

Making an Impact

Artificial Intelligence at the Jet Propulsion Laboratory

Steve Chien, Dennis DeCoste, Richard Doyle, and Paul Stolorz

■ The National Aeronautics and Space Administration (NASA) is being challenged to perform more frequent and intensive space-exploration missions at greatly reduced cost. Nowhere is this challenge more acute than among robotic planetary exploration missions that the Jet Propulsion Laboratory (JPL) conducts for NASA. This article describes recent and ongoing work on spacecraft autonomy and ground systems that builds on a legacy of existing success at JPL applying AI techniques to challenging computational problems in planning and scheduling, real-time monitoring and control, scientific data analysis, and design automation.

AI research and technology development reached critical mass at the Jet Propulsion Laboratory (JPL) about five years ago. In the last three years, the effort has begun to bear fruit in the form of numerous JPL and National Aeronautics and Space Administration (NASA) applications of AI technology in the areas of planning and scheduling, real-time monitoring and control, scientific data analysis, and design automation. Such successes, described in detail in this article, have also set the stage for JPL AI researchers and technologists to seize an unprecedented opportunity: the commitment by NASA to the development of software technology to realize highly autonomous space platforms. This strategic shift by NASA, in which AI technology will play a central and critical role, includes an important historically missing piece of the picture: the availability of space missions whose primary purpose is the validation of new technologies. NASA's New Millennium Program fills exactly this gap. Some of the most important work

described here is in the context of the remote-agent autonomy technology experiment that will fly on the New Millennium Deep Space One Mission in 1998 (a collaborative effort involving JPL and NASA Ames). Many of the AI technologists who work at NASA expected to have the opportunity to build an intelligent spacecraft at some point in their careers; we are surprised and delighted that it has come this early.

By the year 2000, we expect to demonstrate NASA spacecraft possessing on-board automated goal-level closed-loop control in the planning and scheduling of activities to achieve mission goals, maneuvering and pointing to execute these activities, and detecting and resolving of faults to continue the mission without requiring ground support. At this point, mission accomplishment can begin to become largely autonomous, and dramatic cost savings can be achieved in the form of reduced, shared ground staffing that responds on demand to beacon-based requests for interaction originating from the spacecraft. Indeed, a New Millennium Program Mission Operations Study estimated that remote-agent technology could reduce mission operations cost, exclusive of data analysis, by as much as 60 percent.

By 2005, we expect that a significant portion of the information routinely returned from space platforms would not be raw data, and would not simply and strictly match features of stated prior interest, but would be deemed by the on-board software to be interesting and worthy of further examination by scientists on the ground. At this point, limited-communications bandwidth would be used in an extremely efficient fashion, and science alerts from various and far-flung platforms

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would be anticipated with great interest.

The first steps toward realizing this vision are happening now and are described in the following paragraphs. Although the early goal for autonomy technology is the reduction of mission operations costs, the ultimate payoff will be the enabling of new mission classes and the launching of a new era of solar system exploration, beyond reconnaissance. Spacecraft missions in this new era will be characterized by sustained presence and in-depth scientific studies performed by free flyers, orbiters, and ground vehicles, sometimes arrayed in constellations. Autonomy will be the central capability for enabling long-term scientific studies of a decade or more, currently prohibited by cost, and enabling new classes of missions that inherently must be executed without the benefit of ground support, either because of control challenges, for example, small-body (asteroid and comet) rendezvous and landing missions or because of the impossibility of communication for extended periods, for example, an underice explorer at Europa or a Titan aerobot. The vision for future NASA missions based on intelligent space platforms is tremendously exciting.

The need for autonomy technology is nowhere greater than in the set of deep space planetary missions that JPL conducts for NASA. The extreme remoteness of the targets, the impossibility of hands-on troubleshooting or maintenance, and the difficulties of light-time delayed communication (over four hours round trip to the outer solar system) all contribute to make JPL science missions the focus of the development and application of autonomy technology (Doyle, Gor, et al. 1997). JPL has been designated the lead NASA center for spacecraft autonomy not only because of the nature of its missions but also because of its unique combination of resident expertise in AI, spacecraft engineering, space mission design, and systems engineering.

Not surprisingly, the imperative of cost constraints as drivers for the development of autonomy capabilities are balanced against significant perceived risk in on-board uses of AI technology. An important ingredient in making this opportunity credible and real are the previous successes at JPL in the applications of AI. Two of the most notable of these successful applications are the sky-image cataloging and analysis tool (SKICAT) and the multimission VICAR (video image communication and retrieval) planner (MVP). SKICAT (Fayyad, Djorgovski, and Weir 1996b) completely automated the process of reducing

data from digitized photographic plates of the night sky collected at the Mt. Palomar astronomical observatory—identifying and classifying sky objects indexed into a comprehensive catalog containing approximately three billion entries. SKICAT was able to classify extremely faint objects that were beyond the reach of expert-astronomer visual inspection. It was recently utilized to discover 16 new quasars, among the most distant objects in the universe. For the first time, astronomers have an objective basis for conducting unprecedented, large-scale cosmological studies. SKICAT remains one of the most outstanding successes for machine-learning technology to date. This work was led by Usama Fayyad, in collaboration with George Djorgovski of the Astronomy Department at the California Institute of Technology (Caltech).

The MVP system (Chien and Mortensen 1996) applied AI planning techniques to the problem of automatic software configuration for image analysis. The VICAR set of image-processing routines has been developed over a period of many years at JPL. These routines support image-processing steps such as mosaicking and color-triplet reconstruction. Powerful but cumbersome to use, the VICAR routines support an essential processing phase before true scientific image analysis can begin. MVP is a front end for VICAR and allows scientists and other users to simply state their image-analysis goals. The system automatically analyzes data dependencies and other constraints and configures the appropriate VICAR routines to achieve these goals. MVP reduces the time to construct a typical VICAR job from 4 hours to 15 minutes for expert users and from days to hours for novice users. The system is being used to support the analysis of images being returned from the *Galileo* spacecraft during its current tour of the Jupiter planetary system. This work was led by Steve Chien, in collaboration with Helen Mortensen of JPL's Multimission Image-Processing Laboratory.

