Trend Analysis for Spacecraft Systems Using Multimodal Reasoning

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Abstract

This paper describes some current work at the National Aeronautics and Space Administration (NASA) Goddard Space Flight Center's Advanced Architectures and Automation Branch. Trend analysis refers to the process of examining data from a physical system, developing a mathematical model, analyzing the derived information to formulate an evaluation on the condition of the system, and determining if dangerous trends can be detected. If a trend is detected, corrective or preventive actions are pursued. Our goal is to better understand how to effectively use rule-based, case-based and model-based reasoning together to realize a more rigorous and automated trend analysis capability. To reach this goal, we plan to develop an automated system to analyze and predict trends, and diagnose spacecraft status telemetry data. This paper describes a concept, architecture and current work in developing a prototype system, called the Automated Model-Based Trend Analysis System (AMTAS). This system uses multimodal reasoning to perform diagnosis and trend analysis. Model-based reasoning is the primary reasoning component which is augmented with other forms of reasoning including rule-based reasoning and case-based reasoning. This prototype may serve as a basis for a full system implementation at a later time if successful. We are in the process of implementing the prototype system using MATLAB.

Introduction

This paper describes some current work at the National Aeronautics and Space Administration (NASA) Goddard Space Flight Center's Advanced Architectures and Automation Branch. Traditionally, trend analysis of spacecraft telemetry data had been a time consuming, repetitive, and labor intensive activity. Operators inspect telemetry plots manually to determine the current spacecraft health. They use some form of statistical evaluation and comparison with models, but the evaluations still require extensive human expertise which is prone to error, and could result in catastrophic failures.

This project attempts to increase the efficiency, accuracy, and reliability of trend analysis and diagnosis through multimodal reasoning. It concentrates on using model-based reasoning but draws on other techniques, such as case-based and rule-based, to improve results.

Trend analysis is the process of examining incoming spacecraft telemetry data, developing mathematical representations of the data, analyzing the derived information to formulate an evaluation of the condition of spacecraft components, and determining if dangerous trends exist. If a dangerous trend is detected, corrective or preventive measures are identified. Trend analysis is composed of; identifying a trend that indicates a potential failure, explaining the trend and the potential failure to the user, determining corrective action to prevent the failure from actually occurring, and automatically executing commands to prevent the failure or notify the operator.

Trend analysis may be done on as little as one orbit of data, but typically is done over long periods of time -- days, months, even years of a spacecraft lifetime. Trend analysis may also consider the history of a common component from one spacecraft to the next in a series.

Multimodal reasoning is used in both fault diagnosis and trend analysis. Routine problems are handled using rule-based reasoning. In the event that an automated recovery action can be performed, the rule-base component generates the command procedure for automatic execution or an operator is notified. For problems that the rule-base component can not solve, a model-base component is used. For new anomalies, a case-base component is used to find similar cases and gain insight into how to solve the new problem. Once the new problem is resolved, the knowledge-base underlying the model-based diagnosis is updated, new cases describing the anomaly with its resolution are stored in the case-base component, and new rules to handle the new anomaly are written and incorporated into the rule-based component if the problem is expected to be repeated frequently.

Two typical sources of knowledge are expert knowledge and knowledge of past history. Expert knowledge is used in the initial design of the state model, the expected states, and underlying probabilistic knowledge that is essential to the diagnosis process. One of AMTAS goals is to possess sufficient learning capability to automatically update its knowledgebase as it gains more experience during real time operation. Some of the expert knowledge is also encoded as rules that handle well-understood problems.

Knowledge of past events is stored as cases of anomalies and trends, and solutions tried with their outcomes, either successful or not. One of the main barriers to building such systems is that existing knowledge is typically not documented in a formal way that can be directly used. Information must be obtained from human experts. In addition, a lack of a standard terminology among experts also contributes to this deficiency, even when the knowledge is sufficiently documented. Hence, a major step in building such systems is to develop a standard terminology so that the documented knowledge is accurate, concise, and consistent.

