AUTOMATING SATELLITE COMMAND AND CONTROL

Constance J. Golden
Mgr., Mission Operations
Ford Aerospace & Communications Corporation
1260 Crossman Avenue
Sunnyvale, CA 94086

ABSTRACT

Existing spacecraft/satellite control requires access to a group of "experts" familiar with each satellite subsystem to be able to analyze and correct spacecraft malfunctions. When remote, mobile satellite control systems are deployed, these "experts" will not be available. Automation of many of the functions currently being performed by these experts and the operators at the consoles will allow these mobile systems to operate autonomously while correcting for anomalies that can be logically identified. This automation can be achieved by implementing artificial intelligence (AI) processes/techniques to the fault detection, command correction process. Techniques from the artificial intelligence development process and algorithms from statistical forecasting methods will be analyzed and tested for applicability in providing automated spacecraft health and status information for one DOD program. Key issues in applying these processes to all critical DOD programs will be identified and discussed.

INTRODUCTION

The United States has become increasingly dependent on space resources - for communications, surveillance, weather data, navigation and defense. Figure 1 identifies the various segments of a space system that all must operate together to provide this vital information. The space segment is the most costly to develop for each program; however, the ground segment is costly to operate and maintain over the more than 7 year program lifetimes. Most commonly the ground segment facilities are fixed buildings with command & control (C^2) rooms (centers) dedicated to each program. A large staff of technical analysts and spacecraft subsystem experts supports each C^2 center. This arrangement was necessary when each spacecraft was a new development and the support had to be performed in a research and development environment. However, many space programs are now in the operational mode and either would like to reduce the cost of supporting such a large cadre of experts on a permanent basis and/or must operate from a mobile platform where there is no room for a large cadre of experts. The objective of our project is to replace many of the experts with an automated “expert system” in a cost effective manner. Techniques from the field of artificial intelligence (AI) are being analyzed and tested for applicability to such an automated system. Expert Systems are already being used to assist in medical diagnosis. These systems analyze available data to determine the most likely cause of symptoms and then recommend treatment. On the surface, detecting the fault in the spacecraft that is producing anomalous telemetry and then recommending a set of corrective commands appears to be an identical process that could use the same, already developed, software. Indeed, the processes are similar enough that the same general software architecture can be used for both. However, there are several important differences in the two processes that will require unique approaches to be developed before many of the spacecraft ground support functions can be efficiently handled automatically by an “expert” system.

GENERAL STRUCTURE OF EXPERT SYSTEMS

Expert systems (also called expert consulting systems, knowledge-based consultants, or knowledge engineering systems) provide human users with expert advice about specialized subject areas. Expert systems have been built that can diagnose diseases, evaluate potential ore deposits, suggest structures for complex organic chemicals, and even provide advice about how to configure the components of a computer system.

A key problem in the development of expert consulting systems is how to represent and use the knowledge that human experts in these subjects obviously possess and use. This problem is made more difficult by the fact that much of the expert knowledge in many important fields is often imprecise, uncertain, or judgemental (although human experts use such knowledge to arrive at useful conclusions).

In general, expert systems are characterized by:

- A modular knowledge base that allows for flexibility in adding, removing, or changing knowlege in the system.

- Use of domain-specific knowledge imbedded in action rules

- Recognition of a situation and application of action rules appropriate for that situation.

- Maintenance of a line of reasoning that is comprehensible to the domain specialist and the ability to explain its line of reasoning in a language convenient to the user.

- Use of “classical” AI heuristic-search techniques--plan, generate, and test.

Expert systems built by knowledge engineers to date consist of three main parts:

First is the subsystem that "manages" the knowledge base needed for problem solving and understanding.

Second is the problem-solving and inference subsystem that discovers what knowledge is useful and relevant to the problem at hand, and with it constructs - step by step - a line of reasoning leading to the problem solution, the plausible interpretation, or the best hypothesis.

