Sensor Web Dynamic Replanning Architecture

Mark Abramson, David Carter, Stephan Kolitz, Natasha Markuzon, John Miller, Peter Scheidler, Charles Strauss
The Charles Stark Draper Laboratory, Inc.
Cambridge, MA 02139

Abstract:

We present the architecture we have developed for sensor web dynamic planning, for a sensor web consisting of space-based remote sensors, in-situ sensors on unmanned surface vessels (USVs), and remote sensors on unmanned air vehicles (UAVs). We will describe the mathematical modeling and software implementation of the architecture to date. We will illustrate the application of this capability to scenarios of interest, e.g., forest fires, hurricanes, harmful algal blooms. We will also provide an update that describes the current use of Draper's Earth Phenomena Observing System (EPOS) in support of EO-1's target selection process, and the performance improvements that have resulted from its use.

I. EPOS FUNCTIONAL ARCHITECTURE

The fundamental EPOS concept of operation is that of optimized dynamic replanning and execution. Sensor data and model forecasts are inputs to a closed-loop decision-making system. In collaboration with users, EPOS monitors the input, and when appropriate, replans and executes a new plan that optimizes the tasking of available sensing assets to gather data. EPOS provides the science community with innovative capabilities that can be used to advance science modeling of the phenomena of interest. Its capabilities can be also be used to provide governmental agencies and commercial interests early warning of possible hazardous situation. The functional architecture for EPOS is illustrated in Figure 1 and is briefly explained in the following.

Situation Awareness: Situation Awareness provides estimates of current world and system states. The Information Layer utilizes COTS and internally developed tools to extract data from many different types of data sources and protocols (e.g., text, relational databases, XML, email, http, ftp), transform the data (e.g., remove outliers and bad data), and load the data into the format of the EPOS Data Store, our internal data source for the other EPOS functions. The Information Layer capability also contains application specific data transformation algorithms and software (e.g., astrodynamic calculations based on two-line element sets from the Air Force's SpaceTrack website, current cloud cover and cloud forecasts from the Air Force Weather Agency). Over the course of the current AIST-05 project, we will enhance and extend the Information Layer to access a much larger set of science data sources, e.g., EOS satellites and sensors (e.g., through Goddard's Earth Sciences Data and Information Services Center), additional weather data from the Air Force Weather Agency (e.g., winds), current fire data from the National Interagency Fire Center (NIFC), Remote Access Weather Station (RAWS) wind data.

Situation Assessment: Situation Assessment takes Situation Awareness output and uses Information Exploitation technologies, e.g., pattern recognition and data mining, to support monitoring, diagnosis and prediction of world and system states. To achieve this, we will apply a variety of supervised/unsupervised learning and statistical algorithms (e.g., neural networks, Bayesian networks, clustering algorithms, association rules, genetic algorithms, discriminant analysis) to provide optimized input to EPOS Planning and Execution. We plan to incorporate new science models such as prediction models for the phenomena of interest (e.g., fire and hurricane forecasting models).

Planning and Execution: Plan Generation is optimization-based technology that will support a full range of operational autonomy, from manual operator control to full autonomy. To make the solution of complex problems tractable, the problems are hierarchically decomposed into simpler, decoupled subproblems that can be solved (nearly) independently. The hierarchical architecture decomposition preserves system-level objectives while respecting local constraints, and defines interactions and information exchanges between levels. This enables inter-level negotiation and permits local autonomy so that decisions are made at the lowest appropriate level. The hierarchical decomposition aggregates planning information and plant dynamics from lower levels to higher levels in the hierarchy.

For a sensor web system with sensing, communicating and processing entities, activities and resources, a plan consists of decisions about which entities perform what activities at what times using what resources at what locations. A plan includes 1) *tasking and coordination*: specifying which entities perform what activities; 2) *scheduling*: specifying the times each activity is performed; 3) *resource allocation*: specifying which resources are used by the entities to perform the activities; and 4) *routing:* specifying the ordered sequence of locations where the activities take place. Another classification of sensor web planning is

into *observation* planning (of targets by sensors) and *movement* planning (for sensor platforms), which address two important aspects of the planning problem we intend to focus on.

