ever more demanding performance goals. These complex systems must have the capability for fault accommodation to operate successfully over long periods of time. For example, future aircraft and spacecraft will require fault detection, isolation, and control reconfiguration which can respond in a short time under adverse conditions. Those avionics systems will allow aircraft to maintain adequate levels of performance even with failures in one or more actuators or sensors. Future spacecraft will require higher degrees of autonomous operation that allow for health monitoring and fault tolerance over long periods of time without human intervention.

This presentation gives an overview of fault diagnosis and control reconfiguration for complex systems such as those required in the aerospace industry. The presentation starts with a brief review of fault accommodation [1], [2] followed by four specific examples, viewed from the perspective of a control engineer. The first example [3], [4] illustrates issues arising from processing large amounts of information to accomplish real-time fault diagnosis. Here the driving requirement is rapid decision making. The second example [5,6] treats fault accommodation and control reconfiguration for an autonomous unmanned underwater vehicle. The driving requirement is to develop alternative responses to maintain mission performance. The third example [7] treats fault detection, isolation, and reconfiguration for aircraft control surfaces. This requires rapid response under difficult circumstances. The fourth example [8] relates to autonomous control of a spacecraft. Here the emphasis is on the ground-based test bed needed to validate autonomous performance improvement and health monitoring. The last two examples (aircraft and spacecraft) are based on work done by colleagues at Lockheed.

Presented at the IEEE International Symposium on Intelligent Control, Chicago, IL, Aug. 25, 1993. The author is with Lockheed Palo Alto Research Laboratory (92-30/250), 3251 Hanover Street, Palo Alto, CA 94304. This work was supported by the Lockheed Independent Research Program.

Fault Accommodation and Intelligent Control

Fault accommodation is a key aspect of intelligent control. Complex systems require highly sophisticated controllers to insure that demanding performance can be achieved under adverse conditions. Conventional approaches often cannot meet these stringent control requirements whereas intelligent control addresses challenging problems which cannot be solved by

0272-1708/94/$04.00©1994IEEE

conventional approaches. Intelligent control includes several research areas such as systems and control, computer science, and operations research. It uses a diverse collection of technologies and disciplines such as expert systems, neural networks, fuzzy logic, machine learning, and discrete event systems.

In the plenary talk at the 1993 American Control Conference (titled "Perception, Cognition, and Situated Actions") Professor Sanjoy Mitter of M.I.T. made an interesting point which applies equally well to intelligent fault diagnosis. The key issue for intelligence is finding a representation, a way to convert raw data to features. Extracting information from raw data is often difficult because of noise, missing data or occlusions. Phenomena show up at disparate locations. They can have a variety of time scales, from low frequency signals to high frequency vibrations.

Therefore, intelligence comes from measurement of similarity on an appropriate metric. Fault isolation is the ability to distinguish between specific faults. For fault isolation, measurement of similarity has two parts: first, modeling to represent the faults; and second, a probabilistic comparison of modeled with sensed signals.

Sensitivity characterizes the size of the fault that can be isolated. Robustness is the ability to isolate the fault in the presence of modeling errors. Isolation, sensitivity, and robustness improve with careful selection of the plant model, filtering of the measurement data, and appropriate statistical tests.

Three goals for fault tolerance are reliability, maintainability, and survivability. Often these goals conflict. For example, having three identical sets of sensors might increase reliability, but it would also make maintenance more difficult. Using a less capable backup for an actuator might make maintenance easier, but it could reduce survivability.

Modern robust control techniques attempt to achieve satisfactory performance over a variety of conditions. Adaptive control adjusts the parameters of the control to accommodate off-nominal behavior. When a fault occurs, successful control reconfiguration requires some redundancy in sensors, actuators, and other system resources to overcome capability lost due to the fault.

Two types of redundancy are direct redundancy and analytic redundancy. One example of direct redundancy is multiple sensors measuring the same quantity; the best estimate can be obtained by majority vote. An example of analytic redundancy is multiple sensors measuring diverse quantities related by a mathematical model, with best estimates obtained by a Kalman filter. An alternative way to obtain estimates is to operate on the measurements directly rather than processing through a Kalman filter. Transformation of the measurements can emphasize particular faults.

