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Applying AI Tools to Operational Space Environmental Analysis

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Abstract

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The U.S. Air Force and National Oceanic Atmospheric Agency (NOAA) space environmental operations centers are facing increasingly complex challenges meeting the needs of their growing user community. These centers provide current space environmental information and short term forecasts of geomagnetic activity. Recent advances in modeling and data access have provided sophisticated tools for making accurate and timely forecasts, but have introduced new problems associated with handling and analyzing large quantities of complex data. AI techniques have been considered as potential solutions to some of these problems. Fielding AI systems has proven more difficult than expected, in part because of operational constraints. Using systems which have been demonstrated successfully in the operational environment will provide a basis for a useful data fusion and analysis capability.

Our approach uses a general purpose AI system already in operational use within the military intelligence community, called the Temporal Analysis System (TAS). TAS is an operational suite of tools supporting data processing, data visualization, historical analysis, situation assessment and predictive analysis. TAS includes expert system tools to analyze incoming events for indications of particular situations

and predicts future activity. The expert system operates on a knowledge base of temporal patterns encoded using a knowledge representation called Temporal Transition Models (TTMs) and an event database maintained by the other TAS tools. The system also includes a robust knowledge acquisition and maintenance tool for creating TTMs using a graphical specification language. The ability to manipulate TTMs in a graphical format gives non-computer specialists an intuitive way of accessing and editing the knowledge base. To support space environmental analyses, we used TAS's ability to define domain specific event analysis abstractions. The prototype system defines events covering reports of natural phenomena such as solar flares, bursts, geomagnetic storms, and five others pertinent to space environmental analysis. With our preliminary event definitions we experimented with TAS's support for temporal pattern analysis using X-ray flare and geomagnetic storm forecasts as case studies. We are currently working on a framework for integrating advanced graphics and space environmental models into this analytical environment.

1.0 Introduction

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Since the first discovery of radio emissions from the sun, it has become increasingly apparent that solar activity can have a significant impact on the operation of communication and space-based systems. As we deploy increasingly sophisticated communication and satellite systems, understanding the impact of solar activity has become a significant factor in the proper operation and protection of these systems. Because of this need, the U.S. Air Force and NOAA have established units charged with monitoring the sun and the space environment and alerting potential customers of dangerous geomagnetic conditions that can effect their systems.

Since their establishment, the Air Force Space Forecast Center (SFC) and NOAA's Space Environmental Service Center (SESC) are facing an increasing challenge as the size and diversity of requirements provided by their user community has grown. Their fundamental problem, analyzing and predicting the properties of the space environment, is still a difficult scientific challenge. Other more traditional problems result from serving a growing number of customers without a corresponding increase in staff size. Supporting modern space systems has added to the challenge by requiring more timely and accurate forecasts. Producing these kinds of forecasts has led the Air Force to embark on an ambitious project of developing a comprehensive set of space environmental specification and forecast models (Schunk et. al., 1992) and to the creation of the NSF sponsored Geosphere Environmental Modeling program. Although these efforts have been initially successful, problems related to operationally handling and analyzing the large quantities of complex data still need to be addressed.

Because these problems are perceived as being structured, but not amenable to algorithmic approaches, Artificial Intelligence (AI) has been a natural choice for researchers attempting to find solutions. Indeed, there is a fairly lengthy history of attempts to introduce AI into space environmental analysis (Joselyn, 1993; Schunk et. al, 1992; Shaw, 1989; Burov et. al., 1980). Previous attempts to use AI have focused on special research areas and have resulted in limited success in the operational environment. Reasons include difficulty in using and understanding AI based programs in an operational setting. Typically users are reluctant to trust AI methods because of the lack of visibility into the reasoning processes. Another problem is that the output normally has to be reformatted to be operationally useful. In addition, users have varying degrees of confidence in the expert who provided the knowledge. Past experience has shown that expert systems are expensive to build and difficult to maintain (Jesse, 1993). While these factors may pose operational problems (Joselyn, 1993; Schunk et. al., 1992) we believe that previous efforts have demonstrated that expert systems represent a sound method for solving some of these analysis problems.

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Because of past problems with introducing AI systems into an operational context, we have focused on the operational integration issues. To improve our chances of producing a workable solution, we began development using an AI system that has already been successfully used in an operational environment and is flexible enough to the support the analytical tasks we wished to address.