Examples illustrating how we will apply the EPOS functional architecture during our work under AIST-05 are given in the next few sections.
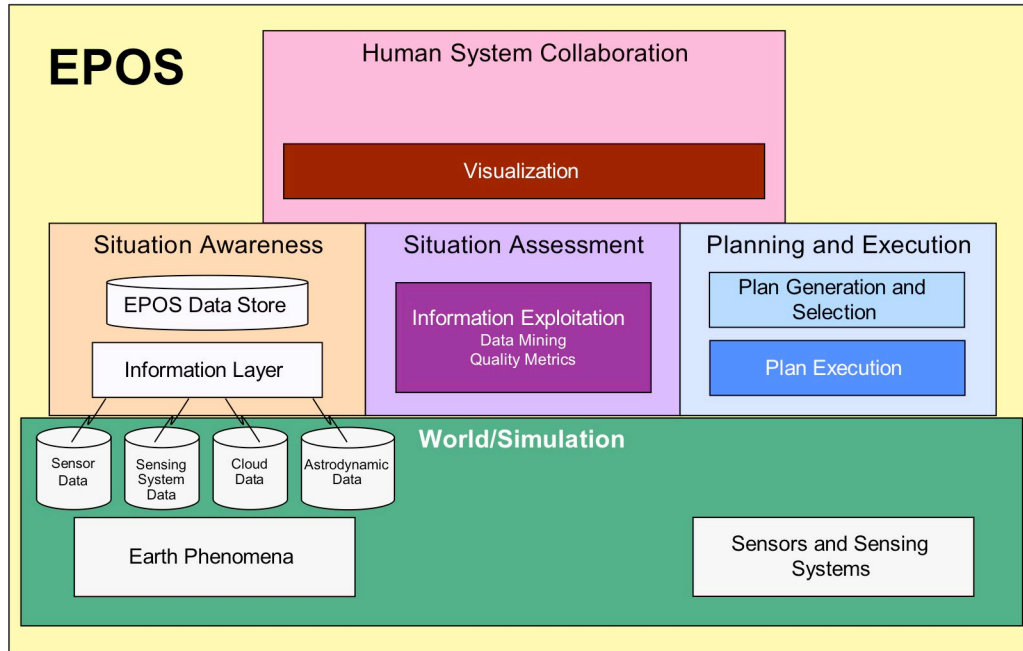

Figure 1: EPOS Functional Architecture

II. INFORMATION EXPLOITATION

The first development of EPOS' Information Exploitation capabilities will support sensor web fire demonstrations that involve multiple AIST-05 projects. The integration work is being done through Dan Mandl's AIST-05 project. We provide a brief overview of this summer's demonstration before describing the work we are doing to support this and future summer's demonstrations.

A. SENSOR WEB DEMO FOR FIRES

We are planning to participate in a sensor web demo (elements of which are illustrated in Figure 2) for observing fires in the western United States in late summer 2007. The sensing platforms will include EO-1, a NASA UAV, Terra (MODIS[1] and ASTER[2]) and Aqua (MODIS). ASTER and MODIS data, fused with fire alerts from the National Interagency Fire Center (NIFC), will be used to cue tasking of EO-1 and the UAV.

The UAV will fly one mission per week for a total of 5-6 flights from mid-July through early September 2007. Each flight will last up to 20 hours with remote piloting from

NASA Ames Research Center. The UAV is an Ikhana class plane (civilian version of the General Atomics Predator-B) that will fly out of Dryden Flight Research Center. There are three potential 1000-mile long flight corridors for the UAV: California/Oregon along the Sierras, Nevada/Idaho over the Great Basin, and Utah/Wyoming/Montana along the Wasatch Range. EO-1 will be available for imaging scenes in the areas of interest.
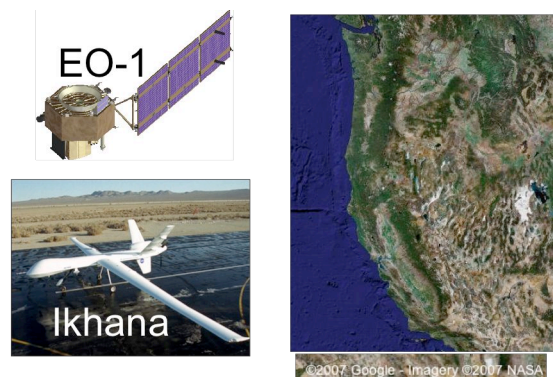

Figure 2: Elements of the Fire Demo

The role for EPOS this summer will be in planning EO-1 imaging, supporting the generation of the UAV's flight plan, and real-time re-planning of the UAV's path (within

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[1] Moderate Resolution Imaging Spectroradiometer
[2] Advanced Spaceborne Thermal Emissions Radiometer

constraints that remain to be determined) and observations. In future years, we plan to utilize EPOS Information Exploitation capabilities and expand the set of sensing platforms for which we develop movement and observation plans.