Model-Based and Model-Free

Model-based methods for fault diagnosis use system models and sensor measurements. They rely on analytic redundancy and statistical procedures to determine the probability of faults. The statistical testing for fault can be based on parallel Kalman filters, representing each specific fault. The innovation for the Kalman filter is defined as the difference between the sensor measurements and the Kalman filter estimates of the measurements. With zero mean white noise and an accurate model, the innovation of a fault free system is also zero mean white noise. The statistical characteristics of the innovation from each filter determine the likelihood of that specific fault.

Fault diagnosis can also be accomplished without explicit mathematical models. Examples of model-free methods include limit checking of sensors, where potential faults are indicated when sensors exceed preset limits. Special sensors check temperature and pressure, or vibration or elongation of a structure. Frequency analysis is useful where the fault has a particular frequency signature.

For further background on fault accommodation, see the survey on model-based fault detection and isolation by Gertler [1] or the survey by Stengel [2]. More recent work by Gertler treats onboard fault detection for automotive engines [9]. More recent work by Stengel treats intelligent flight control for aircraft [10].

The four examples in the following sections are viewed from the perspective of a control engineer in the aerospace industry, but there are other disciplines. Control requirements depend on the discipline and the application, as shown in Table I, which lists some issues for chemical engineering (process control), mechanical engineering (robotics and automotive control), and aerospace engineering (aircraft and spacecraft). The aerospace applications presented here emphasize detailed analytical models, usually linearized, with short time for adaptation.

Real-Time Fault Diagnosis

Rapid fault diagnosis for complex systems is illustrated by two papers from the August 1993 Special Issue on AI Applications of *IEEE Expert* [3], [4]. The first paper, "Integrating Model-Based and Heuristic Features in a Real-Time Expert System," [3] describes an intelligent alarm processor for 1350 substations for public utilities in Singapore. The expert system locates network faults, analyzes fault types, and detects malfunctions in the alarm.

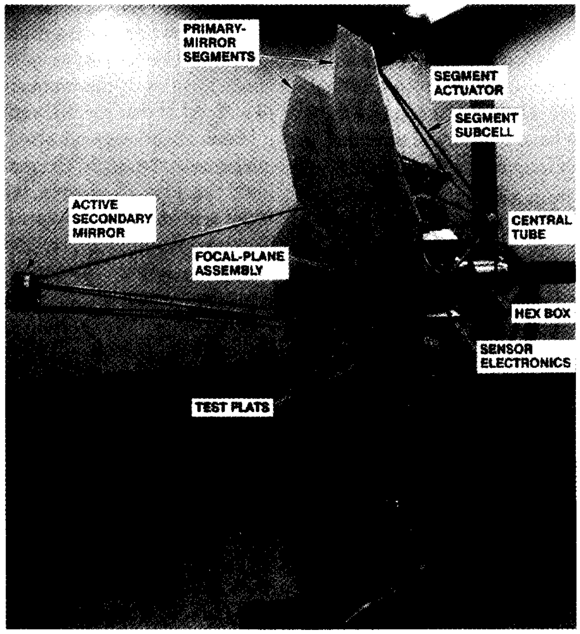
The Singapore expert system [3] has been in operation since 1990. It is complex with 46 000 possible messages, 9000 measurements, and 8000 commands. The model is qualitative, so for example, the alarms might indicate faults in specific components, but they would not give voltages or other quantitative informa-

Table I
Control Requirements Depend on Specific Characteristics of the Application

DISCIPLINE	CHEMICAL	MECHANICAL	AEROSPACE
SAMPLE APPLICATION	PROCESS CONTROL	ROBOTICS/AUTOMOTIVE	AIRCRAFT/SPACECRAFT
QUALITY OF MODEL	APPROXIMATE	ANALYTIC	DETAILED ANALYTIC
MODEL COMPLEXITY	COMPLICATED PROCESS	NONLINEAR TIME-VARYING	LINEARIZED TIME-VARYING
TIME FOR ADAPTING	LONG-TIME INTERVALS	SHORTER INTERVAL	VERY SHORT TIME

tion. Before the expert system was installed, a data acquisition system accumulated alarms from individual substations, while a user interface allowed operators in a central location to investigate faults.