AI research and development activities at JPL are conducted primarily by three research groups: (1) the Artificial Intelligence (AI) Group, led by Steve Chien, which focuses on automated planning and scheduling and design automation; (2) the Machine Learning Systems (MLS) Group, led by Paul Stolorz; and (3) the Monitoring and Diagnosis Technology (MDT) Group, led by Dennis DeCoste. The effort was once housed in the single AI group but has steadily grown: Its 30 to 40 practitioners now make up 3 of the 9 groups in JPL's Information and Computing Tech-

nologies Research Section, led by Richard Doyle.

In the remainder of the article, we describe in greater detail the major AI projects at JPL. In particular, we describe efforts in the areas of planning and scheduling, monitoring and diagnosis, knowledge discovery and data mining, and automated design.

Planning and Scheduling

As the NASA lead for unmanned exploration of deep space, JPL has led missions to the outer reaches of the solar system (as exemplified by the Voyager, Galileo, and Cassini missions). Although these missions have achieved enviable success, NASA is now being challenged to perform future missions with smaller budgets, shorter cycle times, and smaller science and operations teams. One major element in mission operations is the problem of command, control, and scheduling. From an applications perspective, this area encompasses the determination of correct actions and required resources for mission operations, both for the spacecraft as well as for all the elements of the ground system necessary to run the mission. From a technology perspective, this area focuses on planning, scheduling, and task-execution architectures.

In this section, we outline ongoing efforts at JPL in research, development, and deployment of these technologies to automate command, control, and resource-allocation functions to reduce operations teams, reduce command cycle times, and increase the efficiency of the utilization of scarce resources, all targeted at enabling increased science and space exploration at reduced cost. We begin by first describing efforts in the area of spacecraft commanding and on-board task execution, describing projects for the New Millennium Deep Space One Mission and the Earth Orbiter One Mission, the U.S. Navy *UFO-1* satellite, and the data-chaser shuttle payload. We then describe projects in automation of ground systems—specifically in automating operations of the deep space network (DSN), which is used for communicating with spacecraft, navigating spacecraft, and using radio science. We then describe the MVP Project to use planning technology to assist in science data preparation and analysis. Finally, we describe basic technology work in machine learning for next-generation planning and scheduling systems able to automatically adapt to changing problem distributions and context.

Planning, Scheduling, and Task Execution for Spacecraft Commanding

Spacecraft command generation and validation is an expensive and labor- and knowledge-intensive process. Enabling direct high-level commanding of spacecraft by engineering and science personnel greatly reduces the requirements for highly skilled spacecraft-cognizant personnel during nominal operations, thereby cutting down on mission operations costs. A New Millennium Program Mission Operations Study concluded that automating command and control functions could have resulted in a savings of \$14 million a year for a Magellan-class mapping mission and \$30 million a year for a Galileo-class multiple-flyby mission.

In a ground-based context, direct commanding of the spacecraft by science personnel also allows for the opportunity to conduct truly interactive science—an embodiment of the concept of a virtual spacecraft on the internet. In certain cases, automated spacecraft commanding can enhance science return by increasing the efficiency of resource management (for example, data and power management). If it is possible to run the planner on board the spacecraft, additional benefits can be realized: First, communication with the spacecraft can be reduced greatly in that commands do not need to be uplinked, and reduced spacecraft state information can be downlinked. Second, by avoiding the communications loop, autonomous commanding of the spacecraft with an on-board system allows for an immediate response to changes in spacecraft state (for example, faults) or discoveries from science analysis.

In a collaborative effort involving the AI group and the Sequencing Automation Research Group at JPL and the Computational Sciences Division (Code IC) of the NASA Ames Research Center, AI planning, scheduling, and intelligent task control techniques are being developed and applied for on-board control of highly autonomous spacecraft. The automated scheduler and task-execution technologies are being developed for the New Millennium Deep Space One Mission, the first of the deep space missions planned for the New Millennium Program. This small spacecraft will fly by an asteroid and a comet, with a launch expected in 1998. The primary objective of the New Millennium Program is the demonstration of new technologies that will greatly advance the state of the art in space exploration. One of the new technologies for the Deep Space One Mission is an autonomy software package, named the

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remote agent, that will fly on board the spacecraft. The *remote agent* has three components: (1) the smart executive, (2) mode identification and recovery, and (3) the planner-scheduler; these components work together to autonomously control the spacecraft (Pell, Bernard, et al. 1996).

The *planner-scheduler* (Mussettola et al. 1997) generates a sequence of low-level commands, given an initial state and a set of high-level goals from the scientists and engineers. Performing this task requires a significant knowledge of the spacecraft operations, possible spacecraft states, operability constraints, and low-level commands that are executable by the smart executive. In addition, heuristic knowledge about priorities and preferences might be required to generate better-quality solutions in a shorter time. The planner system builds a schedule while it respects the encoded spacecraft constraints, science and engineering preferences, and synchronization with external processes. An incremental refinement approach is used to provide an exhaustive search that guarantees the generation of a solution schedule from correctly encoded goals and knowledge.

In addition to deliberative planning, an autonomous spacecraft requires the ability to execute incompletely specified plans and the ability to respond quickly and intelligently to unforeseen run-time contingencies. The MLS group, in collaboration with the Computational Sciences Division of the NASA Ames Research Center, is developing a smart executive to provide these capabilities for the New Millennium Deep Space One Mission (Pell, Gat, et al. 1996).

The executive is implemented using a language developed at JPL called the execution support language (ESL) (Gat 1997). ESL provides a set of advanced control constructs that simplify the job of writing code to manage multiple concurrent tasks in the face of unexpected contingencies. It is similar in spirit to RAPs (reactive action packages), RPL (reactive plan language), and RS, and its design owes much to these systems. Unlike its predecessors, ESL aims for a more utilitarian point in the design space. It was designed primarily to be a powerful and easy-to-use tool, not to serve as a representation for automated reasoning or formal analysis (although nothing precludes its use for these purposes). ESL consists of several sets of loosely coupled features, including contingency handling, concurrent task management, and a backtracking logical database. A set of constructs for run-time resource management is currently being developed.