A draft version of the primary functions and data interfaces that involve EPOS in the fire demo are illustrated in Figure 3. The particular method of data access is to be determined and might include using OGC[3] capabilities. It is more likely that developmental engineering interfaces will be used in 2007, while OGC capabilities will be used in future demos.
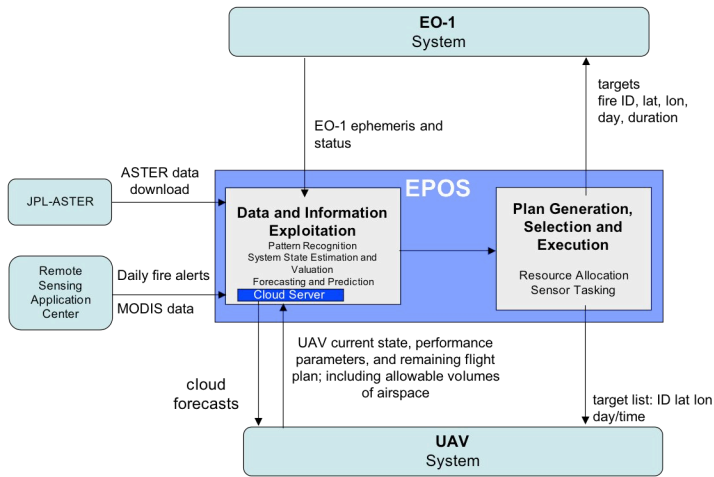

Figure 3: Data Flow for Fire Demo

B. *DATA MINING FOR FIRE PREDICTION*

The initial objective for our Information Exploitation work is to use archived data, e.g., MODIS (on Terra and Aqua), ASTER (on Terra) and AFWA weather data (e.g., wind, temperature) as input to a data mining model of Earth phenomena, e.g., fires, hurricanes. We will develop and apply data mining models for real-time phenomena assessment and warning generation.

The initial application deals with fires, in particular to predict which fires will develop into large and/or threatening ones. The models to be built will use multiple years of archived observations from MODIS and ASTER sensors, fused with wind, temperature and other weather data.

MODIS provides continuous global coverage from 36 spectral bands, most with resolution of 1km. Level 3 MODIS data includes thermal anomalies and global daily fire data at a resolution of 250 m to 1km. ASTER is being used to obtain detailed maps of land surface temperature, reflectance and elevation. It is an on-demand instrument

that collects surface emissivity with 30 to 90-m resolution. Weather data includes temperature, relative humidity, wind speed, wind direction, wind gusts.
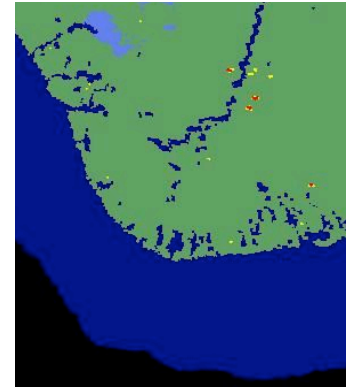
Figures 4: MODIS Thermal Anomalies Data

Figure 4 illustrates MODIS thermal anomalies data from December 5, 2000 along the Gulf of Guinea near eastern Africa leading up the Niger River. Small yellow and red dots represent fires in the area.