The second paper, "A Structural and Behavioral Reasoning System for Diagnosing Large-Scale Systems" [4], describes fault diagnosis for a particle accelerator called the Heavy Ion Super-Conducting Spectrometer (HISS) located at the Lawrence Laboratory in Berkeley, California. The HISS particle accelerator has a large number of complicated, high speed detectors which estimate particle charges and particle "time of flight." To determine if a particular detector is working properly, the diagnostic system collects data from photomultiplier tubes, builds 1000 event samples, and compares them to historical values. Typical faults might include tube or module failure, power supply drift, or connection deterioration.



The system treats extremely large amounts of data because the experiment has 5000 components with 544 output channels, accumulating 1 megabyte of data in 10 s. The behavior model for the fault diagnosis uses the knowledge of expert physicists. Certainty factors and belief networks determine probability for the diagnosis. Simulated data was used for debugging, and simulated faults were used for tuning the system, because accelerator experiments are performed infrequently (one or two years apart) and it was not possible to validate during operation of an accelerator experiment.

Real-Time Issues

Four key characteristics show up in these and other examples of real-time fault diagnosis for complex systems. The first characteristic derives from the hierarchical structure for models and information processing. The hierarchical model for the public utilities follows the organization of the utilities themselves, with substations, zones within each substation (with common voltage levels), and individual components within the zones. The hierarchical information processing follows a related, but different, organization with the first level selecting candidate faults, the second level focusing in more detail on these candidate faults, and the third level looking for facts to confirm the ultimate diagnosis.

The second characteristic relates to integration of heuristics and model-based reasoning. Heuristic models based on experience are combined with detailed analytic models. Heuristic rules speed up decision making by eliminating implausible candidates and by simplifying and replacing detailed mathematical models.

The third characteristic combines qualitative and quantitative data to develop probability calculations. The calculations determine candidate faults and the corresponding responses. Examples of qualitative data include approximations (such as high, medium, and low) and alerts (which show malfunctions or deviation from historical values). Quantitative numerical measurements give more detailed information in specific cases, but processing can be time consuming. Certainty factors can be approximate probabilities assigned to data.

The fourth characteristic results from the time constraint inherent in real-time processing of large amounts of data. Triage, similar to that performed in the medical profession, involves taking a broad shallow look at all data to provide a limited set of the most likely candidate faults. First, examine the most plausible fault candidates. As they say in medical diagnosis, if you hear hoof beats, think horses, not zebras. Second, if the most plausible are not appropriate, examine fault candidates which lead to critical failures. Third, if those candidates are not appropriate, examine the remaining candidates. Because of the tight time constraint, it is desirable to do a prediagnosis of less likely, but potentially critical faults.

Autonomous Underwater Unmanned Vehicle

Control reconfiguration to accommodate faults is illustrated by two papers on unmanned underwater vehicles (UUV) [5], [6]. A surface ship launches the unmanned vehicle which operates autonomously for days or weeks before returning to the home base. The underwater mission could survey the bottom area and report back on contacts, then inspect an underwater installation, and finally return to the mother ship.

Three approaches to implementing control reconfiguration are: 1) to have specific procedures to accommodate modeled (anticipated) potential faults; 2) to represent unmodeled (unanticipated) faults as unknown forces or moments; and 3) to make use of a high level system which replans the mission to mitigate the effects of the fault. The first approach, accommodating modeled (anticipated) potential faults, is treated in the following section on Fault Accommodation for Aircraft Control [7]. The procedure monitors system response to look for specific failure modes. When a failure mode is recognized, the procedure implements the appropriate control change. Control reconfiguration can be based on stored control laws tailored to each anticipated fault condition.

The second approach represents the unmodeled (unanticipated) faults as unknown forces or moments on the vehicle [5]. The procedure is to first estimate forces and moments on-line, and then to adjust the adaptive control to compensate for these disturbances. The disturbances are modeled as state dependent forces and moments. Lateral and longitudinal motion are separated to reduce computation. A rapid estimate recognizes the existence of a fault, but a slower, more deliberate estimate determines the correlation of the fault with a force or moment. Training to estimate the disturbance is based on specified changes in the trajectory, but should be completed while the vehicle is going about its regular mission.

