Automated Data Fusion and Situation Assessment in Space Systems

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Abstract

Spacecraft are key components of military operations and everyday life. To achieve space situation awareness, human operators must monitor large numbers of parameters. During off-nominal conditions (e.g. severe space weather storm or onboard anomaly), it is difficult to cohesively monitor the data to develop an accurate tactical picture. To aid operators, we have developed a prototype Multi-Agent Satellite System for Information Fusion (MASSIF) for event detection and characterization. This system integrates a fuzzy logic system for semantic data processing and a Bayesian belief network system for multi-source data fusion and situation assessment. This paper describes initial research results.

Introduction

Operating and commanding spacecraft is a challenging task. Spacecraft operators must be aware of numerous events (e.g. space weather) that affect vehicle performance and safety. Over time, experienced operators learn the individual characteristics of a vehicle to effectively manage the system. However, less experienced operators (e.g. due to high turnover in Air Force systems) have difficulties understanding system behavior, particularly as it pertains to acquiring situation awareness by fusing multiple data sources. Indeed, demanding operational requirements and the increasing complexity of available command, control, communications, computers, intelligence, surveillance, and reconaissance data exceed the human ability to associate and classify incoming data without decision aids, which motivates the development of automated tools that perform data fusion and situation assessment. This paper describes preliminary research in developing a multi-agent satellite system for information fusion (MASSIF) in ground operations.

Data Fusion and Situation Assessment

Space weather can affect multiple onboard and offboard systems, sensors, and platforms. For example, a heavy meteor shower could break solar panels, causing immediate loss of power and attitude control to multiple vehicles in similar orbits. However, a severe attitude control system (ACS) failure could also cause loss of power to a single vehicle when the solar arrays are not pointed at the Sun. To distinguish between the two, a satellite operator or commander must fuse data from a variety of sources (e.g. space weather data from the 50th Space Weather Squadron, space tracking data on known asteroids, and satellite reliability).

Data fusion is a process that is concerned with intelligently combining data from multiple sources to develop a meaningful perception of the environment (Waltz and Llinas 1990). Humans have long been able to fuse remotely sensed data using mental reasoning methods and manual aids. In recent years there has been considerable interest in developing automated systems capable of combining data from multiple sensors to derive meaningful information not available from any single sensor.

For the military environment, the Joint Directors of Laboratories Data Fusion Subpanel has identified the following several levels of fusion processing products (Steinberg et al. 1998):

- Level 0 (Sub-Object Assessment): Fused estimates of object signals or features
- Level 1 (Object Assessment): Fused position and identity estimates
- Level 2 (Situation Assessment): Friendly or hostile military situation assessments
- Level 3 (Impact Assessment): Hostile force threat assessments

Additionally, a fifth level of fusion processing termed collection management or process refinement can be added to this model, i.e.,

- Level 4 (Process Refinement): Control of assets via process refinement

Across these levels of information products, the generality of the results increases from the very specific (e.g., "surface-to-air missile launcher of type A at coordinates B") to the more general (e.g., "air defense assets protecting target C"). Level 0 processing includes signal detection and feature extraction. At level 1, numeric procedures such as estimation (e.g., Kalman filtering) or pattern recognition dominate the processing operations. Level 1 information products arise from single and multi-source processing (such as target tracking) by sampling the external environment with available sensors and other information sources. The products of this processing are position and identity estimates for targets or platforms in the composite field of view (Waltz and Llinas 1990). Symbolic reasoning processes involving higher levels of abstraction and inference dominate the level 2 and 3 fusion operations. Situation abstraction is the construction of a generalized situation representation from incomplete data sets to yield a contextual interpretation of level 1 products. This level of inference is concerned with deriving knowledge from some type of pattern analysis of level 1 data (Endsley 1988; (Endsley and Garland 2000)). The distinction between levels 2 and 3 is that level 3 products attempt to quantify the threat's capability and predict its intent by projecting into the future, whereas level 2 results seek to indicate current hostile behavior patterns.