Starting with a basic AI framework we have built a system that performs basic assessments and predictions of the space environment. This framework is extensible so it can be used to address problems related to the introduction of new technology aimed at improving forecaster analyses. We plan to augment our current system with advanced visualization techniques and space environmental models. These methods are aimed at increasing a forecasters diagnostic and prognostic abilities, however using them can demand more time then a forecaster in an operational environment can afford. Intelligent control of these systems will reduce the analysts' workload and allow them to take advantage of the new insight these methods provide. Integrating these capabilities will provide feedback on the flexibility of the intelligent framework and

an assessment of the effort required to integrate other new technologies.

2.0 Temporal Analysis System

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Temporal analysis is a commonly used methodology in the military intelligence environment. Temporal analysis involves the study of events as a function of time to determine patterns of behavior. In this context, an event is a discrete activity that is monitored by the analyst. Aside from a specific type, all events are associated with a time and duration. In this application, events are observations of solar activity and the solar-terrestrial environment. The temporal analysis technique involves displaying the events on a timeline. By displaying historical examples of a particular phenomenon in this manner, analysts are able to establish correlations between observed events and the occurrence of the phenomenon. Once identified, these patterns are recorded and used as a basis for analyzing and new data and making predictions. The practical application of this technique relies heavily on meaningful data fusion and data visualization support.

Because of our focus on operational support issues, we chose to use a general purpose system already in use within the military intelligence community, called the Temporal Analysis System (TAS). The TAS core suite of operational tools supports data processing, data visualization, historical analysis, geographical analysis, situation assessment and predictive analysis. These functions are supported by seven major applications: Timeline, Map, Query Panel, Chalkboard, Dictionary, Model Developer, and Knowledge-Based Predictive Analysis and Situation Assessment (K-PASA). The Map which supports geographical analyses and Chalkboard which supports generic data presentation have so far been omitted from this effort

TAS has a domain information-based architecture. The database structure and application

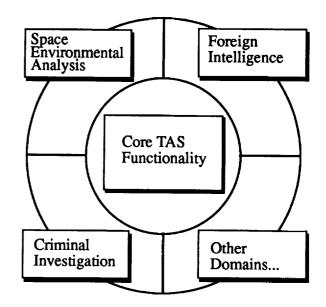


FIGURE 1. TAS Domain Structure.

functionality are separated into general and domain-specific layers. The temporal analysis paradigm provides a broad abstraction around which a significant portion of the system can be built without referring to domain specifics. Support for a particular analysis domain is confined to a separate layer. We often refer to the application specific part of the database and system functions as the domain-dependent layer or simply the "domain". New domains can be layered on top of the core architecture so that new systems can be built reusing 80 to 90% of the core functionality (Figure 1). This approach also has the advantage that functionality developed for one domain is often general enough that it can be promoted to a core capability and shared among the various operational users. The degree of reusability is illustrated by the number of domains currently supported by TAS. These domains include foreign Command, Control and Communications (C3), strategic air, counterdrug, counter terrorism, and criminal investigation.

Data be entered into the database in several ways. The Timeline and Map applications provide basic data entry and maintenance facilities.

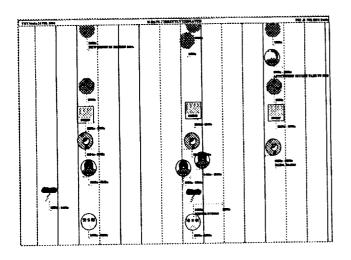


FIGURE 2. Example Timeline Display.

Event data can be loaded manually as well as from real-time message traffic using the local Automatic Message-Handling System (AMHS). Data can also be imported from external historical databases and translated into TAS event specifications.

The Timeline graphically displays events as a function of time (Figure 2). Different event types are identified by icons. For example, in the space environmental domain a radio dish represents radio burst events, a sun with spots represents sunspot report events, and a sun with an eruptive prominence represents general disk and limb activity. Detailed event information can be viewed by clicking an event icon with the mouse. The Timeline supports various data filtering mechanisms designed to aid in the temporal analysis process. Types of filters include event type, icon, keyword, and Area of Interest (AOI). The analyst can customize the Timeline's appearance by changing icon colors, placement, and timescale to create a visually meaningful display. Annotations can be added to communicate additional information such as priority or special significance of a particular event. All of these functions contribute to provide the analyst with an integrated visual summary of complex, multi-source, heterogeneous data.