Autonomous Control Logic

The third approach treats high level fault accommodation [6]. The implementation is called Autonomous Control Logic (ACL), and it is meant to extend the range of mission responses by approximating decision-making of an experienced crew. The two facets of the response are reactive capability which directly accommodates to the recognized faults, and assessment capability which determines how to modify the mission to accommodate faults. The real-time reactive capability monitors the sensors to detect faults and initiates test sequences to isolate faults. Because of the complex logic, it can respond to unanticipated faults. In general, the added computation time for the complex logic can be tolerated in underwater missions because of the overall time scale, but in critical situations heuristics are used to speed up reaction time and bypass the complex logic. The real-time assessment capability evaluates the vehicle degradation and generates an appropriate mission response. For example, elevator control allows the vehicle to point higher or lower to change depth. An alternative way to point the vehicle is to vary the ballast (which can be used as a less capable redundant control). Therefore, when there is a failure in elevator control, it is still possible to change depth by varying ballast, but with degraded ability, it might be necessary to curtail or reorganize tasks involving depth change.

Fault Accommodation for Aircraft Control

The third example demonstrates fault detection, isolation, and reconfiguration (FDIR) for control surfaces using a model of the F/A-18 aircraft [7]. The model of the F/A-18 aircraft is based on linearized equations of motion, but the procedure is equally applicable when the aircraft is represented by nonlinear equations of motion. The block diagram in Fig. 1 illustrates the overall approach. The fault detection activity continuously monitors system response and compares the measured system response to a model representing a healthy system. The fault isolation activity compares the measured system response to models representing systems with specific failure modes. When a sequence of sensor readings corresponds to a fault condition, the calculated likelihood of that fault increases. The detection and isolation algorithms use the Probabilistic Neural Network (PNN) [11] to determine when a fault occurs and to determine the specific fault. Control reconfiguration is based on stored control laws tailored to each anticipated fault condition. Alternatively, a new control law is determined analytically based on the estimated fault.

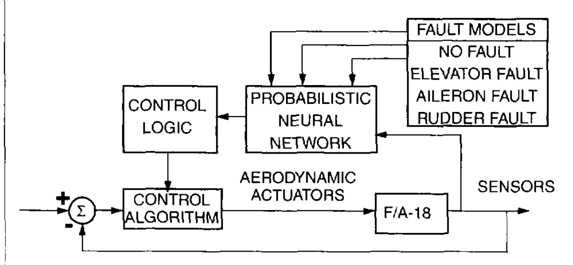


Fig. 1. Block diagram of fault detection, isolation, and reconfiguration for aircraft control surfaces.

Table II
Hypothetical Signal-to-Noise Ratios for Fault Isolation for F/A-18 Aircraft

Sensor	Actuator	Signal-to-Noise
Pitch Rate	Stabilator	68
Normal Acceleration	Stabilator	29
Yaw Rate	Rudder	1.5
Roll Rate	Aileron	6
Lateral Acceleration	Rudder	7

Assumptions: The effect of the failure is to change the control surfaces by 6°. There are 5 measurements spaced 10 ms apart. The sensor noise is independent with standard deviation 1°/s for the rates and 1 ft/s for the accelerometers.

Three advantages the PNN has over feed-forward neural networks with back-propagation are: 1) the PNN is memory-based, which allows instant, one-pass learning; 2) the results translate to Bayesian probability for failure detection; and 3) new failure candidates can be added with minor modification. In addition, the algorithm can be implemented directly in neural network hardware, and the effects of measurement noise can be determined directly.

The linear six degree-of-freedom state-space model of the F/A-18 aircraft represents level flight at 10 000 feet with a speed of Mach 0.6. The model has eight state variables (four longitudinal states and four lateral states) with the longitudinal and lateral motions completely decoupled. The aircraft utilizes five pairs of control surfaces (some of which can be used both symmetrically and asymmetrically) to achieve seven different control inputs. Six sensors measure the dynamic response of the aircraft with three measuring longitudinal motion and three lateral motion. A traditional, linear quadratic regulator (LQR) state feedback, digital control system is implemented with a 100 Hz sample frequency.

Signal-to-Noise Ratio

To evaluate the effectiveness of fault isolation, it is useful to estimate an approximate signal-to-noise ratio as a function of the change in control due to the failure (signal) and the sensor noise. Assume the effect of the failure is to change the control surfaces by a fixed amount (the signal). The sensors measuring pitch rate and normal acceleration can be used to detect asymmetric elevator faults (which influence pitch). The sensors measuring yaw rate and lateral acceleration can be used to detect rudder faults (which influence yaw). The sensor measuring roll rate can be used to detect aileron faults (which influence roll).