Functionality

AMTAS performs the following functions as shown in Figure 1:

- Spacecraft Model -- Generates expected spacecraft states and telemetry values given information about the mode the spacecraft is supposed to be in during the time span being analyzed.
- Comparison and trend - Compares the expected state and telemetry values with those observed in order to locate anomalies, and looks for systematic differences that could grow to the point where the tolerance is exceeded.
- Reasoning - When an anomaly is detected or trend is predicted, a set of hypotheses is determined. These hypotheses ranked by their likelihood are verified by the simulator and their solutions determined. Past experience from stored cases may be used to assist in this process.

Spacecraft Model: In state modeling, sets of telemetry values are grouped together and hierarchically arranged to represent the state of a component, subsystem, system, or space vehicle. For example, at the lowest level, the state of a relay might be represented as two telemetry values. At the next level, the state of the relay control unit might be represented as the state of its set of relays, each with its own telemetry signature. At the next level, the state of the electrical power system might be defined by the states of its various parts such as relay control units, batteries,

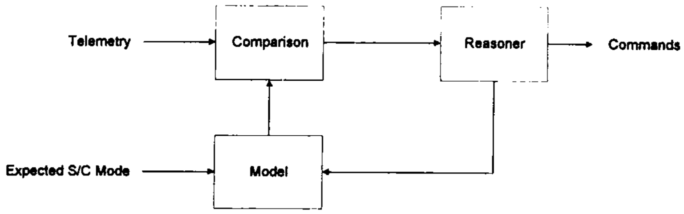

Figure 1 AMTAS Functions

charge control units, solar arrays, etc. At the highest level, the state of the entire vehicle might be defined by the states of all its systems. Therefore, through state modeling, the status of a component, subsystem, or space vehicle can be evaluated in real time through telemetry.

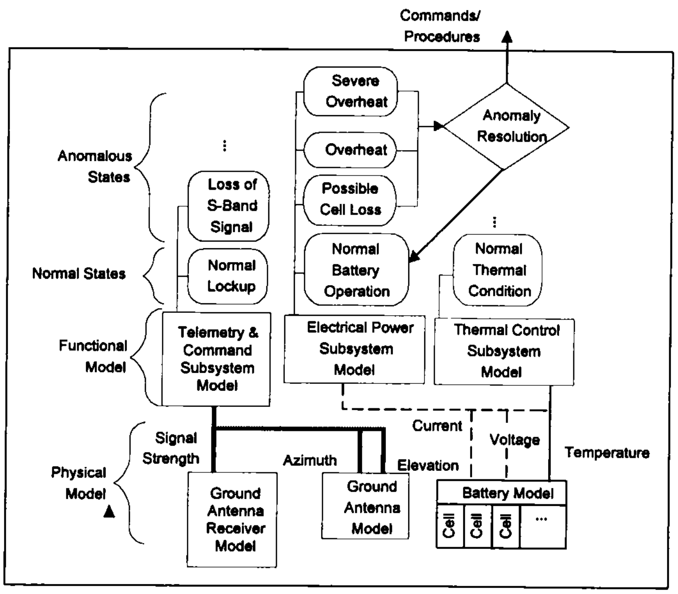

Figure 2. State Modeling

Figure 2 illustrates state modeling. In the physical model, telemetry values indicate the state of a physical component or subsystem. As shown in the figure, current, voltage, and temperature indicate the state of the electrical power system, and temperature indicates the state of the thermal control subsystem. Normal and anomalous states can be modeled. Normal battery operation is a normal state for the electrical power subsystem. Possible cell loss, overheat, and severe overheat are minor and severe anomalous states for the electrical power subsystem. If one of these anomalous states is encountered, an anomaly resolution procedure is executed, and the electrical power subsystem makes a transition from an anomalous state to a normal state. These procedures are executed automatically or presented as recommendations to an operator. More specifically, the state model consists of:

- A set of components of a subsystem connected by a network that represents the functional relationship among the components.
- A set of input variables that represent telemetry data.
- A set of output state variables.
- A set of status variables that represent the status of subsystems or environment, e.g. on/off or night/day.