Based on this hierarchy, Figure 1 illustrates how the overall scope of our proposed MASSIF falls within the overall environment for on-board data fusion in a distributed space-based reconnaissance and surveillance system. As shown, we begin with a specification of the external environment. This includes the specification of all friendly, hostile, and neutral forces, as well as a description of the local terrain and current atmospheric conditions. The sensor suite senses information about the external environment. Data from these sensors/assets are then fused (levels 0 and 1) to generate individual target tracks and to classify and characterize targets. The situation assessment module of the MASSIF uses this fused track data to generate a current and projected situational state from the detected events and a priori knowledge. The total situation assessment state is then forwarded to higher-level processing for threat assessment and decision-aiding.
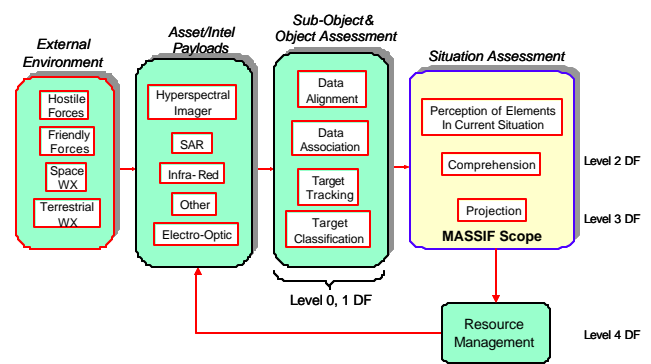

Figure 1: Data Fusion Architecture

System Architecture

To implement the data fusion capabilities described above, we have developed a two-stage, software agent-based architecture, as illustrated in Figure 2. This architecture is an extension of previous work we have done in the areas of data fusion in general, and situation assessment (e.g. (Harper, Mulgund, and Zacharias 2000), (Das, Cunningham, and Gonsalves 2002), (Hanson 2001), and (Gonsalves and Rinkus 1998)). As shown in Figure 2, this architecture contains two major modules: an Event Detector that is based on Fuzzy Logic technology and a Situation Assessor that is based on belief network technology.

The **Event Detector** serves to translate the primarily numerical data generated by the data fusion processor into symbolic data defining key tactical elements (e.g. ground moving target detected) and their states (e.g. time and location). The event detector "engine" can be as simple as a binary threshold logic that converts a numerical value (e.g., threat range) into a Boolean event (e.g., within range of threat envelope). However, we utilize fuzzy logic (FL) (Zadeh 1973) technology to provide a more robust approach to event detection
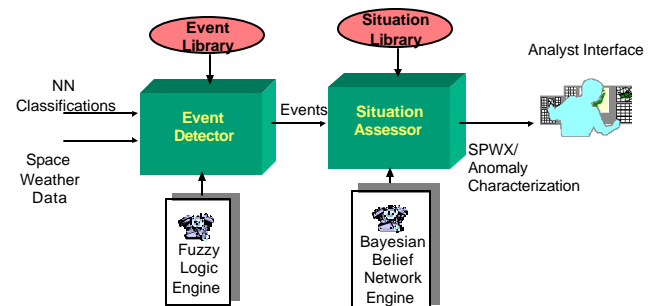

Figure 2: System Architecture

Next, a **Situation Assessor** takes in the detected events and generates an assessed situation state S(t), which is a multi-dimensional vector defining the belief values of a number of

possible situations. The situations, their relation to one another, and their association with detected events are all defined by a set of *situation models*, each model being a tree of possible situations and events. As we discuss in the following section, we utilize Bayesian belief networks (BNs) to implement both the situation models and the situation assessment function. This provides a way of making computationally explicit the extremely complex and inherently uncertain process of situation assessment in a real-time environment, while at the same time ensuring a fair degree of rigor in inferencing via the use of Bayesian reasoning logic. The net result of this stage of processing is the generation of an aggregated set of situation likelihoods (belief values) and their associated event probabilities, which serve to define the overall current and future tactical situation.

BN Technology for Situation Assessment

A BN (Pearl 1988) is a probabilistic *model* of a system. In the present context, the model is a semantic description of the effects of space weather events and satellite anomalies on satellites as learned by satellite engineers and space weather experts. BN models contain nodes and links, where nodes represent situations (e.g. experiencing galactic cosmic radiation (GCR) or single event upsets) and links represent causal relationships between situations (e.g. GCR causes single event upsets). The "strength" of a relationship is contained in conditional probability tables (CPTs) that encode the *quantitative* details of the causal relationship.

BNs are ideal for situation assessment and data fusion. They have the capability to quantitatively represent key SA concepts such as situations and events; they include mechanisms to reflect both diagnostic and inferential reasoning; and they easily incorporate various levels and types of uncertainties. BNs also support many reasoning modes: causal reasoning from causes to effects, diagnostic reasoning from effects to causes, mixed causal and diagnostic reasoning, and intercausal reasoning. Intercausal reasoning refers to the situation in which a model contains two potential causes for a given effect. If we gain evidence that one of the possible causes is very likely, this reduces the likelihood of the other cause. (Russell and Norvig 1995) assert that no other uncertain reasoning formalism supports this range of reasoning modes.