For the purpose of calculating a hypothetical signal-to-noise ratio, assume the effect of the fault is to change the control deflection by 6° (0.1 rad). Let the sensor noise be independent with standard deviation of 1°/s for the rates and 1 ft/s^2 for the accelerometers. The actual numbers will depend on the quality of the sensor. The signal-to-noise ratio can be postulated directly for a single measurement. When there are multiple measurements, the signal-to-noise ratio increases by the square root of the number of measurements. Assume there are five measurements spaced 10 ms apart. The hypothetical signal-to-noise ratio for each sensor under these assumptions is shown in Table II.

In general, if the fault causes a small change in the aircraft motion, it will be difficult to detect. On the other hand, it will not be necessary to detect such a fault immediately, as long as it has little effect on the aircraft behavior. This is illustrated by simulation results where the rudder fault does not show up immediately, because the rudder command is small at the fault time. However, when the rudder command increases, the fault is detected immediately.

Alternatively, if the fault occurs during stressing maneuvers, early detection may be critical. Control authority for each control surface is determined by mechanical limits and aerodynamic forces. When reconfiguration results in significantly reduced control authority, it reduces the stability region. A stressing maneuver may cause the aircraft to be near the stability boundary, and the actuators remaining after the fault may not have enough control authority to bring the aircraft back to nominal operating conditions. Therefore, during stressing maneuvers, fault detection and reconfiguration must take place before the aircraft leaves the fault-reduced stability region.

Control Reconfiguration

The control reconfiguration is based on stored control laws tailored to each anticipated fault condition. Alternatively, the reconfigured control can use a pseudo-inverse approach to implement a feedback control law similar to that of the primary controls. For example, if there is partial loss of a control surface, reconfiguration could be implemented by increasing the gain to compensate for the partial degradation. The new feedback control is calculated by using a pseudo-inverse which tries to equate the product of the new control matrix (B_{new}) and the new control ($\boldsymbol{u}_{new}$) with the product of the previous control matrix (B) times the control ($\boldsymbol{u}$):

$$B_{new}\,\boldsymbol{u}_{new} = B\,\boldsymbol{u}.$$

When there is a complete failure, the control influence matrix B_{new} is derived from B by eliminating the column which corresponds to the failed control input. If there is redundancy in the actuators, the new control ($\boldsymbol{u}_{new}$) to be applied to the system can be calculated using the pseudo-inverse as shown:

$$\boldsymbol{u}_{new} = (B_{new}^T\, B_{new})^{-1} B_{new}^T\, B\,\boldsymbol{u}$$

A slight modification can tailor the relation between the desired states and the resulting controls. For example, there can be different weightings on the individual state and control variables. A more general approach is to develop a new explicit LQR control law based on the model of the system which corresponds to the fault.

Table III
Hypothetical Satellite Scenario from Autonomous Structural Control Symposium, August 24-25, 1992, U. S. Air Force Academy, CO.

DAY 1	SATELLITE DEPLOYED LOW NATURAL FREQUENCIES, LOW MODAL DAMPING HIGH MODAL DENSITY, FAIR MODEL ACCURACY
DAY 2	GROUND TELEMETRY RESTRICTED TO EMERGENCIES
DAY 3	ACTUATOR FAILS, DEGRADED PERFORMANCE BUT STILL STABLE
DAY 10	LOAD-BEARING STRUCTURAL COMPONENT DESTROYED, MARGINALLY STABLE, BUT ADEQUATE CONTROL AUTHORITY EXISTS WITH REMAINING ACTUATORS
DAY 100	MATERIAL PROPERTIES AND ACTUATOR/SENSOR DYNAMICS SIGNIFICANTLY DIFFERENT THAN DAY 1 VALUES EVOLUTIONARY CHANGES BUT STRUCTURAL INTEGRITY OKAY
DAY 200	SATELLITE MODIFIED BY MOUNTING NEW INSTRUMENTS ALTERED INERTIAL AND STRUCTURAL PROPERTIES

Autonomous Control for a Space Vehicle

The fourth example treats issues leading toward a ground-based test bed for autonomous structural control of a space vehicle [8]. Future space missions will require control systems that are capable of meeting stringent requirements over long periods of time while operating autonomously under a great deal of uncertainty. After establishing a system operating regime, the overall control systems will perform tasks such as improving performance, monitoring health, diagnosing faults, and coordinating maintenance and repair. As much as possible, the control should be autonomous, with capability for human override if necessary.