Comparison and trend: The comparison function identifies if the deviation between the observed and expected values for each state variable, lies beyond a threshold of tolerance. This function will also accumulate information on the comparisons, even when the agreement is acceptable, looking for systematic differences that could grow to the point where the tolerance is exceeded.

Finally, although telemetry data are the most frequent data to be trended, second order quantities such as the spacecraft altitude or sensor misalignments may also be trended. This data enters AMTS along with the telemetry, but is calculated in other parts of the ground system.

There are several methods for detecting trends in a data stream. However, there is no single method that will work for all data type. Care must be taken in selecting a suitable method for each data type. A thorough understanding of natural behavior of each data is essential. Moreover, the trends for future failure may be disguised in several different forms, such as gradual deviation from average value, sudden change in the noise level, frequency of occurrence of spikes, etc. Each data should be analyzed and possible trends identified and catalogued. For each identified trend, suitable method is selected. These identified trends will be encoded into the knowledgebase of the state-model, including initial hypothesis sets, solution sets and mass functions (see below). The actual trend analysis process can be processed real-time or as a batch process. When the data shows a trend, the diagnosis process is activated and proceeds as described below.

Figure 3 shows an example of a trend in spacecraft data. This example compares the speed of one of the reaction wheels on the Solar and Heliospheric Observatory (SOHO) with a model (solid line) based on the expected attitude motion and solar pressure torque. The agreement appears good for the first few days, but a trend of the wheel decreasing toward the limit of -3000 RPM faster than expected becomes evident.

Reasoner: The reasoner takes the output of the comparison function and tries to determine when a failure will occur, gives a reason for the failure and recommends a solution. This function is the heart of AMTAS, and in fact is where this system really parts company with traditional trend analysis, which incorporates most of what has been described so far, although in a manual way.

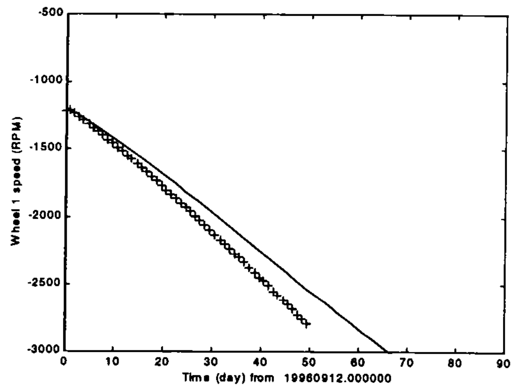

Figure 3. Example Trend Graph

Reasoning Process

In this section, we describe the model-based diagnosis, which diagnoses both a detected anomaly and a predicted trend. The task of this component is to determine the hypothesis that best describes the problem and its solution. The reasoning used in this process are the followings:

- Well-understood events are handled by a rule-based system. In the event that an automated recovery action can be performed, the rule-based component generates the command procedure for automatic execution or an operator is notified.
- Events with incomplete knowledge are handled by a diagnosis process based on model-based reasoning.
- Human intervention might be needed for unseen anomalies and trends, in the event that model-based reasoning fails.

Case-based reasoning is used to improve the diagnosis performance. Some useful information can be stored in a case, such as description of subsystems/components, symptoms of the anomaly, its causes, the action taken to resolve the anomaly, and the outcome of implementing the solution. In our implementation, an anomaly case is composed of a set of anomalous variables or symptoms for the anomaly, the date and time the anomaly occurred, the command sequence executed to resolve the anomaly, and the outcome of executing the command sequence. A trend case is composed of a pointer to a trend graph, the date and time the trend was detected, the predicted anomaly, the recommended resolution, including the command sequence for resolving it, and the outcome of implementing the recommended resolution.

Diagnosis component is illustrated in Figure 4. The larger boxes in the figure indicate the actions performed and the smaller boxes indicate the component that performs the action.