Third are the methods of interaction between human and machine, in modes and languages that are "natural" and comfortable for the user. Ordinary human natural language is often preferred, but the stylized notations of some fields like chemistry are also desirable for specific groups of users.

Knowledge-based management, problem solving and inference, and human interaction functions have all been approached in our present expert systems via software innovations that have pressed traditional von Neumann hardware architectures to their limits. However, new specialized parallel hardware architectures have been developed that more effectively implement these AI functions.

Knowledge-Based Management

The knowledge in the knowledge base must first be represented in symbolic form, and in memory structures, that can be used efficiently by the problem-solving and inference subsystem. This representation can take many forms. One of the most common is the "object", a cluster of attributes that describe a thing. An object is usually associated with other objects by symbolic references (links) in the memory. A typical kind of associative network is the taxonomy, known as "The ________ is - a hierarchy." For example, "The sparrow is - a kind of bird." In this case, both sparrow and bird are objects within the knowledge base. If the knowledge base is informed that "The bird is - a kind of animal that can fly", the knowledge-based management system must automatically propagate the deduction that sparrows can fly. It must also be able to handle the exceptions it is told about, such as flightless birds like ostriches, penguins, and kiwis.

Another common and useful representation is the "rule". A rule consists of a collection of statements called the "if" part, and a conclusion or action to be taken called the "then" part. For example, "IF the fog ceiling is below 700 feet and the official weather forecast calls for no clearing within the hour, THEN landing is dangerous, will violate air traffic regulations, and diversion to a neighboring airfield is recommended." To find out if a rule is relevant to the reasoning task at hand, the problem-solving program must scan over the store of “ifs” in the knowledge base. That search can be immense for some practical applications. Here again, the knowledge-based management subsystem is designed to organize the memory in ways that will reduce the amount of processing to be done. Parallel processing capabilities in both the software and hardware levels of the system will also speed associative retrievals.

Knowledge is stored in a large file known as a relational data base. The job of automatically updating the knowledge in the file, and of organizing appropriate searches for relevant knowledge, will be performed by the knowledge-based management software. The interaction between the hardware file and the software file manager is handled by a logical language called a relational algebra.

Problem Solving and Inference

Knowledge serves as the basis for reasoning by a knowledge information processing system, but it is not sufficient in itself to discover and use lines of reasoning. Piecing together an appropriate line of reasoning that leads to the solution of a problem or the formulation of a body of consultative advice is the job of the inference process and the problem-solving strategy that employs it. Inference processes can be very much of the common sense sort in which relevant knowledge is simply chained. A syllogism (IF X implies Y and IF Y implies Z, THEN X implies Z) is an example of such an inference process. Inference processes have been studied by logicians and mathematicians for centuries, and many different procedures for inference are known. From this logician’s tool kit, artificial intelligence uses routinely only a few devices. Some of these methods allow for reasoning “inexactly” from knowledge that is uncertain. One, a favorite of AI, is “resolution”, constructed on a foundation of mathematical logic formulated in the 1960s by the logician Allan Robinson. “Resolution” is subtle, nonintuitive, and especially suited for computer processing.

An inference process is the tool of some problem-solving strategies. For example, the strategy of one kind of problem solving might be goal-directed backward chaining. One works backwards from a desired set of end results through all the steps that must be taken along the way to ensure that all objectives are met. Forward Chaining is used when data or basic ideas are the starting point to solving a problem. Forward and backward chaining are combined when the search space is large or it can be divided hierarchically. It is particularly applicable to complex problems incorporating uncertainties, such as satellite control.

Human Interaction

Most knowledge-based systems are intended to be of assistance to the human endeavor; they are almost never intended to be autonomous agents. An operator-system interface subsystem is therefore a necessity - one that allows interaction to be as natural as possible for users in both language and mode of interaction. This requirement means language understanding the ability to speak directly to the machine - as well as image understanding the ability to show it pictures.