The Query Panel provides a point and click interface for retrieving data. The user can perform ad hoc queries and have the results piped to external applications for viewing. Displays currently supported are the Timeline, Map, a histogram tool, and a table tool. The Query Panel uses a set of descriptions that provide the attributes and sources that comprise an entity or concept in the users environment. This abstracts the user from the underlying Database Management System (DBMS) and makes it possible to add databases or layer the Query Panel over new databases without modifying the code. The Query Panel graphical interface generates a semi-natural language (SNL) description of the query as it is being built. This capability allows the user to keep track of complex queries and understand their request without having to know the underling data access mechanism (for example, SQL).

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The Chalkboard and Dictionary applications are relatively minor. The Chalkboard is a generic drawing tool used to develop briefings. The Dictionary is a user defined lexicon of information. This information includes terminology, definitions and synonym relationships relevant to the specific application domain. Other TAS applications use the Dictionary data to identify keywords and synonyms in incoming data.

The applications discussed so far aid analysts with the manual process of temporal analysis. K-PASA and the Model Developer are expert system tools which help automate temporal analysis by analyzing incoming events for patterns. Model Developer is a knowledge acquisition tool is used to define the knowledge base upon which expert system operates. K-PASA is the engine that compares events against the models stored in the knowledge base to identify situations of interest. The user may select the types of activities that the system should search for among the incoming events. Assessments are displayed in a list ordered by decreasing confidence. The user may select an assessment and receive either an explanation or a prediction of future activity.

3.0 Knowledge Acquisition & Analysis

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Expert systems face a number of special challenges in operational environments. Knowledge may rapidly evolve and require that the knowledge base be constantly maintained. Hard coding systems or systems that require specialized AI knowledge prove to be neither cost effective nor logistically practical. Consequently, the knowledge base must be maintainable by a user who works with the system on a day to day basis. This requires a flexible and simple knowledge representation that is easy for users to understand and use.

K-PASA operates on a knowledge base of temporal patterns that are encoded using a knowledge representation called Temporal Transition Models (TTMs or "models") in conjunction with the event database. TTMs are specifications of generalized event patterns that characterize a particular activity of interest. TTMs combine concepts derived from Augmented Transition Networks (ATNs) used in Natural Language Processing (Woods, 1970) and decision trees. Like ATNs, TTMs are composed of states and transitions. States correspond to events in the application area. Transitions describe the temporal relationships between events. States specify the type and characteristics of events which may match the state. For example, a state may specify a type 1B flare that occurs in region 7640. State syntax supports several operators which may be used to constrain event attributes. These operators can be used to define equality, subset or numerical comparison specifications. Temporal constraints can be absolute like "occurs only at noon local time", or can be relative such as "follows in one to ten minutes". Multiple transitions from a particular state are considered a branch. Transitions in a branch are designated as either "AND" or "OR" transitions.

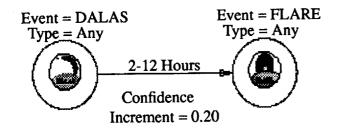
The evaluation of AND/OR transitions is similar to decision trees where OR branches are evaluated independently and AND branches are evaluated together. Each transition has an associated confidence factor assigned by the user. The confidence factor represents the incremental belief that the reported events indicate the phenomenon described in the TTM. Refer to Jesse (1993), for details on the confidence specification and evaluation implementation.

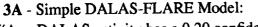
For a simple pedagogical example consider a two state TTM that begins with the observation of disk and limb activity (DALAS) with a transition to an optical solar flare within two to twelve hours (Figure 3A). If no state attribute constraints are in place then the simple existence of a DALAS event satisfies that state. If the system is asked to make a prediction at this point it will only predict the existence of a flare, because in this model the final state is not constrained. For the model to be fully satisfied, a flare event must be detected two to twelve hours after the initial DALAS event. New models can be evolved or updated from existing models. One option for refining this model could be limiting the first event to certain types of DALAS that are more likely to produce flares: more energetic types such as loops, surges, or eruptive prominences (Figure 3B). The final state could also be more specific by constraining the flare to type 1B or greater. K-PASA is capable of evaluating both models.

Associated with TTMs is a graphical specification language developed to be consistent with the manual analysis methods. This language utilizes the same icon notation found in the TAS timeline. The Model Developer implements this graphical language allowing the user to maintain the expert system's knowledge base by means of manipulating the TTMs. The ability to manipulate TTMs in a graphical format gives non-computer specialists an intuitive way of accessing the knowledge base. The ease with which the knowledge base can be created and maintained by domain rather then computer specialists has directly contributed to TAS's operational success (Jesse, 1993).