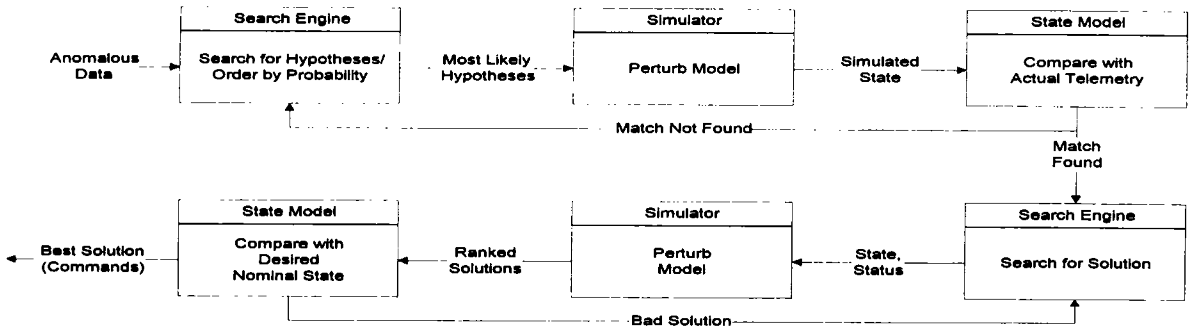

Figure 4. The Reasoning Process

The diagnosis component of AMTAS consists of hypothesis determination and solution determination.

Hypothesis determination searches for a hypothesis that may explain the anomaly or trend in terms of a set of faulty components or components that are about to fail respectively. The efficiencies of combination of components are varied until the output state matches the actual anomaly. Solution determination searches for a solution of a given hypothesis, by adjusting the mode of operation of components in the faulty model until the expected output state is reached. The algorithms of both processes are the same and we will discuss only the hypothesis determination in detail.

If the simulation is performed without additional knowledge of the situation, the search algorithm is exponential time since the total number of possible choices of hypotheses is exponential. Moreover, not every hypothesis makes physical sense, even though they are logically possible. This suggests that a probability measure is needed to curb the complexity of the algorithm and to avoid unrealistic hypotheses. This is done as follows: To each known anomaly, we associate a belief function that assigns a degree of belief to each hypothesis that may be responsible for the anomaly. This induces a partial ordering on the set of hypotheses. Similarly, at the other end of the spectrum, a degree of disbelief could also be given to unlikely hypotheses that do not make physical sense for that anomaly. These two measures assign to the set of all hypotheses a partial order that guides the search routine. The most likely hypotheses are evaluated first. If no match is found, exhaustive search is done on the set of neutral hypotheses that are neither believed nor disbelieved. The last to be evaluated are the unlikely hypotheses. If no match is found, it means that the state model is incomplete and human intervention may be needed.

Hypothesis determination: The belief function discussed above is initially given by experts' probabilistic knowledge concerning each known anomaly and trend. This knowledge is given in terms of a set of likely hypotheses that may be the cause of the anomaly, together with a belief function on the set. In the beginning, the hypothesis sets may be incomplete and the belief functions may be inaccurate. The success of AMTAS depends on whether the probabilistic knowledge can automatically revise itself as new knowledge is obtained. We discuss this in the next section

The belief functions are defined via the Local Dempster-Shafer (LDS) theory adapted from Dempster-Shafer (DS) theory described in Dempster (1967) and Shafer (1976). Let H be a set of components. A subset of H is a hypothesis. It should be interpreted as a minimum set of components that claims to be the cause of the anomaly or trend. DS theory consists of a mass function on the set of hypotheses, $m{:}2^H \rightarrow [0,1]$, which assigns a degree of belief that supports the extent to which a hypothesis is believed to be true. The mass function satisfies the following conditions

a) $\sum_{X \subseteq H} m(X) = 1$, and b) $m(\varnothing) = 0$

Two mass functions, m_1 and m_2 on H can be combined into a single mass function as follows:

$$m_{12}(X) = \sum_{A \cap B = X} m_1(A) m_2(B) \qquad (1)$$

which may require normalization to guarantee that conditions a) and b) are simultaneously satisfied.

