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A Fuzzy Logic Intelligent Diagnostic System for Spacecraft Integrated Vehicle Health Management[1]

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ABSTRACT

Due to the complexity of future space missions and the large amount of data involved, greater autonomy in data processing is demanded for mission operations, training, and vehicle health management. In this paper, we develop a fuzzy logic intelligent diagnostic system to perform data reduction, data analysis, and fault diagnosis for spacecraft vehicle health management applications. The diagnostic system contains a data filter and an inference engine. The data filter is designed to intelligently select only the necessary data for analysis, while the inference engine is designed for failure detection, warning, and decision on corrective actions using fuzzy logic synthesis. Due to its adaptive nature and on-line learning ability, the diagnostic system is capable of dealing with environmental noise, uncertainties, conflict information, and sensor faults.

1. INTRODUCTION

Automated data analysis plays an important role in the success of future space missions. The basic concept of automated data analysis is to extract data measured from existing systems, reduce them to a point where logical decisions can be deducted. Due to the complexity and the large amount of data involved, greater autonomy in data analysis and fault diagnosis is indispensable for mission operations, training, and vehicle health management.

Being a standard part of next generation spacecraft, the onboard integrated vehicle health management system will process current and historical measurement data to make failure diagnoses and corrective decisions. As an important constituent of the vehicle health management system, a diagnostic system decides which part of the measurement data to use, how to preprocess and process these data, and how to deduce the judgment and decision from the processed data. Therefore, the reliability and effectiveness of the diagnostic system are closely related to the mission success. However, the diagnostic system's performance is complicated by its working environment: the extremely large amount of the measurement data, the existence of uncertainties, and interactive vehicle operational conditions [Simpson (1994)].

In this paper, we develop a fuzzy logic intelligent diagnostic system within the frame of vehicle health management system

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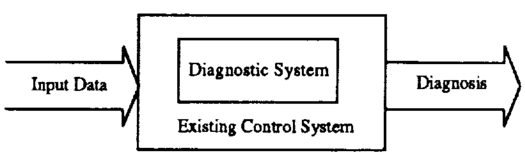
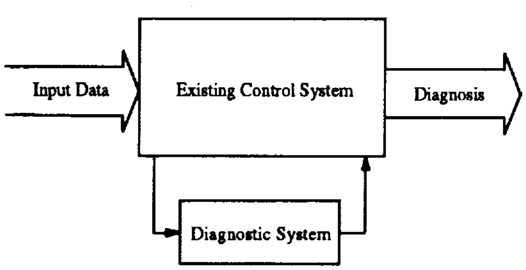
performing two major functions: (i) data reduction and information extraction; (ii) failure detection and diagnosis. These functions are performed by data filter and inference engine subsystems respectively. The data filter is designed to intelligently select only the necessary data for analysis, while the inference engine is designed to provide failure detection, warning, and corrective action decision, based on fuzzy logic synthesis and statistical analysis. Due to its adaptive nature, the diagnostic system is capable of dealing with environmental noise, uncertainties, conflict information, and sensor faults. Assisted by neural networks with learning algorithms, the system is able to conduct self-learning from previous flight data and real-time flight data.

As shown in Fig. 1, the fuzzy logic diagnostic system can be either an integrated part of the existing spacecraft control system (Fig. 1a), or an attached independent unit to assist the control system in its working process (Fig. 1b).



a. Diagnostic system as a part of existing control system



b. Diagnostic system as an independent unit

Fig. 1. Diagnostic system and control system

The diagnostic system can be easily added to and interfaced with existing control software and testbeds to accelerate the diagnostic process and to increase the precision of the diagnosis. Physically, it can be located either with ground-based control facilities or with onboard computing facilities. More specifically, it can be incorporated into the integrated vehicle health management systems for the Space Station and space shuttles.

2. DIAGNOSTIC SYSTEM STRUCTURE

Figure 2 is a schematic diagram of the general structure of the diagnostic system. Basically, this system consists of two subsystems: data filter and inference engine. The former performs data reduction and information extraction function, while the latter performs failure detection and diagnostics function.