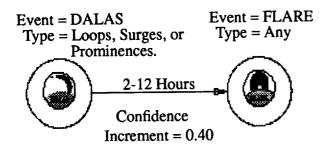
K-PASA performs its assessments by mapping events to TTMs. The core comparison process starts at the TTMs' initial states' specifications. If one or more initial states are satisfied then the system searches for events that satisfy the subsequent transitions and states. This TTM traversal process continues until all TTM branches either terminate or no events satisfy the next transition/ state specifications.

The TTM traversal process uses two techniques to increase the flexibility with which models can be applied and accommodate deviations from expected patterns. Deviations can be expected when critical events go unobserved, unreported or if the full range of behavior for the phenomena is not captured by the model. These tech-





"Any DALAS activity has a 0.20 confidence of transitioning to a flare."



3B - Extended DALAS-FLARE Model: "Any energetic DALAS activity has a 0.40 confidence of transitioning to a flare."

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FIGURE 3. Example TTMs.

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Partial state activation allows user acceptable deviations within the reported events. The degree of tolerance in partial state activation is defined in the states. Each state attribute specification has an associated activation threshold. The possible thresholds are COMPLETE (exact match), UNKNOWN (unknown values are acceptable but a a lower confidence), and MIS-MATCH (wrong values are acceptable but at an even lower confidence). The level of state activation is derived from the "completeness" of the fit measured by a weighted average of the degree for which each attribute specification has been satisfied. This average is factored into the overall assessment confidence.

Non-linear traversal provides additional flexibility in processing the overall TTM structure. Instead of strictly adhering to the event sequences specified in the TTM, K-PASA will also search for skipped activity and relax the temporal constraints. Relaxing temporal constraints is performed by expanding the expected timeframe defined by the transitions by user defined temporal variances. These variances are relative to the timeframe for which the events should have occurred. As the temporal variance increases, the confidence in the assessment decreases.

Another type of problem is introduced when data is spread across multiple reports. Sometimes, instead of being entered into the system as a single event, information on about a single occurrence is entered as several events. K-PASA compensates for this problem by searching for and combining events that together satisfy a single state. These multiple events contribute to the creation of a meta-event. K-PASA, during the event mapping process, will aggregate those events in order to satisfy the state. A related problem is that an event may be encapsulated into a larger event. The system will also parse larger events to find embedded events.

K-PASA is integrated with the Dictionary in order to utilize synonym relationships when comparing events to state specifications. Synonym relationships in the Dictionary define terminology equivalency. Examples include acronyms or alternative spellings. Without this integration the user would have to enter all phrases and their associated synonyms in the state specification, even though they semantically represent the same activity.

K-PASA predictive analysis processing is relatively straight forward. The system predicts future events by looking at states yet to be fulfilled. Paths stemming from the last states matched in the assessment are analyzed using the event(s) matching those last states as time references. The constraints in the state specification provide additional information about the predicted event attributes.

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In addition to providing analysis capabilities, K-PASA contains an explanation subsystem which justifies system conclusions using a combination of graphics and natural language text (Figure 4). The graphics include a view of the model, with the satisfied states filled, and a view of the timeline that shows only the events which satisfy

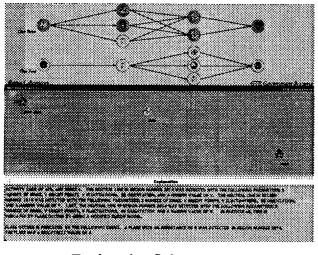


FIGURE 4. Explanation Subsystem

the model. The graphics allow for quick superficial explanation in situations where the analyst is pressed for time. The natural language text provides explanation details when the user has the time and inclination for a more in-depth explanation. Simply reciting the events which matched the TTM is not appropriate. The text must be comprehensive enough to communicate the reasoning behind the assessment without overwhelming the user with irrelevant details. To provide this capability, the text is structured in multiple paragraphs with each paragraph describing the events supporting a particular concept satisfied in the TTMs. The prediction explanation is presented in a similar fashion. The TTM associated with the assessment is shown with the satisfied states filled. States associated with predicted events are highlighted in yellow. The text describes each predicted event along with the expected timeframe of occurrence.