To realize these objectives across the spectrum of human knowledge and images is one of the most difficult of the long-term goals of artificial intelligence research. But if constraints are applied to the amount of vocabulary and areas of subject matter the subsystem is expected to handle, the problem becomes tractable, though still very difficult.

Knowledge-based expert systems are important for the task of automating satellite control because the methodology is domain-independent (hence applicable to a diversity of domains) and they are emerging as practical systems. Some developmental systems (DENDRAL, for example), created primarily for the purpose of advancing AI, have yielded useful results in the specific domains in which they operate (e.g., in the case of DENDRAL, inferring chemical structures). We have finally reached the point at which practical expert systems are appearing outside the laboratory environment. It is important that we apply their architectures and search techniques to similar problems that can’t be solved using traditional techniques.

APPLICATION TO SATELLITE CONTROL

The functions that need to be automated to perform satellite control include elements of planning, detection of abnormal situations, diagnosis, problem-solving, and many such simple and straightforward tasks as verifying that a message has been received. They include:

- Off-line, prepass planning, including the preparation and verification of commands to be sent during the pass is performed. Schedules, checklists, and logs to be used during the pass and contingency plans that are dependent on information received from the spacecraft during the pass are generated and made easily accessible.

- Circuits are set up and tested on line and prior to the pass. The various equipment and software to be employed during the pass are tested and verified, and commands are then loaded in readiness for transmission to the spacecraft.

- During the pass, the analyst first determines whether or not the spacecraft is in the expected condition, so that transmission of the planned commands can proceed. He does this by looking at displays generated from telemetry data received from the spacecraft. The displays are formatted to show relevant parameters and conditions, and may also show allowable ranges or flag parameters that are out of limits. If everything is in order, the analyst sends the commands. If not, a contingency plan may be executed. If the situation is not covered by a contingency plan, the situation may be diagnosed and corrected during the pass - or many have to await off-line analysis and possible action during a subsequent pass. The diagnosis may require consultation with experts knowledgeable about almost any aspect of the spacecraft. Following the transmission of commands to the spacecraft, a copy of its command memory is retransmitted to the ground station for verification by the analyst.

- After the pass, the analyst records, reviews, and verifies the preceding events, and makes appropriate entries in the log.

- Off-line, in-depth analysis may be required after the pass to diagnose a problem. If the problem is serious, the lead analyst will be called, as well as other appropriate experts. Telephone consultation may take place any time of day or night. Meetings may be necessary to review the data, possibly followed by analysis, simulation, and/or experimentation.

Some of the above functions have already been automated using a deterministic approach. Figure 2 indicates the differences between using a deterministic, table-driven approach and a heuristic, expert-system approach to automate the satellite control functions. The table-driven approach is adequate and most cost effective for automating the routine functions and anomalies that are easy to identify and resolve.

Automation of the more complex aspects of satellite control lies in the areas of symbolic modeling and representation, two of the pivotal areas of AI. Presently, the human's presence in the loop is required to make connections between what the human's symbolic model of the mission and spacecraft say should be happening at any moment and what is actually happening. In this role, the human monitor draws primarily upon his knowledge of cause-effect relationship, ones which are specific to the craft and others which are of a more generic nature. Because of what he knows about the current phase of the mission, he is able to compare the incoming parametric data with the expected conditions supplied by his model. When anomalies arise, he can not only recognize them, but also use them in combination with his symbolic model to hypothesize the nature of the, fault. He can then issue further diagnostic commands to the craft, commands that will remedy the fault, or commands to reconfigure and bypass it. This process is what the expert system must automate. Figure 3 indicates the recommended approach for each level of spacecraft anomaly resolution. The data base set up for the deterministic approach can also be used by the expert system providing it was set up within the context of an expert system architecture. Thus automation can proceed from the simple, straight-forward tasks to the more complex, heuristic tasks by building on existing techniques and expanding existing data bases.