Data Filter. The filter works at two data sampling frequencies. The important data are collected and sent to the inference engine with a high frequency. Conversely, the less important data are collected and sent to the inference engine with a low frequency. The fuzzy inference engine assigns each data source into one of the frequency groups. Data are represented by their current measurements, long-term characteristic functions, and short-term characteristic functions. Meanwhile, these data representations are also stored in a relational database. Fuzzy logic inference rules are used in the determination of the levels of importance for any given data source. Data fusion is performed by a fuzzy logic multiple-level, multiple-criteria aggregation algorithm. The weighting parameters of the generalized mean operator are determined by a neural network.

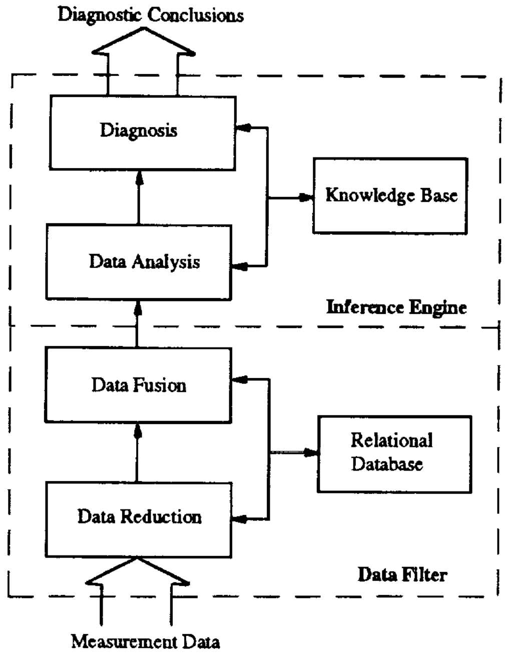


Fig. 2. System structure

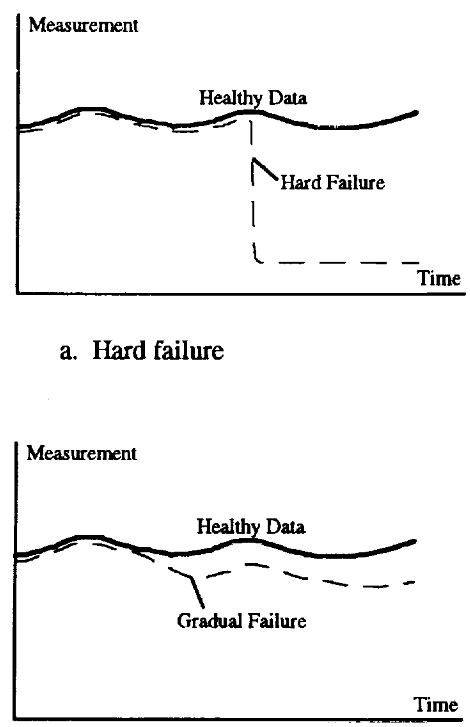
Inference Engine. The inference engine has three tasks: (1) data analysis; (2) failure diagnosis; and (3) updating knowledge base. The inputs of the inference engine are the outputs of the data filter. The outputs of the inference engine are the diagnostic conclusions and corresponding corrective actions.

The selected fused data set comes from the data filter. Data analysis is performed as the first step to decide whether any failures are existing. Fuzzy relations are used in the data processing, assisted by statistical and fuzzy clustering methods. Diagnosis of the possible system failures is conducted by the inference engine using symptom patterns and degrees of conformity methodologies. A hierarchical clustering analysis is performed to find the data subset which causes the failure. Multiple even conflict criteria are dealt with fuzzy compatibility calculations.

The knowledge base is updated during its operation to be adaptive to deal with unscheduled events, unpredictable failure, parameter changes due to system aging. A self-learning neural network is designed for the training and tuning the knowledge base during the design and development stages of the fuzzy logic system, and for adaptively updating the knowledge base in real-time operations.

3. Data Reduction and Fusion

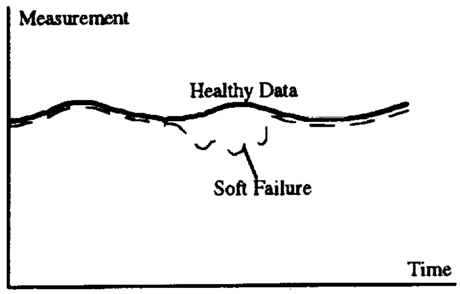
Faulty Conditions. For the design of a diagnostic system, to have basic understanding of all the possible faulty conditions is necessary. First, there are four types of failures of a system variable with respect to time and spatial difference: hard failure (Fig. 3a); gradual failure (Fig. 3b); soft failure with full recovery (Fig. 3c); and soft failure without full recovery (Fig. 3d).