In addition to the deployment of on-board planning and task control technology on the New Millennium Deep Space One Mission, there are additional projects under way to deploy planning and scheduling technology in a ground-based context using the automated scheduling and planning environment (ASPEN) and also the data-chaser automated planning and scheduling system (DCAPS) for direct-science commanding.

A number of successful applications of automated planning and scheduling of spacecraft operations have recently been reported in the literature. However, these applications have been one-of-a-kind applications that required a substantial amount of development effort. To reduce this development effort, the AI group at JPL has been working on ASPEN (Fukunaga et al. 1997a), a modular, reconfigurable application framework that is capable of supporting a wide variety of planning and scheduling applications. ASPEN provides a set of reusable software components that implement the elements commonly found in complex planning-scheduling systems, including an expressive modeling language, a resource-management system, a temporal reasoning system, several search engines, and a graphic user interface (GUI).

The primary application area for ASPEN is the spacecraft operations domain. Planning and scheduling spacecraft operations involves generating a sequence of low-level spacecraft commands from a set of high-level science and engineering goals. ASPEN encodes complex spacecraft operability constraints, flight rules, spacecraft hardware models, science experiment goals, and operations procedures to allow for the automated generation of low-level spacecraft sequences by using constraint-driven planning and scheduling technology. ASPEN is currently being used in the development of automated planner-scheduler systems for commanding the *UFO-1* naval communications satellite and the New Millennium *Earth Orbiter One* spacecraft as well as a scheduler for ground maintenance of the highly reusable space transportation.

Figure 1 shows information on the application of ASPEN to generating operations plans for the New Millennium Earth Orbiter One Mission. The top portion of figure 1 shows the interface to the scheduler, displaying the relevant observation activities (the observation activities shown at the top on the ActTL timeline), the resources used (the observation instrument/ETM, data storage device/SSR, transponder, for example), and relevant exogenous events (such as sun angle state).

The bottom section of figure 1 shows a small portion of the temporal constraint network relating to the synchronization of a downlink activity with ground stations used to derive the schedule. The squares correspond to important events (activities, states, and resource values), and the brackets indicate the minimum and maximum time between the events.

DCAPS (Rabideau et al. 1997) is a collaborative effort involving the AI group and the Sequencing Automation Research Group at JPL and the Colorado Space Grant Consortium at the University of Colorado at Boulder. In DCAPS, AI planning and scheduling techniques are being developed and applied to enable direct goal-based science and engineering commanding.

Data-chaser is a shuttle payload scheduled for flight in July 1997. Data-chaser contains three solar science instruments and is part of the Hitchhiker Student Outreach Program. DCAPS uses iterative repair planning and scheduling techniques to automatically generate the low-level command sequence involving spacecraft operability constraints, science and engineering preferences, and synchronization constraints with external processes. The iterative repair approach to planning and scheduling is useful in that it allows for natural interaction with the user.

Automated Planning and Scheduling for Operations of the Deep Space Network

Each day at sites around the world, NASA's DSN antennas and subsystems are used to perform scores of tracks to support earth-orbiting and deep space missions (Chien, Hill, et al. 1996; Hill, Chien, et al. 1996). However, the actual tracking activity is merely the culmination of a complex, knowledge-intensive process that actually begins years before a spacecraft's launch. When the decision is made to fly a mission, a forecast is made of the DSN resources that the spacecraft will require. In the resource-allocation process, the types of service, frequency, and duration of the required tracks are determined as well as high-level (for example, antenna) resource requirements. Although the exact timing of the tracks is not known, a set of automated forecasting tools is used to estimate network load and assist in ensuring that adequate network resources will be available. The Operations Research Group has developed a family of systems that use operations research and probabilistic reasoning techniques to allow forecasting and capacity

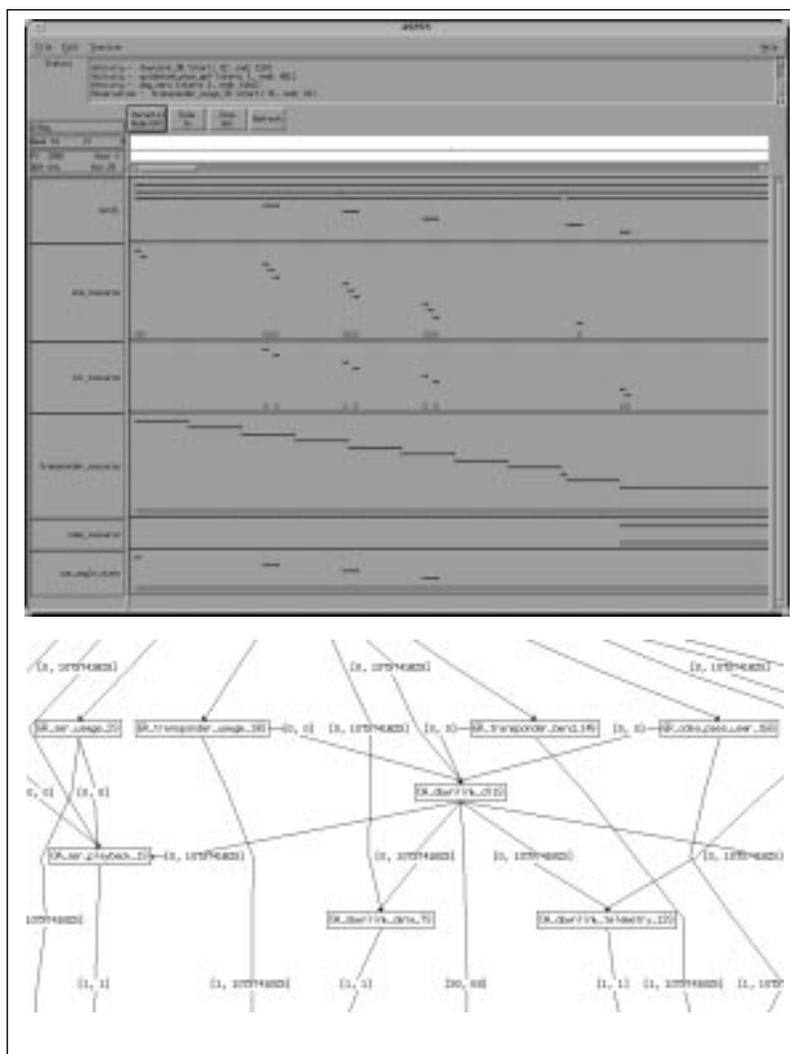


Figure 1. ASPEN-Generated Plans for the New Millennium Earth Orbiter One Spacecraft.