ACCOMPLISHMENTS TO DATE

Basic tracking, telemetry and command (TT&C) and electrical power distribution subsystem functions have been analyzed for one spacecraft program to identify the deterministic “rules” that should be followed whenever an anomaly appears. Heuristic rules to expand this knowledge base are being added as they are identified and can be quantified. The inference logic that searches and draws on this knowledge base to arrive at a solution has yet to be selected. There are many alternatives for choice of solution direction, reasoning in the presence of uncertainty and searching a large knowledge base space. Existing medical diagnosis expert systems have inference architectures that might be adaptable to our application, but the degree of modification required has yet to be established. Some aspects of the satellite control function that will require modification of the medical diagnosis expert system architecture are: (1) The medical expert systems ask questions of the operator to eliminate unprofitable search areas. The satelite control expert system will get most of its information from a data base of raw and processed telemetry data. The inference logic will have to be modified if the data necessary to decide which path next to pursue is not in the data base (reasoning in the presence of uncertainty). This difference is particularly important if the satellite controller is operating autonomously and has no access to spacecraft system experts. (2) Existing diagnostic systems are focused in one area of application. The satellite control system must accommodate multi-disciplines and complex relationships between subsystems. (3) The expected spacecraft state must usually be forecast from previous data. Therefore comparing current telemetry to a “forecasted” state to determine if there is an anomaly or not only identifies whether the forecast agrees with the actual data or not. If there is disagreement, the forecast may be wrong or the spacecraft may actually be in an anomalous state. Current diagnostic systems assume that the desired state is known with certainty.

CONCLUSION

Recent advances in the design of expert systems and the hardware/software developed to support these systems allows this approach to be considered for automating higher levels of satellite control than was possible using table-driven deterministic approaches. By developing such a system for one spacecraft program, we hope to develop enough insight so computer system size and performance requirements for various levels of automated anomaly resolution can be provided. Another goal is to identify a “basic TT&C” expert system that automatically would control “most” spacecraft. Spacecraft unique rules could then be added to the basic knowledge base for each program as required.

The potential application of expert systems for automation of network scheduling, mission planning, image processing, and configuration status and control is a parallel effort. AI promises to simplify the operation of space support systems in general and hence reduce operation costs significantly.

REFERENCES

1. Gevarter, William B, “An Overview of Expert Systems,” NBSIR 82-2505, U.S. Dept. of Commerce, Washington D.C., 20234, May 1982.

2. Feigenbaum, E.A., “Knowledge Engineering: The Applied Side of Artificial Intelligence,” Computer Science Dept., Memo HPP-80-21, Stanford University, July 1980.

3. Feigenbaum, E.A., “Knowledge Engineering for the 1980’s,” Computer Science Dept., Stanford University, 1982.

4. Nii, H.P., and Aiello, N., “AGE (Attempt to Generalize): A Knowledge-Based Program for Building Knowledge-Based Programs,” Proceedings of the Sixth International Conf. on Artificial Intelligence, (IJCAI-79), Tokyo, August 20-23, 1979, pp. 645-655.

5. Buchanan, B.G., “Research on Expert Systems,” Stanford University Computer Science Dept., Report No. STAN-CS-81-837, 1981.

6. Hayes-Roth, F., “AI The New Wave - A Technical Tutorial for R&D Management,” (AIAA-81-0827), Santa Monica, CA, Rand Corp., 1981.

7. Duda, R.O., “Knowledge-Based Expert Systems Come of Age,” Byte, Vol. 6, No. 9, September 1981, pp. 238-281.

8. Stefik, M., et al., “The Organization of Expert Systems: A Prescriptive Tutorial”; XEROX, Palo Alto Research Centers, VLSI-82-1, January 1982 (also in Artificial Intelligence 18(2), March 1982, pp. 135-173).

9. Davis, R., and Lenat, D.B., Knowledge-Based Systems in Artificial Intelligence, New York, McGraw-Hill, 1982.

10. Lindsay, R.K., et al., Applications of Artificial Intelligence for Organic Chemistry: The DENDRAL Project, New York, McGraw-Hill, 1980.