Potential demands on a spacecraft are illustrated in Table III, which is a hypothetical satellite scenario developed for the 1992 Autonomous Structural Control Symposium [12]. Pointing control systems are of particular interest. For example, large space antennas must be able to operate successfully under a variety of unforeseen conditions. Large segmented mirrors must maintain high geometric precision in the presence of thermal and dynamic loads.

Test Bed Examples

Fault accommodation must be demonstrated on a ground-based test bed before it goes into orbit. *IEEE Control Systems Magazine* has published a number of papers on test beds for control of flexible structures [13]-[20].

One example of a test bed for pointing and structural control is the Lockheed Advanced Structures/Controls Integrated Experiment (ASCIE) which is a test apparatus for control of a segmented, high precision reflector (mirror) [13]. The ASCIE test bed consists of a Cassegrain optical configuration with a two-meter, seven segment primary mirror supported by a lightweight, flexible truss structure. There are 18 actuators and 24 sensors (three actuators and four sensors for each of the six controlled segments). The current control implementation has a 99 state Kalman filter and 200 Hz sample frequency. The closed-loop feedback control system has a bandwidth of about 30 Hz.

An example of high speed hardware for adaptive control is the Lockheed programmable analog neural processor (PANP) which implements the control algorithm for focusing a parabolic metal mirror [21]. The control actuators are metal points which deform the metal mirror to focus the image. There are 21 actuators and 42 sensors (two for each actuator). Each of the 21 actuators uses data from the surrounding five sensors so there are 105 (21 times 5) linear control coefficients.

A microprocessor is used in conjunction with the least-mean-square (LMS) adaptive algorithm to update the analog control coefficients every three seconds to respond to environmental changes. The coefficients are adjusted on the fly, without interrupting the control loop. For this experiment the closed loop control law is implemented at 173 Hz, but the analog neural processor has the capability to implement a control law with up to 2048 coefficients (such as 256 by 8) at an analog bandwidth of 90 KHz. A limitation in the processor is that the feedback coefficients have five bit accuracy. A breadboard model of a more advanced processor has 8 bit accuracy for coefficients.

Test Bed Issues

A test bed could be used to demonstrate adaptive structural control and fault accommodation for a pointing antenna or mirror. One approach to autonomous control is to have a two-level architecture with a (low level) high speed computation element, such as the analog processor, and a (high level) intelligent decision element. The decision element continually monitors system response and makes decisions to improve performance, evaluate health, and accommodate faults. Continuous performance improvement allows the control algorithm to adapt over time. Changes are accomplished in real-time so the control loop is not interrupted.

If there is a fault indication, the decision element identifies the particular fault, and determines a specific control reconfiguration, based on stored responses for each fault condition. The decision element implements the required changes by downloading information (control gains) to the computation element. After control reconfiguration, the decision element returns to the mode of evaluating performance and adapting over time.

The steps leading to verification of a test bed for autonomous structural control are similar to those that arise in the practical utilization of any control system. They include preliminary analysis and design (with simplifying assumptions), software simulation (perhaps with benchmark problems), and experimental validation on the test bed.

Underlying issues for any complex, adaptive control system relate to a) treatment of distributed, hierarchical systems; b) determining observability, controllability, and stability; and c) training and learning for adaptive systems. Issues in modeling deal with a) model complexity, which includes treatment of nonlinearities and discontinuous behavior; b) model validation using hardware experimentation; and c) combining software simulations and hardware experiments. Issues in experimental test bed validation of fault accommodation require a) choosing complexity of fault simulation including partial and intermittent faults; b) treating both anticipated and unanticipated faults, and c) experimentally verifying control reconfiguration, health monitoring and fault accommodation over long periods of time.

Conclusions

This presentation has used specific examples to illustrate issues relating to intelligent fault diagnosis and control reconfiguration. Real-time fault diagnosis for complex systems depends on a number of characteristics such as 1) the hierarchical structure for models and information processing, 2) integration of heuristics and model-based reasoning, 3) combination of qualitative and quantitative data to develop probability calculations, and 4) the time constraint inherent in real-time processing of large amounts of data.