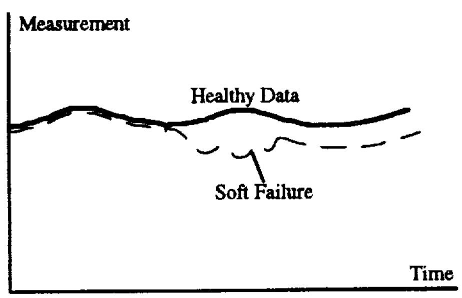
a. Hard failure

b. Gradual failure

Fig. 3. Failure types



c. Soft failure with full recovery



d. Soft failure without full recovery

Fig. 3. Failure types (continued)

Among them, all the failures are to be dealt with the diagnostic system except the hard failure which can be handled by an expert system for a quick conclusion. Next, a failure can be the result of the following: a single system failure; a single sensor failure; multiple system/sensor failures; measurement inaccuracy; and other faults including display or reading mistakes. Finally, an observed failure occurrence can be the result of a single failure or simultaneous failures.

Data Reduction. One of the important objectives of the diagnostic system is to reduce the data it uses to make failure detection and diagnosis quickly. The data filter of the fuzzy logic system is capable of performing this job intelligently [Wu (1994)]. The principle is sorting data to different levels according to the level of importance that a specific data source has in the detection and diagnosis. The subsystem works at two data sampling frequencies. The important data are collected and sent to the inference engine at the high frequency which can be the regular frequency used for data processing. Conversely, the less important data are sampled for the inference engine at the low frequency which is a frequency set for data filtering only. If some data in the high frequency group are determined by the inference engine to be insignificant for decision making, they will be degraded to the low frequency group. Conversely, if some data in the low frequency group are determined by the inference engine as important for the decision making, they will be upgraded to the high frequency group. In this way, the data needed for decision making can be reduced considerably, while retaining all significant information.

Healthy Data and Failure Signatures. The diagnostic system is designed for monitoring spacecraft in real time. It is impossible for the system to handle all the historical data because of the limitation of the computing facilities. However, if we only use the current measurements, we could miss a lot of important information residing in historical data. To solve this problem, we use (i) current measurements, (ii) long-term characteristic functions, and (ii) short-term characteristic functions to represent all the data. The characteristic functions vary from data source to data source, generally being fuzzy sets to store corresponding data patterns from their sources. This data representation scheme is helpful in data fusion, feature extraction, and diagnosis. For diagnostic purposes, these data representations are organized in a relational database.

In real operation, a failure in a given part of the spacecraft system comes with some abnormal features in the data measurements. It is possible for us to catch these features, i.e., its failure signature, with computational methods.

Data Fusion. Using the data representations we have, data fusion is performed by a fuzzy logic multiple-level, multiple-criteria aggregation algorithm [Loskiewicz-Buczak (1993), Barrett (1992) and Yager (1992)]. Here, the data fusion provides all possible anomaly symptoms to the inference engine instead of making conclusions by itself.

The generalized mean operator for data fusion is defined as

$$g(x_1, x_2, \ldots, x_n; p; w_1, w_2, \ldots, w_n) = \{\sum_{i=1}^{n} w_i x_i^p\}^{1/p}, \tag{1}$$

where x_i's are the input data with the total number of information sources as n, w_i's are the relative importance factors to be determined for different criteria, satisfying

$$w_1 + w_2 + \ldots + w_n = 1, \tag{2}$$

and p is the parameter to be determined. The generalized mean operator's values lie between the minimum and the maximum, and increase with an increase in p. By varying p between $-\infty$ and $+\infty$, the generalized mean operator can be used as union or intersection in the extreme cases. The weighting parameters w_i's and p are determined by a neural network. See Krishnapuram (1992) for details of this procedure.

4. Fuzzy Inference

An inference engine is an expert system assisted by a knowledge base to perform evaluations. The inputs of the inference engine are the outputs of the data filter. The outputs of the inference engine are the conclusions of the rules that have been fired. For our system, we use a fuzzy inference engine [Kandel (1992) and Zemankova (1989)].