The belief function associated to the mass function m is defined as:

$$b : 2^H \rightarrow [0,1]; \ b(X) = \sum_{A \subseteq X} m(A) \qquad (2)$$

Having a well-formulated foundation makes DS theory a suitable choice for an autonomous diagnosis. However, there are two major drawbacks that must be overcome. First, the complexity of the DS theory is exponential. Our solution to this problem is to reduce the size of the domain by localizing the mass function. This forces us to drop condition b). Second, the combination of two very different mass functions usually leads to an unrealistic result. This is partly due to the exhaustive assumption b) and hence localization of the mass function seems to partially minimize this effect. We consider the "dual" of DS theory and localize it as follows:

Definition 1. *Local Dempster-Shafer (LDS) Theory* on a *global domain H* consists of a family of triples $\{A_i, m_i, N_i\}$ where the *local domain* A_i is a subset of *H*, The *local mass function* $m_i : 2^{A_i} \rightarrow [0,1]$ is a function satisfying condition a), but not necessarily b). N_i is a positive integer called the *sample size* of m_i. We identify a triple with its mass function.
The *belief function* associated to m_i is defined by:

$$b_i : 2^{A_i} \rightarrow [0,1]; \; b_i(X) = \sum_{Y \supseteq X} m_i(Y) \qquad (3)$$

Two mass functions $\{A_i, m_i, N_i\}$ and $\{A_j, m_j, N_j\}$ combine to form a new mass function $\{A_i \cup A_j, m_{ij}, N_i + N_j\}$, with

$$m_{ij}(X) = \sum_{A \cup B = X} m_i(A) mj(B) \qquad (4)$$

In the hypothesis determination process, the triples in the LDS theory are indexed by the set of all anomalous states and identified trends. The mass function of multiple anomalies is the combination of mass functions associated to each anomaly. When one or more anomalous states are detected, the belief function associated to the combined mass function defines the required partial order on the hypothesis set. As discussed above, LDS theory can be applied to avoid unrealistic hypothesis by defining a degree of disbelief to unlikely hypotheses associated to each anomalous state, which defines a partial order on the global hypothesis set in the negative direction.

Hypothesis verification: Each hypothesis is simulated against the state model until a match is found. The simulator varies the weight of the components in the model to reflect the hypothesized condition of the component. A weight of 0 means the component is completely malfunctioning. If the simulated output state matches all of the actual states, within a certain tolerance, the hypothesis is acceptable, otherwise it fails.

Solution determination: If at least one hypothesis is found, the system will begin searching for possible solutions. The same algorithm used for the hypothesis determination and simulation is repeated for solution determination and simulation. The global domain of the LDS theory in this part of the application is the set of all status values of the state model, and the triples are indexed by the set of all components in the state model. An example of a solution would be a set of status values of relevant components. Such set represents a sequence of commands that change the status of the components. Other solutions may not be as easily identified. When a hypothesis is suggested for an anomaly, the associated belief function defines a partial order to the set of solutions associated to all blamed components in the hypothesis. These solutions are simulated against the model, and if the simulated state is expected, the solution is acceptable.

If one or more solutions are found, commands are invoked or an operator is notified of the action needed to fix the anomaly. After the command procedure has executed onboard the spacecraft, subsequent processing confirms that the problem has actually been fixed.