11. Brooks, A., "A Comparison Among Four Packages for Knowledge-Based Systems," Proc. of Int. Conf. on Cybernetics and Society, 1981, pp. 279-283.

12. Ennis, S.P., "Expert Systems: A User's Perspective of Some Current Tools," AAAI-82, pp. 319-321.

13. Barr, A., and Feigenbaum, E.A., The Handbook of Artificial Intelligence, Vol. 1 and Vol. 2, Los Altos, CA, W. Kaufman, 1981 and 1982.

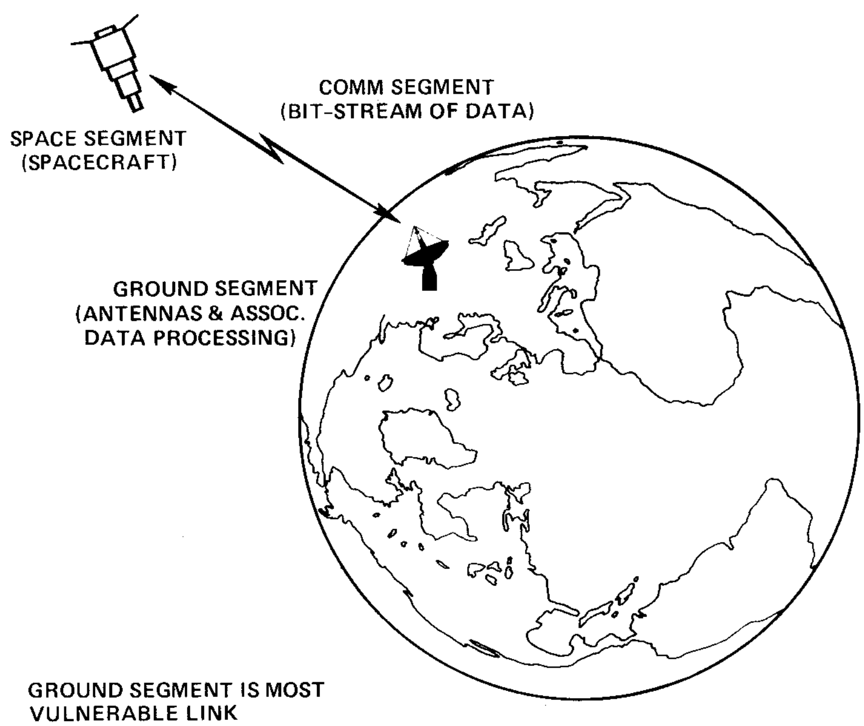

FIGURE 1. MAJOR SPACE SYSTEM SEGMENTS

Ford Aerospace &
Communications Corporation

Functions	Expert System Approach Based on Heuristics	Table Driven Approach Based on Absolutes
• Deterministic control rules	X	X
• Heuristic Control rules - Dynamically prioritizes rules based on current situation - Provides problem solving strategies (with incomplete data) - Permits multiple lines of reasoning to proceed concurrently - Uses associative and logical links between rules - Explains how rule was selected	X	
• Production rules - Discrete, quantitative relationships - algorithms - If - then rules	X	X
• New rule generation or modification - Based on recent experience	X	

FIGURE 2. COMPARISON OF AUTOMATION APPROACHES

Ford Aerospace & Communications Corporation

Recommended Automated Approach		
Table Driven	Level I -	• Easily identified - Single indicator • Previously encountered • Solution is straight forward - Configuration command
Expert System	Level II	• More complex to identify cause - More than one indicator - Non unique solution • Previously encountered • Solution may be complex - Command procedures required
Expert System Plus Technical Analysts	Level III	• Most difficult to identify - Not always apparent • Not previously encountered • Solution needs to be identified through: - Analysis - Options - Command procedures

FIGURE 3. RECOMMENDED APPROACH FOR EACH LEVEL OF ANOMALY RESOLUTION