Issues relating to control reconfiguration show up in the examples for unmanned underwater vehicles. Three approaches to implementing control reconfiguration are: 1) to have specific procedures to accommodate modeled (anticipated) faults; 2) to represent unmodeled (unanticipated) faults as unknown forces or moments; and 3) to make use of a high level system which replans the mission to mitigate the effects of the fault.

Accommodating modeled (anticipated) potential faults is treated in the example on fault accommodation for aircraft control surfaces. Measured system response is compared to models representing specific failure modes. When a sequence of sensor readings corresponds to a fault condition, the calculated likelihood of that fault increases. Control reconfiguration can be based on stored control laws tailored to each anticipated fault condition.

A ground-based test bed to demonstrate fault accommodation is discussed in the example on an autonomous space vehicle. The steps leading to verification of a test bed for autonomous structural control include preliminary analysis and design (with simplifying assumptions), software simulation (perhaps with benchmark problems), and experimental validation on the test bed.

Fault accommodation is a key aspect of intelligent control. Complex systems must have active fault accommodation to operate successfully over long periods of time. This presentation has given an overview of fault diagnosis and control reconfiguration for complex systems such as those required in the aerospace industry.

References

[1] J. Gertler, "Survey of model-based failure detection and isolation in complex plants," *IEEE Control Syst. Mag.*, Dec. 1988.

[2] Robert F. Stengel, "Intelligent failure-tolerant control," *IEEE Control Syst. Mag.*, June 1991.

[3] Monika Pfau-Wagenbauer and Wolfgang Nejdl, "Integrating model-based and heuristic features in a real-time expert system," *IEEE Expert*, Aug. 1993.

[4] Robert K. Paasch and Alice M. Agogino, "A structural and behavioral reasoning system for diagnosing large-scale systems," *IEEE Expert*, Aug. 1993.

[5] J.W. Sullivan, P. McCarty, G. Yoshimoto, R. Gargan, R. Pelavin, "Intelligent system for autonomous UUV monitoring, diagnosis, and control," in *Proc. 1992 AIAA Guidance, Navigation, and Control Conf.*, Aug. 1992.

[6] Jay Farrel, Torsten Berger, and Brent Appleby, "Using learning techniques to accommodate unanticipated faults," *IEEE Control Syst. Mag.*, June 1993.

[7] Herbert E. Rauch, Robert J. Kline-Schoder, J. Carl Adams, and Hussein M. Youssef, "Fault detection, isolation, and reconfiguration for aircraft using

neural networks," in *Proc. 1993 AIAA Conf. Guidance, Navigation, and Control*, Aug. 1993.

[8] Herbert E. Rauch and David B. Schaechter, "Neural networks for control, identification, and diagnosis," presented at Congress on Space Research (COSPAR), Sept. 1992; also in *Advances in Space Research.* Pergamon.

[9] Janos Gertler, Mark Costin, Xiaowen Fang, Ronil Hira, Zdzislaw Kowalczuk, and Qiang Luo, "Model-based on-board fault detection and diagnosis for automotive engines," *IFAC J. Control Eng. Practices*, Jan. 1993.

[10] Robert F. Stengel, "Toward intelligent flight control," *IEEE Trans. Syst., Man, Cybern.*, pp. 1699-1717, Nov./Dec. 1993.

[11] Donald F. Specht, "Probabilistic neural networks and the polynomial adeline as complementary techniques for classification," *IEEE Trans. Neural Networks*, Mar. 1990.

[12] *Proc. Auton. Control Symp.*, Aug. 24-25, 1992.

[13] Kenneth R. Lorell, Jean-Noel Aubrun, Donald F. Zacharie, and Ernesto Perez, "Control technology test bed for large segmented reflectors," *IEEE Control Syst. Mag.*, Oct. 1989.

[14] Umit Ozguner, Stephen Yurkovich, Joseph Martin, and Paul Kotnik, "Laboratory facility for flexible control experiments," *IEEE Control Syst. Mag.*, Aug. 1989.

[15] Gary W. Crocker, Peter C. Hughes, and Tony Hong, "Real-time computer control of a flexible spacecraft emulator," *IEEE Control Syst. Mag.*, Jan. 1990.