Top: Earth Orbiter One operations plan derived by the ASPEN scheduler. Bottom: Temporal constraint subnetwork used to derive temporal constraints on activities relating to data transmission to a ground station.

planning for DSN resources (Fox and Borden 1994; Loyola 1993).

As the time of the actual tracks approaches, this estimate of resource loading is converted to an actual schedule, which becomes more concrete as time progresses. In this process, specific project service requests and priorities are matched up with available resources to meet communications needs for earth-orbiting and deep space spacecraft. This scheduling process involves considerations of thousands of possible tracks, tens of projects, tens of antenna resources, and considerations of hundreds of subsystem configurations. In

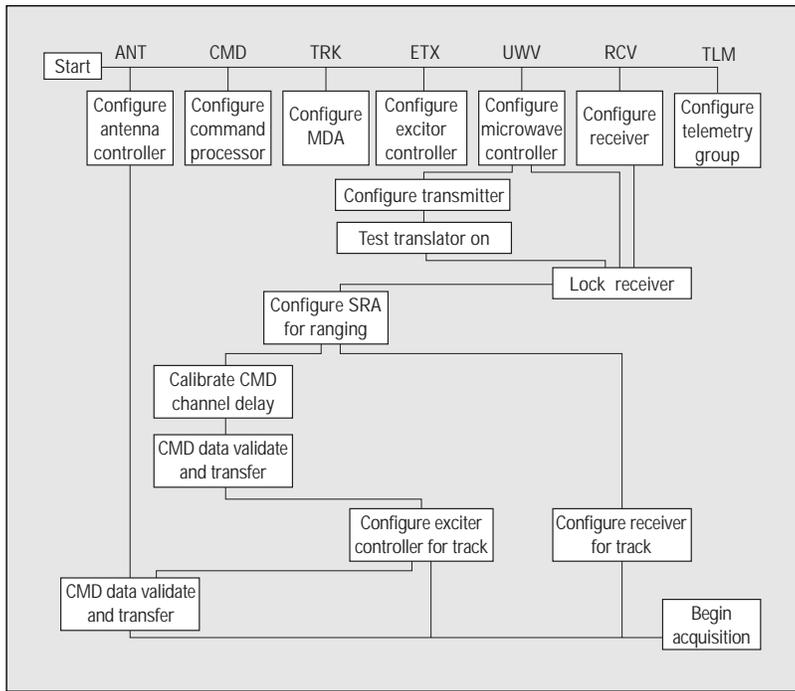


Figure 2. Plan Constructed by Deep Space Network Antenna Operations Planner for Precalibration of a 34-Meter Beam Waveguide Antenna for a Telemetry Commanding and Ranging Track.

addition to adding the detail of antenna subsystem allocation, the initial schedule undergoes continual modification as a result of changing project needs, equipment availability, and weather considerations. Responding to changing context and minimizing disruption while rescheduling are key issues.

In 1993, the OMP-26M scheduling system was deployed, partially automating the scheduling of the network of 9-, 11-, and 26-meter (m) antennas. Use of OMP-26M resulted in a fivefold reduction of scheduling labor, and network use doubled. The demand-access network scheduler (DANS) (Chien, Lam, and Vu 1997) is an evolution of the OMP-26M system designed to deal with the more complex subsystem and priority schemes required to schedule the larger 34- and 70-m antennas. Because of the size and complexity of the rescheduling task, manual scheduling is prohibitively expensive. Automation of these scheduling functions is projected to save millions of dollars a year in DSN operations costs.

DANS uses priority-driven, best-first, constraint-based search and iterative optimization techniques to perform priority-based rescheduling in response to changing network demand. With these techniques, DANS first considers the antenna-allocation process

because antennas are the central focus of resource contention. After establishing a range of antenna options, DANS considers allocation of the 5 to 13 subsystems (out of the tens of shared subsystems at each antenna complex) that are used by each track. DANS uses constraint-driven, branch-and-bound, best-first search to efficiently consider the large set of possible subsystem schedules.

Once a specific equipment and timing assignment has been made, there is the problem of determining how to operate the equipment to achieve the requested services. Because of the complexity of the equipment, the large set of communications services (in the tens), and the large number of supported equipment configurations (in the hundreds), correctly and efficiently operating this equipment to fulfill tracking goals is a daunting task.

The DSN antenna operations planner (DPLAN) (Chien, Govindjee, et al. 1997, 1996) is an automated planning system developed by the AI group to automatically generate antenna-tracking plans to satisfy DSN service requests. To generate these antenna operations plans, DPLAN uses the project-generated service request (planning goals), the track equipment allocation (initial state), and an antenna operations knowledge base. DPLAN uses both hierarchical-task network-planning techniques and operator-based planning techniques to synthesize these operations plans. By allowing both operator-based and hierarchical-task network representations, the antenna operations knowledge base allows a modular, declarative representation of antenna operations procedures. In contrast, consider the two non-AI alternatives proposed: (1) operations script and (2) an exhaustive library of plans. Neither operations scripts nor an exhaustive library of plans explicitly record the generality and context presumed by operations procedures. Planning representations' explicit representation of such information should make them easier to maintain as DSN equipment and operations procedures evolve.

DPLAN was initially demonstrated in February 1995 for *Voyager* downlink, telemetry tracks at the DSS-13 antenna at Goldstone, California. DPLAN is currently being integrated into the larger network monitor and control upgrade being deployed at DSN stations that will enable automation projected to reduce DSN operations costs by over \$9 million a year. The current DPLAN system supports the full range of 34-m and 70-m antenna types, all standard service-request classes, and

approximately 20 subsystems. Figure 2 shows a plan generated by DPLAN to perform precali- bration of a 34-m beam waveguide antenna to provide a telemetry, commanding, and ranging services track. Current work on the DPLAN system focuses on enhancing the sys- tems replanning capability and its ability to represent and reason about plan quality (Chien, Hill, et al. 1996).