Failure Diagnosis. If the inference engine determines that there is an anomaly in vehicle performance, it sends a message to the failure diagnostics subfunction. Diagnosis of the possible system failures is conducted by the inference engine using fuzzy matching of symptom patterns and degrees of conformity methodologies. Using fuzzy logic as the computational tool, a hierarchical clustering analysis is also performed to determine the data subsets causing the failure. Multiple, even conflicting criteria are dealt with by fuzzy compatibility calculations. An objective function matrix is set and adjusted in real-time operations. Neural networks are used to achieve near-optimal performance.

Besides the diagnostics function, the inference engine also presents a list of possible choices of corrective actions to vehicle manager.

Knowledge Base Updating. The knowledge base contains knowledge and human expertise. It is represented by production rules as its knowledge representation method. In the process of applications, it is updated to be adaptive for dealing with unscheduled events, unpredictable failure, parameter changes due to system aging, and to enhance the performance.

Neural Network-Fuzzy Inference Mapping. A neural network is used for tuning the fuzzy inference engine and its knowledge base during the design and development stages of the fuzzy logic system, and for its updating in real-time operations. A mapping between the neural network and the fuzzy inference engine is needed. As a generalization of normal fuzzy logic rules, fuzzy associative memories are used to be mathematically transferred to neurons in the neural network. A modified error backpropagation algorithm is then applied to the network. Fig. 6 is a schematic of the mapping.

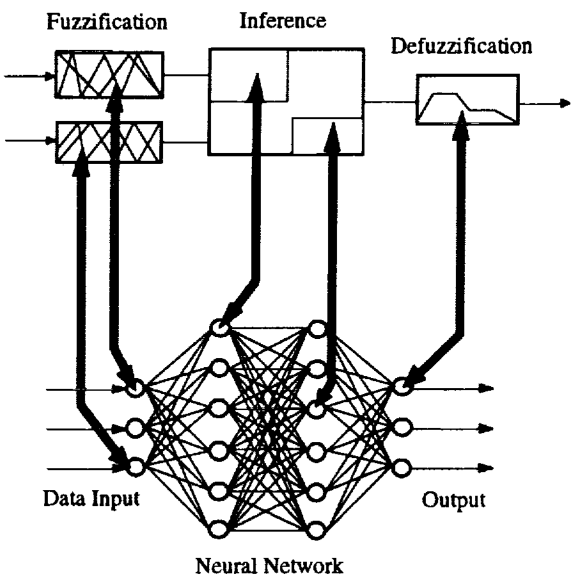


Fig. 4. Neural network-fuzzy inference mapping

5. IMPLEMENTATIONS

System Design. The project approach uses an optimization process based on performance comparison. First, the general structure is decided by study of system and performance requirements. The detailed requirements of mission operation control systems are studied to ensure that the fuzzy logic system is built to satisfy all the system requirements. Then, a comparison is conducted using different performance criteria to evaluate different structural details for the diagnostic system.

Training and Tuning. After the system is built, i.e., with its structure and algorithms decided and software developed, we proceed to the training and tuning stage in the completion of the intelligent system. First, we train the system with historical data to initiate system weights at an appropriate initial point in vector space. The knowledge base of the inference engine subsystem is then built. Meanwhile, fuzzy membership functions are tuned accordingly.

Testing and Verification. The testing and verification of the diagnostic system are conducted mainly by utilizing historical data recorded during previous flights and with existing testbeds. The use of existing testbeds greatly reduces the time and cost of system test and verification. Different performance indices are designed to test the robustness of the system and the precision of the diagnosis. Since the system can be run in parallel with existing systems, the performance of the diagnostic system is compared with that of available diagnostic techniques.

6. CONCLUSIONS

This paper discusses the principles and algorithms of a fuzzy logic diagnostic system designed for the spacecraft integrated vehicle health management. The diagnostic system contains a data filter and an inference engine. The data filter is designed to intelligently select only the necessary data for analysis, while the inference engine is designed for failure detection, warning, and decision on corrective actions using fuzzy logic synthesis. Due to its adaptive nature and on-line learning ability, the diagnostic system is capable of dealing with environmental noise, uncertainties, conflict information, and sensor faults.

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