[16] Stephen Yurkovich and Anthony P. Tzes, "Experiments in identification and control of flexible link manipulators," *IEEE Control Syst. Mag.*, Feb. 1990.

[17] Emmanuel G. Collins, Douglas J. Phillips, and David C. Hyland, "Robust decentralized control laws for the aces structure," IEEE Control Syst. Mag., Apr. 1991.

[18] Chen Hsieh, Jae H. Kim, Ketao Liu, Guoming Zhu, and Robert E. Skelton, "Control of large flexible structures — An experiment on the NASA Mini-Mast Facility," *IEEE Control Syst. Mag.*, Oct. 1991.

[19] K.B. Lim, P.G. Maghami, and M. Joshi, "Comparison of controller designs for an experimental flexible structure," *IEEE Control Syst. Mag.*, June 1992.

[20] A.N. Mosher, "Designing controllers with flexible structures for $H\infty/\mu$-Synthesis," *IEEE Control Syst. Mag.*, Apr. 1993.

[21] W.A. Fisher, R.J. Fujimoto, and R.C. Smithson, "A programmable neural network processor," *IEEE Trans. Neural Networks*, Mar. 1991.

Herbert E. Rauch is a Senior Member of the Research Laboratory at Lockheed in Palo Alto, CA. He received the B.S. degree from the California Institute of Technology and the M.S. and Ph.D. degrees from Stanford University, all in electrical engineering. He has served as Editor of the *IEEE Control Systems Magazine* for eight years, as Founding Editor of the *IEEE Transactions on Neural Networks*, and for six years as Editor of the *Journal of the Astronautical Sciences*, published by the American Astronautical Society. For the International Federation of Automatic Control (IFAC), he served three years as Chair of the IFAC Technical Committee on Mathematics of Control. He is a Fellow of the AAS, the AIAA, the IEEE, and the American Association for the Advancement of Science. In 1994, he serves as President of the IEEE Control Systems Society.

In 1994, he received the Robert E. Gross Award from Lockheed as Engineer of the Year. At Lockheed, he has worked on a variety of activities in estimation and control, including early applications of matched asymptotic expansion to optimal control (for low-thrust interplanetary transfers), optimal control for solar heating and cooling, and economic optimization for an aquaculture facility (for growing lobsters). He also worked on hardware for a very special purpose residue arithmetic processor (republished in an IEEE Press Book), pattern recognition, data fusion, neural networks to route communication traffic (also republished in an IEEE Press Book), and neural networks for identification, control, and fault accommodation.

Sampled Data

Oral Examination Procedure

In these brief notes, the purposes of an oral examination are set forth and practical rules for conducting one are given. Careful attention to the elementary rules is necessary in order to assure a truly successful examination. From the standpoint of each individual examiner the basic purposes of the oral examination are: to make sure that the examiner appears smarter and trickier than either the examinee or the other examiners, thereby preserving his self-esteem, and to crush the examinee, thereby avoiding the messy and time-wasting problem of post-examination judgment and decision.

Both of these aims can be realized through diligent application of the following time-tested rules:

1. Before beginning the examination, make it clear to the examinee that his whole professional career may turn on his performance. Stress the importance and formality of the occasion. Put him in his proper place at the outset.

2. Throw out your hardest question first. (This is very important. If your first question is sufficiently difficult or involved, he will be too rattled to answer subsequent questions, no matter how simple they may be.)

3. Be reserved and stern in addressing the examinee. For contrast, be very jolly with the other examiners. A very effective device is to make humorous comments to the other examiners about the examinee's performance, comments which tend to exclude him and set him apart, as though he were not present in the room.

4. Make him answer each problem your way, especially if your way is esoteric. Constrain him. Impose many limitations and qualifications in each question. The idea is to complicate an otherwise simple problem.

5. Force him into a trivial error and then let him puzzle over it for as long as possible. Just after he sees his mistake but just before he has a chance to explain it, correct him yourself, disdainfully. This takes real perception and timing, which can only be acquired with some practice.

6. When he finds himself deep in a hole, never lead him out. Instead, sigh, and shift to a new subject.

7. Ask him snide questions, such as, "Didn't you learn that in Freshman Calculus?"

(continued on page 102)