Planning Systems for Science Data Preparation and Analysis

In the MVP (Chien and Mortensen 1996; Chien 1994) project, planning techniques are being applied to develop a system to auto- matically generate procedures to satisfy incoming science requests for data. MVP allows a user to input image-processing goals based on the availability and format of rele- vant image data and produces a plan to achieve the image-processing goals. This plan is then translated into an executable VICAR program.

In contrast, manual writing of VICAR scripts is a knowledge-intensive, labor-inten- sive task requiring knowledge of image-pro- cessing techniques, knowledge of image

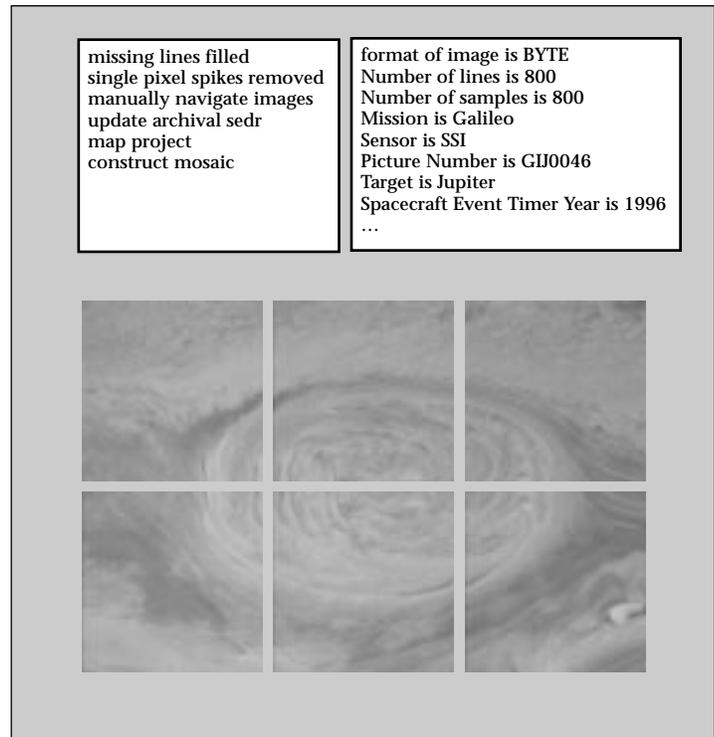


Figure 3. Goals, Initial State, and Raw Images.

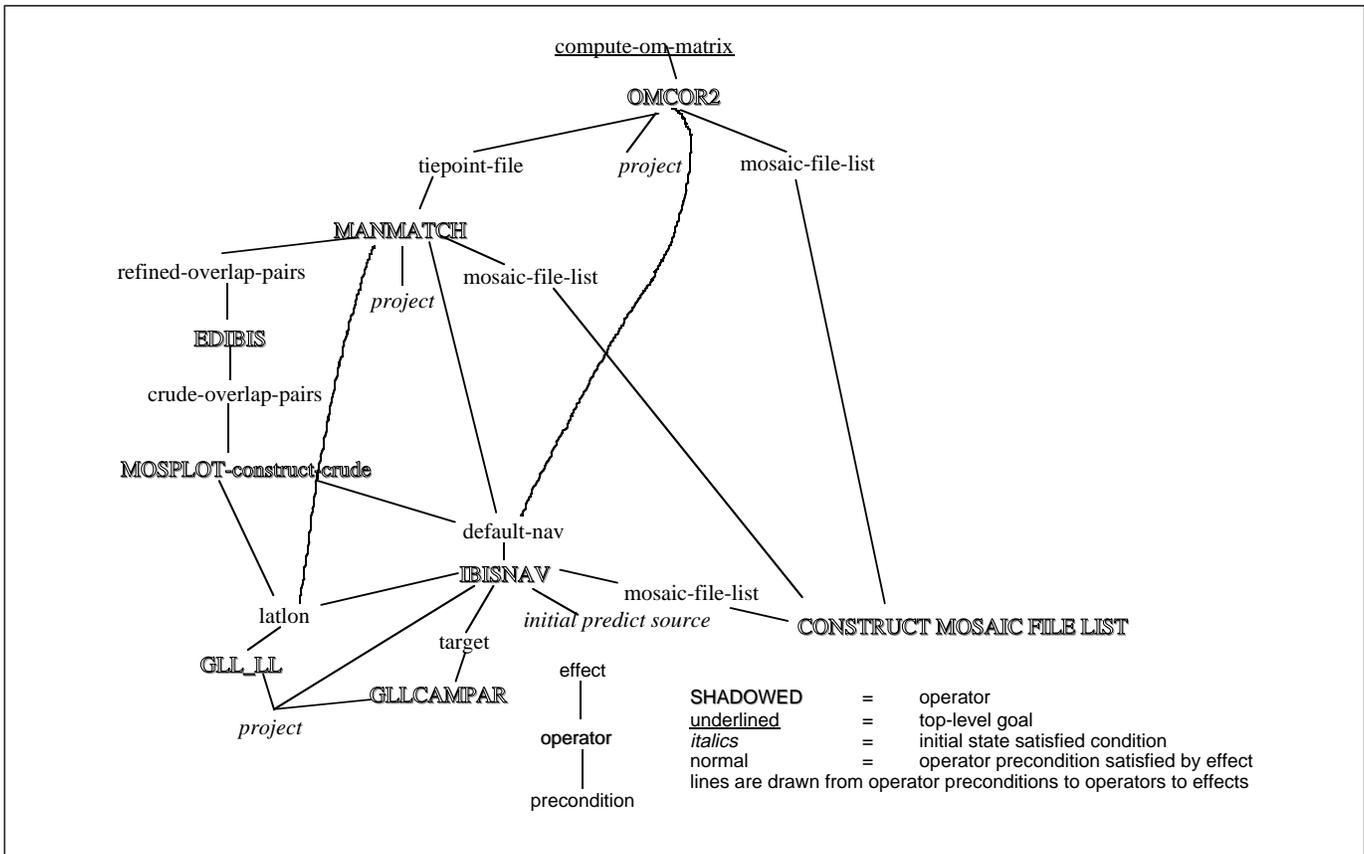


Figure 4. Subplan.