For automated data fusion and situation assessment in space systems, we input evidence from multiple sources and monitor the likelihood or beliefs in key nodes. When new evidence is input to a node in a BN, that variable updates its own belief vector, and then sends out messages indicating updated predictive and diagnostic support vectors to its children and parent nodes, respectively. The other nodes then use these messages to update their belief

vectors and propagate their own updated support vectors. In this manner, a consistent tactical picture is developed from the data.

Application to Space Weather and Spacecraft Anomalies

Applying BN technology to automated data fusion and situation assessment in space systems is a three-step process. First, effort (e.g. knowledge engineering) is required to obtain a detailed understanding of the physics of the situation in terms of what are the causes and effects. Second, this understanding must be captured in a BN model. Third, the model must be verified and validated. We now consider each of these steps.

Knowledge Engineering

To demonstrate feasibility, we considered two classes of events, namely space weather and onboard anomalies that affect satellite operations on a generic geosynchronous satellite. For simplicity, we assumed correct ground operations. For onboard anomalies, we did not focus on component level anomalies (e.g. reaction wheel failures); but instead, focused on sub-system level anomalies (e.g. anomaly in the ACS). For space weather, we considered single event upsets (SEU) and ionospheric disturbances.

Table 1 lists several known causes of these space weather events. For example, GCR and solar proton events associated with high-energy particles can cause SEUs, while geomagnetic storms can alter the atmosphere leading to scintillation. GCRs are not readily measurable, but are more prevalent during the solar minimum. Sensors onboard National Oceanic and Atmospheric Administration (NOAA) satellites measure solar proton events and geomagnetic storms.

Table 1: Short List of Space Weather Effects on a Geosynchronous Communications Satellite

Space Weather Event	Effects	Measurements
Galactic Cosmic Rays (GCR)	Single Event Upsets (SEUs)	None, though GCR are highest by about 25% during solar minimum
Solar Proton Events	• SEUs • Surface charging	Flux of particles with energies > 10 MeV
Geomagnetic Storms	• Surface charging • Scintillation	K or Kp index, ranging from 0 - 9 where 0 = quiet & 9 = severely disturbed

Working with satellite Subject Matter Experts (SMEs), we then performed a cause-effect analysis to quantify the effects of these events on six major satellite subsystems:

the attitude control (ACS), electrical power (EPS), thermal, payload, propulsion, and tracking, telemetry, and control (TTC) sub-systems. Table 2 shows a typical result. The magnitude of the effect is coded using a simple weighting system corresponding to high, medium, low, and none.

Table 2: Qualitative Effects of Space Weather Events on a Geosynchronous Communications Satellite – Moderate Event

Subsystem	External Cause	
	Single Event Upset	Ionospheric Disturbance
Attitude Control	High	Low
Electrical Power	High	Low
Thermal	Low	Low
Payload	High	High
TTC	High	High
Propulsion	Low	Low

BN Development

Based on the above information, two preliminary belief networks were developed. Using BNET 2000, our in-house BN model engine, Figure 3 shows a model developed for assessing space weather effects. The model is a graphical, interpretation of the cause and effect analysis and results discussed above. For example, the BN model shows that SEUs are caused by high-energy solar particles (e.g. optical flares) and random galactic cosmic radiation, which is causally related to solar cycle time. Together, SEUs and ionospheric disturbances produce effects on satellites that can be quantified in terms of problems in the ACS, EPS, thermal, propulsion, TTC, and payload subsystems. It is assumed that telemetry data is processed in by an external method (e.g. a neural network telemetry processor) to provide this quantification. Each subsystem node has two states – either 'yes' or 'no' for reflecting a belief concerning whether or not there is a sub-system error.