4.0 Space Environmental Domain

Automation of the analytical processes within the forecast centers has been heavily biased towards quantitative methods. These methods include statistical techniques and more recently numerical modeling. While there is a strong agreement that these tools are necessary for improving forecasts, there is some concern that not enough is known about how to properly integrate them into the forecasting process. This stems from the lack of understanding about the physical processes involved and having no well defined analysis model of how the data should be integrated. Human forecasters are able to produce forecasts by working around these problems. They do this largely by applying their experience to determine likely behavior where the quantitative tools cannot be used. This process of predicting results without the use of a mathematical model is known as model-free estimation (Kosko, 1992). Understanding forecasting as a model-free estimation process provides additional insight into the requirements for intelligent tools.

TAS is especially well suited for the role of supporting qualitative estimation and data integration. As previously shown, TAS focuses on capturing heuristic knowledge. It does not require that a mathematical model be known, but it can use the output of quantitative techniques for analysis. TAS also supports a well defined analysis methodology, which provides a high level framework for systematically integrating various observations. Operational TAS users have reported that the use of the temporal pattern matching methodology closely follows their own reasoning processes when performing event identification, situation assessment, and activity prediction (Jesse, 1993).

For example, in a geomagnetic substorm forecast situation, an analyst might consider current flare activity, the state of the interplanetary magnetic field (IMF), and the configuration of the magnetosphere (e.g. the current dipole tilt, etc.). There are quantitative models which provide at least some degree of insight into these effects, but there is no model which quantitatively describes the relationships. The forecaster accommodates these factors by weighing past experience and considering the similarities and differences in the current pattern. TAS works in conceptually the same manner. From the discussion above, we could build a simple four state model that integrates flare event data such as indicators of the IMF (e.g. solar sector boundary crossings) and magnetospheric indicators (e.g. the time from the last equinox to predict substorm activity).

The first step in implementing the space environment domain, after determining its suitability for applying temporal analysis, was to identify the key abstractions or events that would be needed. This process usually requires an ongoing dialog between the software engineers and several domain experts. We utilized a wealth of literature from the SFC, SESC, and the space physics community and relied on the experience of one of our authors (six years of various space environmental assignments within the military) for our prototype. The framework which abstracts domain specific information from the core functionality allowed easy implementation of the specific event abstractions that we needed. Our first prototype was aimed at building a simple proof-of-concept demo. Extending the prototype will require working with a broader variety of domain experts.

In order to keep the level of effort in line with our goal of only providing an initial proof of concept we narrowed the area of investigation to flare and geomagnetic storm forecasting. Some simple guidelines were established which made the final implementation of the system more useful. For example, we designed event definitions that corresponded to data which could be extracted from real-time message traffic, thus alleviating the need for manual entry of events.

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After some initial iterations, we settled on eight event types: BURST, DALAS, FLARE, NEU-TRAL LINE, SPOT, STORM, SWEEP, and X-RAY. Table 1 shows these events, a brief description of each, and the message sources from which they can be derived. In order to keep in step with the operational flavor of the work, with one exception, we used the government message formats (USAFETAC/UH-86/ 003, 1986) to dictate the possible event attributes.

The first step in developing the domain was designing the logical database tables and building the database. The primary database design constraint in the TAS architecture is that the tables must be normalized so that all of the domain independent data resides in a single generic event data table. The index between the domain independent and domain dependent data is a unique event sequence number. After the creation of the database, certain domain dependent portions of the code were modified. These portions were primarily concerned with inserting event data into and extracting it from the database. In addition, new icons were created which helped visually represent the new event types. The actual code changes required about four man-weeks for the initial prototype plus two weeks for testing and refinement.

5.0 Preliminary Experiments

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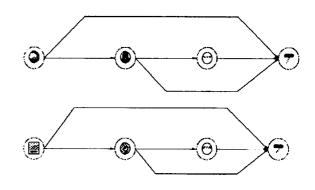
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Once the fairly straight forward process of building the domain was complete, we began a series of tests focusing on the ability to bring knowledge into the system and conduct analyses. This primarily consisted of building models, constructing test data, and using K-PASA to compare the test data with the models.

The first set of models were based on fairly simple high level descriptions of possible solar causes for geomagnetic storms (AWS Course 2546-001, 1989; Nishida, 1979; SESC Forecasters Manual, 1989). The basic pattern consisted of a long term precursor (up to a day in advance), an energetic event, detection by satellite sensors, then followed by a storm. For example one of the models consisted of an initial DALAS event that was constrained to be one of the more energetic types. It was followed by an





optical flare event after a 0 to 1 hour transition. The flare was followed by a GOES x-ray report after a 0 to 3 hour transition and then a storm event after another 1 to 6 hours. Additional transitions allowed for sequences that bypassed one or two of the initial states. Alternatively, the non-linear processing could have been used to handle such cases. Several similar models were built with different constraints, event types (SWEEPS instead of DALAS etc.) and transition values (Figure 5). In conjunction with an artificial set of test data, these first models simply validated the ability to create and evaluate models.