Conceptual Steps	VICAR Code
get initial navigation information	IBISNAV OUT="file_list.NAV" PLANET=target_0_10 + PROJECT="GLL" * SEDR=@RIMSRC FILENAME="file_list.ilist"
construct initial overlap pairs	!! Construct initial overlap pairs MOSPLOT MOSPLOT inp="file_list.NAV" nl=lines_0_6 project="GLL" * ! mos.overlap is just a holder for the overlap plot. dcl copy printnx.plt mos.overlap dcl print/need mos.overlap
refine initial overlap pairs	!! Refine initial overlap pairs edibis EDIBIS INP="file_list.OVER"
find previous tiepoint file (if present)	!! Manmatch mosaic file list !! If there is no existing tiepoint file.... !! Check if a tiepoint file exists. !! The following code is in written VMS !! LOCAL STR STRING INIT = "" LET _ONFAIL = "CONTINUE" !! Allow the pdf to continue !! if a file is not found. DCL DEASSIGN NAME DCL DEFINE NAME 'F\$SEARCH("file_list.TP") LOCAL STR STRING TRANSLONG NAME STR LET _ONFAIL = "RETURN" !! Set PDF to return on error
use manmatch program to construct or refine tiepoint file	IF (STR = "") MANMATCH INP=("file_list.NAV","file_list.OVER") + OUT="file_list.TP" PROJECT="GLL" * SEDR FILENAME="file_list.ILIST" !! If an old tiepoint file exists... !! The old tpoint is part of input and later overwritten. ELSE MANMATCH INP=("file_list.NAV","file_list.OVER","file_list.TP") + OUT="file_list.TP" PROJECT="GLL" * SEDR FILENAME="file_list.ILIST"
use tiepoints to construct OM matrix	!! OMCOR2 OMCOR2 INP=("file_list.NAV","file_list.TP") PROJECT="GLL" * GROUND=@GOOD OMCOR2 INP=("file_list.NAV","file_list.TP") PROJECT="GLL" * GROUND=@GOOD

Figure 5. MVP-Produced VICAR Code.

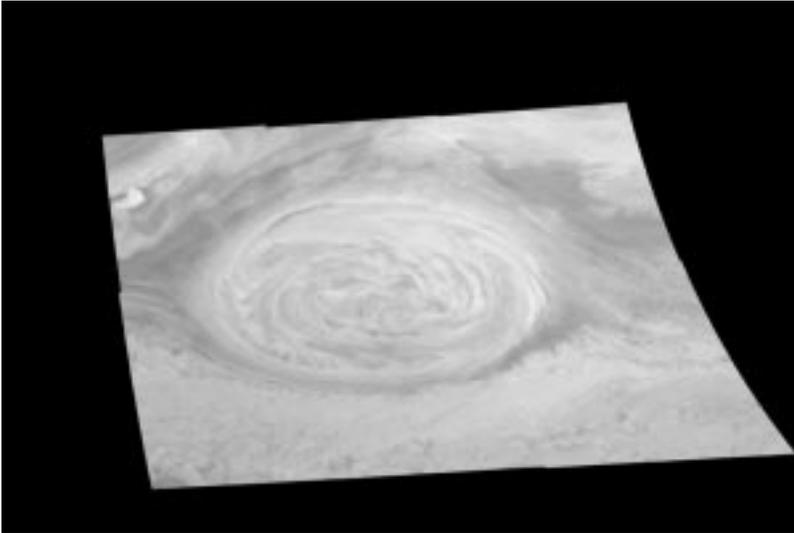


Figure 6. Final Images Produced by MVP.

database organization and metadata conventions, and knowledge of the VICAR programming environment. Analysts require several years to become VICAR experts, and producing each VICAR script takes hours to months of analyst effort. Automating the filling of more routine tasks by the MVP system frees up expert analyst time for more complex, unique processing requests.

MVP is currently being used to produce sci-

ence products for the *Galileo* Jupiter encounter. For radiometric correction, color-triplet reconstruction, and simple mosaicking tasks, MVP reduces the effort to generate an initial VICAR script for an expert analyst from 4 hours to 15 minutes and for a novice analyst from several days to 4 hours.

Figure 3 shows the beginning of the succession of steps. At the top, the image-processing goals (stated by the user using a GUI), image state (derived automatically from the image database), and input raw images are shown. In figure 4, the plan structure for a portion of the overall plan is shown. In this graph, nodes represent image-processing actions and required image states to achieve the larger image-processing goal. Figure 5 shows the actual MVP-generated VICAR code, highlighting the correspondence to the image-processing steps in the plan. Finally, in figure 6, we have the produced (output) science product—a mosaic of Jupiter's Red Spot constructed from the raw images received from the *Galileo* spacecraft currently in orbit around Jupiter.

Although MVP successfully automates certain image-processing tasks, in deploying MVP, we learned the high cost of knowledge base maintenance (approximately 0.8 work-years of effort during the first year of operation). Correspondingly, current work focuses on knowledge base analysis tools to assist in the process of planning knowledge base development, validation, and maintenance (Chien 1996).

Machine Learning for Large-Scale Planning and Scheduling

Although most scheduling problems are NP-complete in worst-case complexity, in practice, for specific distributions of problems, domain-specific search strategies have been shown to perform in much better than exponential time. However, discovering these search strategies is a painstaking, time-consuming process that requires extensive knowledge of both the domain and the scheduler. The goal of adaptive problem solving (APS) is to automate this process of customization by learning heuristics specialized to a distribution of problems.