The strength or magnitude of the effects on each subsystem was derived from the qualitative effects knowledge (i.e. high, medium, low, and none) provided by the SMEs. Each sub-system CPT contains four independent values, which were developed by applying a simple expert system, which stated that the minimum value for a given CPT element is equal to the maximum of the individual values from the SME tables. For reference, Figure 4 shows the actual CPT for the EPS problems node. According to Table 2, the likelihood of an EPS problem given SEUs is high and low given ionospheric disturbances. This is reflected in Figure 4 where the likelihood of an EPS problem given *only* an ionospheric event is 0.2 and 0.95 given *only* an SEU. If a SEU and ionospheric event occur simultaneously, the likelihood must be greater than or equal to the likelihood of an SEU by itself. Here, we defined it to be equal.
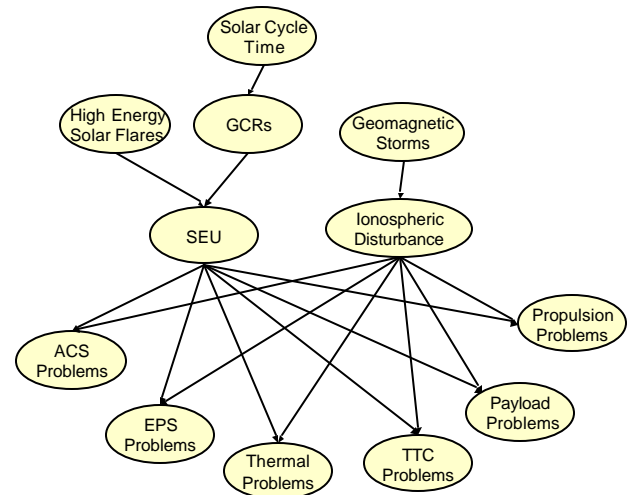

Figure 3: BN for Space Weather Assessments

Figure 4: CPT Example

Model Verification and Validation

We used two major test classes to verify and validate the BN models. First, to verify that the networks accurately reflected the cause-and-effects information, we performed deductive and abductive tests. In deductive tests, we input data into an individual parent node (e.g. evidence that says there are SEUs) and observed the resulting belief in the child nodes (e.g. what is the resulting belief in ACS problems). We then qualitatively compared the belief values with the high, medium, low, and none descriptions obtained from the SMEs. These tests assess how acurate the models capture forward reasoning. In abductive tests, we input data into an individual child node and observed the resulting change in the parents. These tests assess correlation between the parents.

The second test class involved entering patterns of data to the models (e.g. a simulated SEU). Figure 5 shows the results of simulated a TTC anomaly as a function of evidence posted for each sub-system (1 = apriori values, 2 = ACS, 3 = EPS, 4 = thermal, 5 = payload, 6 = TTC, and 7 = propulsion). As expected, the model correctly detected and identified the anomaly. In reaching this conclusion, the belief states for other nodes increased and decreased based on the evidence presented. This pattern is consistent with actual human decision-making where new information influences beliefs.
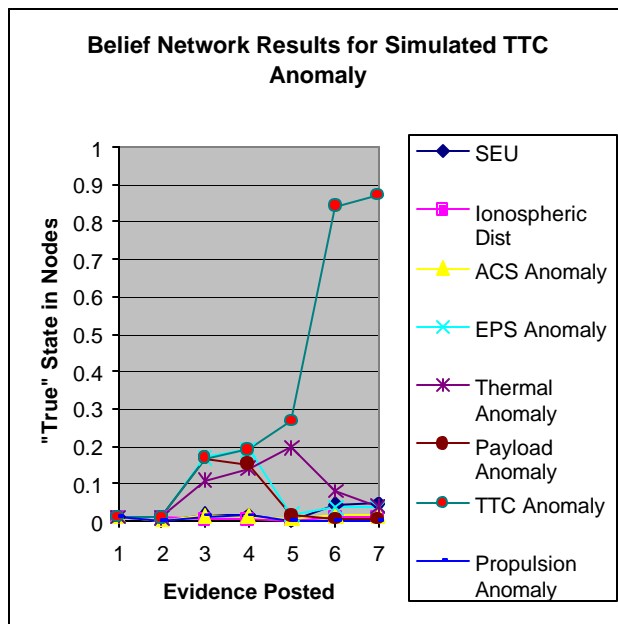

Figure 5: BN Results for Simulated TTC Anomaly

Conclusions

Automated data fusion and situation assessment tools are crucial in helping satellite operators accurately detect, identify, and characterize events that influence operations. As part of on-going research into data fusion and the application of Bayesian belief networks, we performed preliminary research on developing an automated data fusion and situation assessment tool for space system operators. Working with spacecraft satellite engineers, we developed and verified initial BN models for event-based, on-line situation assessment of space weather and satellite anomalies for a generic geosynchronous communications satellite. We feel that this is an important step towards future embedded situation assessment tools for operators.

In follow-on work, we plan to refine the initial BN models by considering additional events and operational issues, incorporating temporal belief networks, and developing models from data. We plan to continue validation efforts using a high-fidelity simulation test environment and real spacecraft data.

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