Revision Process

An operational spacecraft is a dynamic system, and hence the state model and simulator used to monitor and diagnose satellite behavior must be revised frequently to reflect the current state of the spacecraft. When a known state transition takes place, whether initiated automatically by AMTAS or manually by the ground control center, the new state is verified by a state verification process. After which, a revision process takes place. This includes:

- Updating the current status values of subsystems.
- Updating the probabilistic knowledge including the local domain, solution sets and mass functions associated to the event.
- The resolved problem is added to the casebase and linked to the anomalous state in the state model, or a new state is added to the state model if it does not exist.
- If the updated mass function yields a degree of belief close to one for this result, then new rules are added to the rulebase to handle this well-determined anomaly in the future.
- The functional model is revised if the expected system behavior has changed. This may involve modifying functions such as MATLAB functions, static values, high/low limits, or retraining a neural network.

The revision of the mass functions is done every time an anomaly is resolved. The mass of the resolved hypothesis is increased to reflect additional piece of information. The more often a hypothesis/solution correctly solves an anomaly, the more likely it would be successful in solving the same anomaly in the future. To revise the mass functions we define

Definition 2. Let $c \in H$ be a component, and let $\{A, m, N\}$ be a mass function. An instance of m with result c is a mass function $\{\{c\}, e, 1\}$, with $e(\{c\}) = 1/(N+1)$ and $e(\emptyset) = N/(N+1)$. The *revision* of m is the combined mass function $\{ A \cup \{c\}, m', N+1 \}$, given by definition 1.

Definition 2 is a simplification of a more general case of multiple fault situation where the accepted hypothesis C consists of more than one faulty component. In which case, the mass function e on the power set 2^C is slightly more complicated. For single fault hypothesis, the revised mass function can be simplified to:

$m'(S) = m(S) N/(N+1)$ if S does not contain c,

$m'(S) = m(S) + m(S - \{c\})/(N+1)$, if S contains c,

where $m(S)$ in the second equation is taken to be zero if A does not contain c. It is clear from definition 2 that, given a new evidence, c, the mass of a hypothesis that contains c is increased, otherwise it is decreased. The domain of the revised mass function is increased to include the new hypothesis if it is not already in the domain . The sample size of the revised mass function is increased by 1. The larger the sample size, the more believable the mass function becomes. In practice mass functions are initially given by human expert, which usually come from an ad hoc estimate and may not be derived from actual series of experiments. However, the sample size is not critical to our application. It simply reflects the level of confidence the experts have on their estimation of the mass function. It serves as a starting point for the revision algorithm. We conclude this section with the following results:

Proposition 1. Let $\{A_0, m_0, N_0\}$ be a mass function associated to an anomalous state x. Let $x_i, i = 1,2,3,\ldots$, be a series of anomalies, with each $x_i = x$, and each is resolved by the same hypothesis $c \in H$. Let $\{A_i, m_i, N_i\}$ be the revised mass function obtained after resolving the i-th anomaly. Then

1) $A_i = A \cup \{c\}$, $N_i = N + i$, and for $B \subseteq A \cup \{c\}$
   $m_i(B) = m(B) N/(N+i)$ if c is not in B and
   $m_i(B) = m(B) + m(B - \{c\})\ i/(N+i)$ otherwise
2) $\lim_{i\to\infty} m_i(B) = 0$ if B does not contain c, and
   $\lim_{i\to\infty} m_i(B) = m(B) + m(B - \{c\})$ if B contains c
3) $b(B) = 1$, if $B = \{c\}$. The converse is true if $m(\emptyset)$ is assumed to be non zero.

Proposition 1.3 confirms the claim that when an anomaly reoccurs many times, the limit of the mass function yields a degree of belief of one for the anomaly. This implies that the anomaly is now well understood. In which case, a set of rules should be added into the rule base component to handle this anomaly in the future. The proofs of both propositions are straight forward and are left as an exercise.

In case of multiple hypotheses, similar revision results also exist but in a slightly more complicated form.

Conclusion

This paper describes a novel approach to trend analysis and diagnosis using multimodal reasoning with an emphasis on model-based reasoning. The purpose of this approach is to improve the way trend analysis and diagnosis is currently performed in NASA control centers. We are in the process of implementing a prototype system based on these concepts using MATLAB. This prototype may serve as a basis for a full implementation if successful.

Acknowledgments

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