Our APS work focuses on statistical learning methods used to search for and recognize superior problem-solving customizations and heuristics (Gratch and Chien 1996; Chien, Gratch, and Burl 1995). Work to date has achieved strong results. Using the LR-26 scheduler on scheduling data for 1996 to 1997, statistical machine-learning techniques

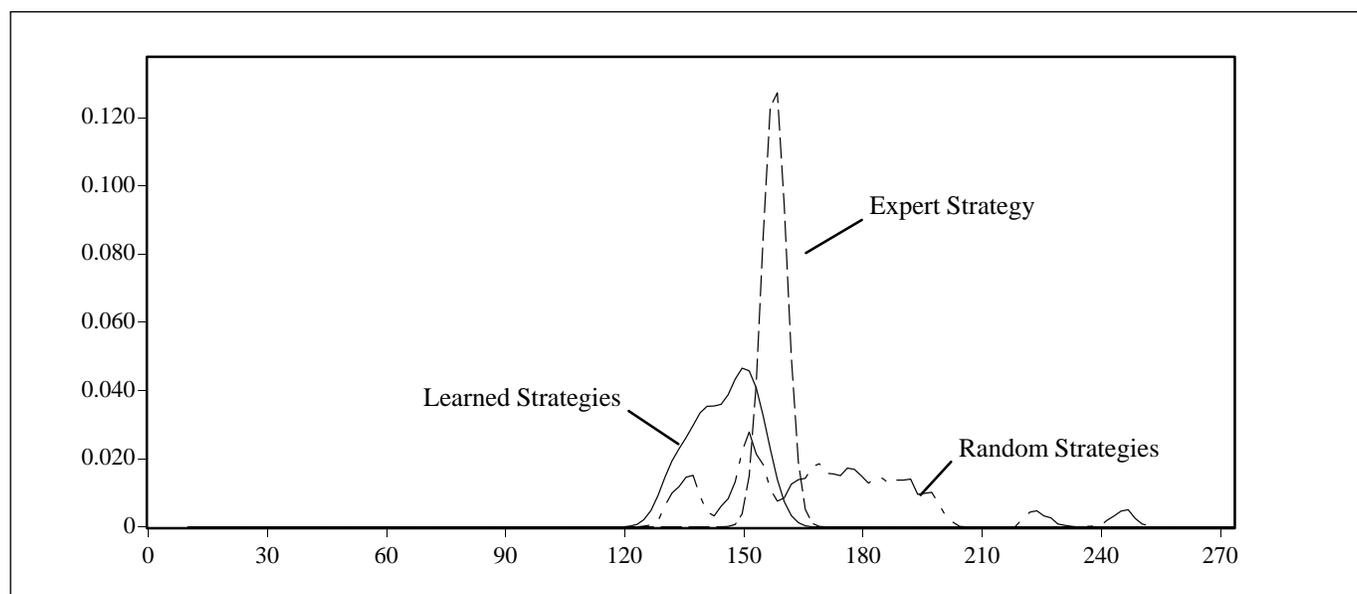


Figure 7. Estimated Expected Utility of Machine-Derived, Human Expert-Derived, and Randomly Generated Strategies for Antenna Scheduling.

found strategies that improved on human expert-derived strategies by decreasing central processing unit time for solvable problems by 50 percent and increasing solvable problems by 15 percent. We are currently extending techniques to allow for specialization of control strategies as directed by empirical learning methods and allow for control of constraint relaxation to improve schedule quality.

Figure 7 illustrates the effectiveness of the machine-learning techniques. It shows the probability density functions for the utility of strategies derived using APS, the human expert-derived strategy, and randomly selected strategies in the entire encoded strategy space. In this data set, higher utility corresponds to lower problem-solving time (toward the left of the graph), and the data clearly indicate the superiority of the APS-derived strategies over the human expert-derived strategy (which is already significantly better than an average strategy in the complete strategy space).

Monitoring and Diagnosis

To address the key NASA goals of faster, cheaper, and better mission operations, the MDT group and the MLS group have been developing a set of complementary methods that are suitable for both on-board and ground-based robust anomaly identification.

Both in research and in practice, diagnosis work on complex analog domains tends to

oversimplify the initial task of symptom identification. In such work, anomaly detection typically does little more than limit-sensing sensor data against static, manually predefined *red lines*, or predictions of expensive simulations. However, the smaller budgets and novel challenges of future NASA missions demand cheap, robust, and early detection to maximize the opportunities for low-cost preventive operation. Because complex NASA domains typically contain both large volumes of both engineering sensor data and human expertise, our collective work at JPL pushes both machine-learning and knowledge engineering methods but strives to find an effective balance. In the following paragraphs, we summarize our recent work in these areas.

Initial work in this area focused on the task of continually identifying which sensors are currently the most interesting, using information-theoretic metrics. This work led to the selective monitoring (SELMON) system (Doyle 1995; Doyle et al. 1993). SELMON compares histograms of current data against those of historic data, identifying sensors whose binned frequency distributions are more distinct than historic (expected) ones. It can also use causal orderings among the sensors to help conditionalize and isolate anomalies. SELMON overcomes the oversimplicity of traditional limit sensing but ignores the significance of global context and temporal ordering. Thus, it is most appropriate for data sets that are statistically stationary.

The ELMER system focuses on the task of automated real-time detection of anomalies in time-series data.

The ELMER (envelope learning and monitoring using error relaxation) system, recently developed by the MDT group (DeCoste 1996), focuses on the task of automated real-time detection of anomalies in time-series data. It specifically addresses the issues of context dependencies and nonstationary time-series data. It is being field tested in several NASA domains, including the space shuttle, the extreme-ultraviolet explorer, and DSN. Each such complex real-world domain requires monitoring thousands of sensors and provides millions of historic samples of each sensor for training.

ELMER provides a data-driven, iterative, three-stage approach to multivariate time-series prediction: (1) systematic selection of input feature reencodings (for example, time-windowed mins, maxs, means, derivatives, lag vectors), (2) greedy (linear-time complexity) nonlinear feature construction (for example, products, sigmoidals), and (3) linear regression (with relaxed error metrics). ELMER's third stage is particularly novel: explicitly learning two separate functions, for high- and low-expectation bounds (envelopes) for future data versus one traditional overall least squared fit. By starting with each envelope as the two static red-line values traditionally used in monitoring operations, ELMER can incrementally tighten the values toward simulation-quality function bounds in an any-time manner.

