Model-Based Anomaly Management for Small Spacecraft Missions

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Model-Based Anomaly Management for Small Spacecraft Missions

- Introduction
- Model Based Reasoning for Anomaly Management
- Application to Small Spacecraft Missions
- Ongoing and Future Work
Space System Anomaly Management

- **Health analysis and anomaly detection**
  - On-orbit operations can typically consume 25-60% of mission lifecycle costs
  - "Constant" telemetry filtering - a significant fraction of operations costs
  - Typically based in predominantly *experiential* techniques
  - Detection of an anomaly kicks off additional management tasks

- **Experiential reasoning**
  - Based on human-based experience in working with the system
  - Informal knowledge based which is often loosely organized
  - Design information intertwined with control information
  - Human-executed reasoning – leads to “standing armies” of mission controllers
  - Automated reasoning – typically implemented as an “expert system”
    - Production rules with experiential data

- **A useful technique, but improvements can be made**
Model-Based Fault Detection and Diagnosis

- **Model-Based Reasoning (MBR)**
  - “First principles” reasoning based on fundamental design information
  - Models of “structure and behavior”

- **Fault Detection & Diagnosis**
  - Detection: consistency of real outputs vs. modeled outputs
  - Diagnosis: identify model misbehaviors to explain real, faulty outputs

- **Heritage**
  - Formal MBR theory ~20 yrs old
  - Applied to circuit evaluation, copy machines, automobiles, spacecraft, etc.
  - Extensions: optimal active diagnosis, time-varying behavior, empirical probabilities, etc.
Our Extended Conceptual Framework

- **Motivation**
  - “Non-fault” anomalies exist – define & address via a common reasoning approach

- **Expanded Theory and Reasoning System**
  - Several formally-defined “classes” of anomalies: all are violated assumptions
    - **Fault** – violation of an assumed behavior
    - **Hazard** – violation of an assumed operating constraint
    - **Mis-configuration** – violation of an assumed configuration value
  - Several management tasks: common reasoning framework, distinct from models
    - **Detection** – Identify a “symptom,” an inconsistent observation from the real system
    - **Diagnosis** – Identify assumptions whose violation explains the symptom
    - **Resolution** – Identify actions to re-establish consistency
Model-Based Reasoning - Composability

Component Descriptions
Inputs, Outputs, States, Behaviors, Constraints
System Composition
Inputs, Outputs
Connectivity
Constraints

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Model-Based Reasoning - Composability

Mission Description
- Requirements
- Environment
- Constraints

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Model-Based Reasoning - Anomaly Management

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Anomaly Management Theory

→ Anomaly Management Conjectures
Model-Based Reasoning – Other Capabilities

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Anomaly Management
- Theory
  - Anomaly Management
    - Conjectures
  - Functional Analysis
  - Design Validation
  - Trade-off Analysis
  - Command Planning
  - ...

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Our Reasoning Framework

- **Theory**: Definitions of engineering system, operational system, anomalies, tasks, etc.
- **Implementation**: Algorithms & software for automation & decision support
- **Experimentation**: Verification/validation with real, operational, end-to-end systems
- **Context**: Configuration management of distributed space systems
- **Formulation**: Detection (residual), Diagnosis (estimation), Resolution (Control)
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![Diagram showing the relationship between operators, systems, anomaly manager, resolutions, simulations, diagnoses, and detections.]

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RF Behavior: If operating nominally, power is good, and temperature is within operating constraints, the output will be a (Mode) RF broadcast at (Power) with a (Freq), with (Info) modulated in the (Packet) format with a (Rate).
# End-to-End Experimental Space Systems

## GeneSat-1 Space System
- Launched 2006
- NASA Ames (academic partners)
- Biological lab tech demo
- 2.4 GHz cmd/tlm, amateur beacon
- SRI stn, Ames MMOC, internet ground CDH
- Operations ongoing

## Sapphire Space System
- Launched 2001
- Student-based university mission
- MEMS & automation tech demo
- Amateur cmd/tlm/beacon
- OSCAR stn network, SCU MOC, internet
- Operated through 2005
Examples of Managed Anomalies

- Scale of anomaly management:
  - **Modeling**: 10’s to 100’s of components → 1000-10,000’s constraints
  - **Management**: Detection < 1 sec; Diagnosis 1-10’s sec, Resolution 10-1000’s sec

- Fortunately (unfortunately?), we’ve had many anomalies...
  - Satellite CPU reset due to low batteries during eclipse
  - Overheating of transmitter amplifier
  - Power outage at communication station
  - Networking outages
  - Communication antenna servomotor failure
  - Equipment misconfigurations (TNC and transmitter settings)
  - Software misconfigurations (time, KEPS, IP, etc.)
  - Physically restrained antennae
Example - Sapphire

Requirement – collect real-time IR sensor data
Symptom – invalid sensor data
Diagnosis – 3 valid single-case anomalies
Resolution – 2 resolutions (reconfigure or de-scope mission)

Decision Support
Complete AM ~3.5 sec
Contact objectives met
Lessons Learned

- **MBR anomaly management a powerful tool for configuration control**
  - Use of simple, symbolic models provides:
    - Appropriate resolution of diagnosis and resolutions for real-time operations
    - Limited computational complexity permitting near-realtime performance

- **Room for improvement for application to more sophisticated systems**
  - Optimization of algorithms
  - Iterative hierarchical analysis
  - Compilation of algorithms
  - Parallel processing

- **Performance of human operators using the technique improves**
  - They adopt an MBR style of reasoning
  - Their experiential knowledge based improves

- **Need tools for model composition and transparency of reasoning**

- **Complements other techniques – hybrid approaches desired**
Future Work

- **Improvements**: theoretical extensions, improved efficiency, etc.
- **Implementations**: on-board processing, hierarchical decomposition, etc.
- **Auxiliary applications**: composition tools, design analysis tools, etc.
- **Application to new systems**: motivating several extensions…

**NASA PharmaSat Space System**
Future Work

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Summary and Conclusions

- **Model-Based Reasoning**
  - Systematic reasoning approach based on fundamental system information
  - Computational demands addressed through abstraction and hierarchy

- **Our MBR Framework for Anomaly Management**
  - Formal reasoning framework for computing anomaly conjectures
  - Algorithms developed for multiple symptom / multiple anomaly situations
  - Matlab / Simulink functions and toolboxes implement algorithms
  - Successful application to several missions for configuration control:
    - Demonstrated completeness and accuracy of resulting conjectures
    - Superior speed of reasoning compared to expert operators
    - Demonstrated applicability for simple small satellite missions

- **Development Continues**
  - New theoretical extensions
  - New and diverse systems
  - Broadened analytic scope
  - Hybrid reasoning systems
QUESTIONS
Simple Component-Level Example

-20°C < T < 80°C

If the component is nominal, the power is applied and the temperature is within operating specifications, the output should be the sum of the two signal inputs

\[ \neg AB(b_{Adder}) \land Pwr(Adder)=ON \land T(b_{Adder}) \geq -20°C \land 80°C \geq T(b_{Adder}) \]

\[ \Rightarrow OUT(Adder) = SUM[IN1(Adder), IN2(Adder)] \]
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Example – GeneSat-1 Comm Station Diagram

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Example - GeneSat-1 Simulink Comm Stn Model