The knowledge discovery process that we will use for estimating fire danger will be interactive, with exploratory data analysis followed by supervised learning. This is illustrated in Figure 5. Figure 6 illustrates the supervised learning process and how the resultant model will be used for real time prediction of fire danger.
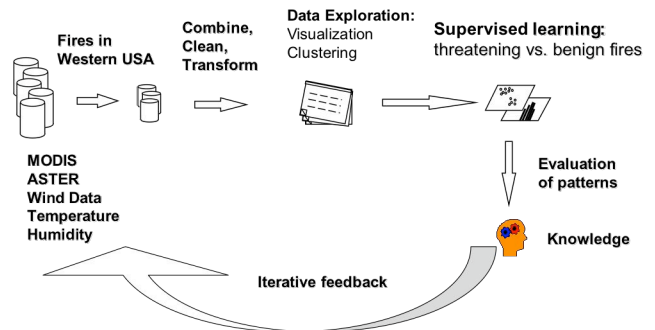

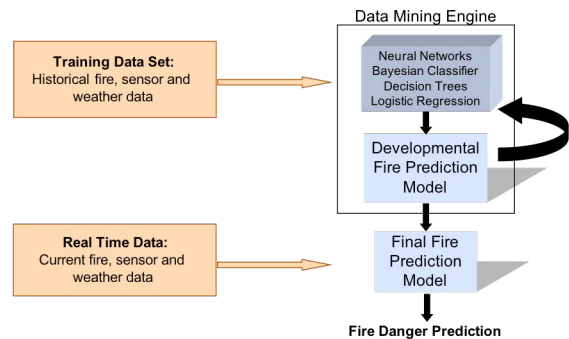**Figure 5: Knowledge Discovery Process for Estimating Fire Danger**

Figure 6: Real Time Prediction of Fire Danger

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[3] Open Geospatial Consortium

III. PLAN GENERATION AND SELECTION

In the EPOS Functional Architecture, the Planning and Execution function contains Plan Generation and Selection as well as Plan Execution. EPOS Plan Generation and Selection for a sensor web is hierarchically decomposed, as illustrated in Figure 7. Situation Awareness and Situation Assessment provide input to the Plan Generation and Selection function. The key input needed by the Observation Coordination Planner consists of two data categories: 1) targets (and all associated parameters, such as ID, location, etc.) and 2) a system-level value function that describes the value of observing targets (and all associated parameters, such as sun-angle, cloud cover, simultaneous observation, sensor type). The Observation Coordination Planner allocated targets and value functions to each domain planner, the SBS[4] planner, the UAV[5] planner, and the USV[6] planner. Each of the lower level planners produces a plan for each sensor platform, including both movement and observation plans for non-space-based sensors and observation plans for space-based sensors.
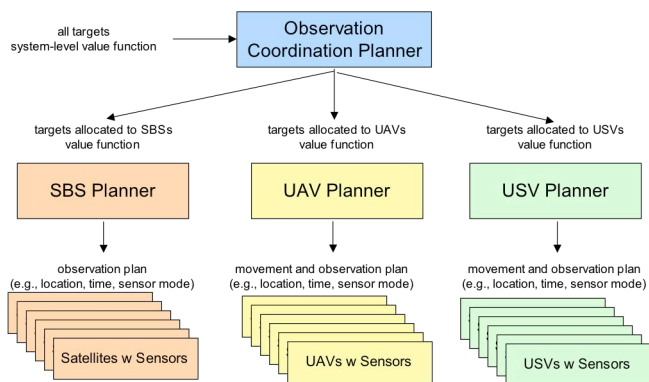

Figure 7: EPOS Functional Architecture for Sensor Web Planner

In our previous years' ESTC papers, we have presented a number of Space-Based Sensor Planner optimization-based formulations developed and integrated within EPOS. The formulations were developed to address: 1) single maneuverable (phase-changing) pointable and taskable satellites observing multiple targets (2001); 2) multiple pointable and taskable satellites observing multiple targets (2002 - 2004); 3) single modal satellites with complex modes (2005 - 2006). We are using previously developed SBS planning formulations for the fire demo in 2007.

Currently we are developing a USV planner, described in the next section. Results from ongoing EO-1 operations, described in detail in our ESTC paper from 2006, are given in the section after that. UAV planning for the fire demo

will be based on previous single UAV planner development Draper has done; future work in our AIST-05 project will extend and enhance UAV Planner capabilities to handle multiple vehicles and more complex missions.