The next set of models, captured more detailed behavior and could realistically be compared to actual data. These models were based upon a

Event Message Sources		Description			
BURST	SEON BURST messages.	Solar discrete radio burst information.			
DALAS	SEON DALAS messages.	Disk and limb activity summary reports.			
FLARE	SEON FLARE messages.	Solar optical flare information.			
NEUTRAL LINE	SESC neutral line analysis charts.	Orientation, and special characteristics of the solar neutral line.			
SPOT	SEON SPOTS messages.	Sun spot characteristics, by region.			
STORM	SESC/SFC STORM messages.	Geomagnetic storm information.			
SWEEP	SEON SWEEP messages.	Solar swept frequency radio burst information.			
X-RAY	GOES X-RAY messages.	X-ray measurements from the GOES satellites.			

TABLE 1. Space Domain Event Types.

paper by Burov (Burov et. al., 1980) as cited by Sawyer (Sawyer et. al., 1986). Burov's paper extrapolated rules that could be used by a generic rule-based system using a cluster analysis technique with archived x-ray flare data. Burov's rules mixed negative logic (A flare will not occur if...) and positive logic (A flare will occur if...). Since TAS is event oriented and is not geared towards making an assessment driven by the absence of events, the first step was to invert the negative logic. This process was performed using a semi-analytical method that utilized basic symbolic logic. This method compensated for some of the vagaries of the English language and ensured global consistency as individual rules were modified. During the process of defining a TTM for the Burov rules, the use of the Model Developer had a number of advantages as a documentation tool. The ease of use and the clarity of the TTM graphical specification language resulted in an unambiguous and easy-to-follow representation of the knowledge. Evaluation of the Burov rules required more data than the seven events could supply. One or two of these were ignored, based on the premise that they represented rare special cases, or on belief that the data would not be available in an operational environment. For one or two others, reasonable proxies that were available from the current event attributes were substituted. However, since the Burov rules used neutral line characteristics in several ways, this necessitated the addition of a NEUTRAL LINE event. Fortunately this analysis is fairly easy to perform and should only be required to be entered by a user once a day.

The final results were documented as four models. The model representation appears on inspection to capture all of the salient points of the Burov rules. The model representation also has several advantages. As mentioned above, the graphical displays provide a powerful method for documenting the process encapsulated in the model. Also, in conjunction with K-PASA, the TTMs can help the analyst by providing intermediate assessments of the confidence that a flare will occur. Since the Burov rules do not associate a quantitative value to individual steps, the transition confidences were approximated and will be refined later by comparisons with real data.

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6.0 Future Work

We are currently developing a framework for integrating advanced graphics and space environmental models into this analytical environment. This framework will be based on an extended decision support architecture with a central information manager. This intelligent system will configure and execute the appropriate subsystems, as necessary, to support analyst tasks. Examples of potential subsystems include data formatting modules, visualization displays, environmental models, and report generation tools. The planning process will be knowledgebased and utilize criteria such as the forecast product development steps, subsystem execution requirements, and current operational status. Preliminary analysis has indicated that casebased reasoning (CBR) techniques are a viable approach.

As users evaluate the system, additional modifications to the existing prototype will be required. Existing event types will require modification and new ones added to the system. This process can be accelerated by training analysts on the knowledge specification tool, allowing them to construct models, and validating those models with operational data.

Additionally, we plan to reconfigure the TAS AMHS to accept the message formats needed to experiment with the real-time mode. Other enhancements will require precisely defining an inter-process interface to K-PASA so that the new capabilities can be added such as the environmental models.

7.0 Summary

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As with many other fields, space environmental forecasters are facing a potentially overwhelming information overload. AI techniques can be utilized to mitigate the problems associated with handling and analyzing large quantities of complex data. AI tools, such as TAS, that are operational in other areas have the potential to solve some of the problems. Whether TAS can be utilized in an space environment operational setting remains to be seen. However, its demonstrated successes elsewhere indicate this approach will prove sound. Once this method of AI assistance is determined to be valid, we hope to expand the framework to include various other data visualization techniques and space environmental models.

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