A. UNMANNED SURFACE VESSELS PLANNING

Each USV is regarded as part of a sensor web that also includes in-situ (e.g., buoys), airborne, and space-based sensors. The USVs collect scientific data autonomously, e.g., atmospheric, air/sea temperature; relative humidity; wind velocity; chlorophyll concentrations. In particular, we assume that they can carry sensors to measure temperature below the surface, of particular benefit for hurricane prediction modeling.

Example vehicles include the OASIS boats (pictured below) and the DoD Spartan 11-meter USV.

Figure 8: OASIS Boat

The USV planning problem is the following: given a number of vessels, with known initial starting locations, available to assign to different scientific goals, decide what boats should be assigned to which observation areas at what times with given time restrictions. Example application scenarios include temperature observation collection for hurricane forecasting, and tracking a harmful algal bloom outbreak.

Model inputs include:

1. Number of USVs available
2. Number of targets
3. Coordinate locations of USV starting locations and targets
4. Velocity and direction of the tidal current
5. Velocity of each USV
6. Required target observation times
7. Target observation values
8. Time windows of opportunity for each target to be observed
9. Planning horizon

Model outputs include:

1. Inter-target observation path used in plan for each USV
2. Finished observation times for each location observed
3. Idle times at each leg for each USV
4. Total value for each USV plan

[4] Space-Based Sensor
[5] Unmanned Air Vehicle
[6] Unmanned Surface Vessel

The combinatorial nature of the mathematical problem means that for realistic-sized problems, pure optimization is impractical. Branch-and-bound integer programming optimal algorithms work for small cases, e.g., problems of 40 target observation areas and 4 boats were solved in 30 minutes.

Heuristics are needed for larger problems, e.g., 20 boats with many thousands of observation areas. New solutions need be generated as the environment changes. Hence, we need to be able to generate new solutions relatively quickly, e.g., within a few minutes. Appropriate heuristics will yield optimized, but not provably optimal, solutions for realistically sized problems.

Example results are illustrated in Figure 9. The scenario includes a hurricane located to the southwest of the 100-mile square grid. The projected path of the hurricane to the northeast results in the value function illustrated, with red for high value locations and blue for low value locations, with other colors having intermediate values. The resulting paths for the 12 boats traveling at 2 knots for a 24-hour period are shown. Time windows for locations closer to the hurricane are shorter. The planner sends boats to make observations during the time window close to the hurricane before moving to high-value areas.

A full description of the USV planner can be found in John Miller's MIT Operations Research Center Master's thesis: Large-Scale Dynamic Observation Planning for Unmanned Surface Vessels.
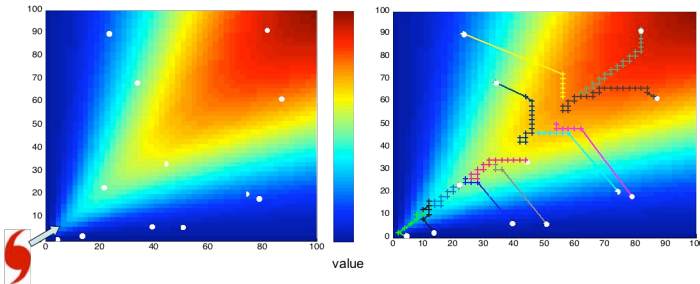
Figure 9: Example Hurricane Scenario Results from Local Search

B. *RESULTS FROM ONGOING EO-1 OPERATIONS USING EPOS*

We are continuing to plan imaging selection for EO-1 operations, based on cloud forecasts developed from Air Force Weather Agencies SCFM[7] data. Table 1 provides the results from the last six months of operations, as well as the nine previous months for comparison. Overall, EPOS selections have a 76.4% success rate.

Evaluation period	January 2 - September 30, 2006 (271 days)	October 1, 2006 to March 29, 2007 (177 days)
Total number of orbital revolutions with a scheduling scene	3750	2577
Total number of opportunities for target picks	396	179
Total number of alternate targets picked by EPOS	61	49
Total numbers of our picks that EO-1 actually imaged	55	43
Number of successful picks (less cloud cover over EPOS pick)	47 (out of 61)	37 (out of 49)
Number of unsuccessful picks	14 (out of 61)	12 (out of 49)

Table 1: Results from Ongoing EO-1 Operations using EPOS

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[7] Stochastic Cloud Forecast Model