ELMER differs notably from common alternatives, such as neural networks, by being highly constructive and using novel error metrics that are particularly appropriate for the constraint-checking nature of monitoring tasks (versus prediction as such). In particular, we can bias the error metrics to avoid false alarms (which commonly plague other automated approaches) at the expense of obtaining bounds that are weaker than typical neural network predictions (but still much tighter than traditional red lines). We are exploring several extensions to this work, including using both hidden Markov model learning and qualitative reasoning to better guide feature construction and selection.

We are also extending ELMER to address the more general problem of summarizing the behavior of sensor data over large windows of time, in a project called engineering data summarization (ESUM). For example, a planned mission to Pluto would spend nearly eight years in mostly uneventful cruise mode, for which automated weekly summaries of behavior (with low-downlink bandwidth) would be critical to achieving low operations costs.

Automating this process involves not only detecting and summarizing anomalies but also providing enough detail for ground engineers to verify whether the remaining behavior is truly nominal. Traditional summarization techniques focus on fixed gross statistics (for example, mins, maxs, means), prespecified event logging, and information-theoretic compression.

The goal of ESUM is to automatically select subsets of downlink data (that is, specific sensor values for specific times) sufficient for ground operators to perform diagnosis and verification tasks. ESUM can also, in part, be viewed as intelligent prefetching of data that are likely to be desired if current trends lead to clear anomalies later. Thus, it might prove useful for data archive compression management (both on board and at ground) as well. The basic approach is to select those data that ELMER's trained and adaptive envelope functions indicate are most relevant to detecting anomalies and prespecified events. We are currently exploring this work for two future NASA missions: a Pluto express flyby and a beacon experiment on New Millennium *Deep Space One*.

The MLS group is applying machine-learning techniques to the problem of modeling engineering time-series data as well. The group has developed a prototype software package that segments telemetry streams for individual sensors into distinct and statistically significant modes of activity. These algorithms provide a basis for an automated mechanism for identifying and classifying distinct system modes of operation. The software makes use of probabilistic and hierarchical segmentation algorithms (such as hidden Markov models) that observe past telemetry streams and identify distinct regimes of activity based on elemental features of the sensor time series. The software has been applied successfully to various space shuttle and extreme ultraviolet explorer satellite telemetry streams. Currently, we are investigating the application of this technology to future spacecraft design and operations, with potential benefit in the areas of prediction, anomaly detection and diagnosis, query by content, and data summarization and compression.

Whereas the previous work focused on data-driven time-series prediction and machine-learning techniques, it is also important to cost-effectively leverage the large base of human expertise available in NASA domains—particularly because historic sensor data for complex systems such as spacecraft are seldom fully representative of future

behaviors. Thus, the MDT group has also been developing methodologies and semiautomated tools for knowledge engineering, integrating, and testing of qualitative and quantitative spacecraft models suitable for robust monitoring and diagnosis.

Our current work in modeling and testing focuses on the Deep Space One Mission. We are streamlining the process of designing and implementing on-board monitoring software with the creation of a family of reusable monitoring components that are easily configured to detect important changes in status. The resulting status information feeds into the remote-agent mode-identification module (Williams and Nayak 1996) for mode tracking and diagnosis. Our monitoring components perform functions such as noise and transient filtering, min-max thresholding, sensor-limit detection, phase-plane analysis, and summarization for a much-reduced telemetry stream.

In the iterative spiral model of spacecraft design and development used for *Deep Space One*, software and hardware modules need to be integrated several times through the project. By reusing meta-information already available for defining software interfaces as messages and function calls, we are exploring the use of graph-dependency analysis techniques (Rouquette 1996) for coordinating the integration of tightly coupled software tasks, tracking complex multitask software interactions, and detecting behavioral discrepancies at the level of message passing and function calls.

Deep Space One also challenges conventional verification and validation because its fast-paced spiral-development process does not generate formal testable requirements. Instead, testing is driven by mission scenarios, and test behavior is filtered through flight rules and localized episodes of expected events. A perfect test is one that satisfies positive flight rules, avoids negative flight rules, and accounts for every data log as part of an expected episode. Our objective here is to create a scenario-based test methodology (and tools) that finds the bugs without requiring hard-to-obtain requirement specifications.

Flight software in modern spacecraft combines event-driven (reactive) programming with continuous control. Typically, both have been implemented in a procedural language such as C, but reactive designs beg for a situation-action directive in the language so that programmers can specify what to do rather than when and where to do it. Toward this goal, we are exploring the use of R++, a tight integration of C++ and path-based rules (Crawford et al. 1996).

Knowledge Discovery and Data Mining for Scientific Data Analysis

The MLS group is heavily involved in a number of projects designed to understand and exploit large-scale scientific data sets. These efforts can roughly be classified into two groups: One group consists of data-mining methods focused on the extraction of scientific insight from massive data sets, usually on the order of gigabytes to terabytes in size. These data are typically collected by spaceborne and other sensors and are then archived and managed on the ground. This work features a mixture of techniques drawn from machine learning, statistics, databases, and high-performance computing. The other major theme is the transference of machine learning and data-mining successes to the realm of space-borne computing and autonomy. By performing intelligent data processing on board spacecraft, new scientific experiments are enabled that exploit and enhance the capabilities of autonomous spacecraft. These science-driven autonomy ideas complement other work being conducted in the AI and MDT groups, with the common goal of enabling efficient autonomous spacecraft.

The data-mining work covers a broad spectrum, including nearly every major scientific subdiscipline relevant to NASA. These subdisciplines include atmospheric and earth science, planetary science, and solar physics. Several prominent themes are shared by each of these projects: an emphasis on data-driven modeling, the application of computationally intensive statistics as a major tool, and the use of a number of prominent machine-learning techniques such as decision trees and neural networks. At the same time, there are distinct differences: Some are more crucially dependent on high-performance computing than others (although in the long run, all will be driven in this direction as NASA data sets dramatically increase in size). Several are deeply concerned with temporal and spatiotemporal processes, but others focus on the accurate analysis of spatial patterns only. A major challenge for the future is to develop a systematic approach to this range of problems that allows powerful algorithms to be applied in many contexts but also accounts for the subtleties of individual data sets and problems in the process.

As an example of the scientific insight that can be obtained by merging data-mining ideas with scalable computation, consider the

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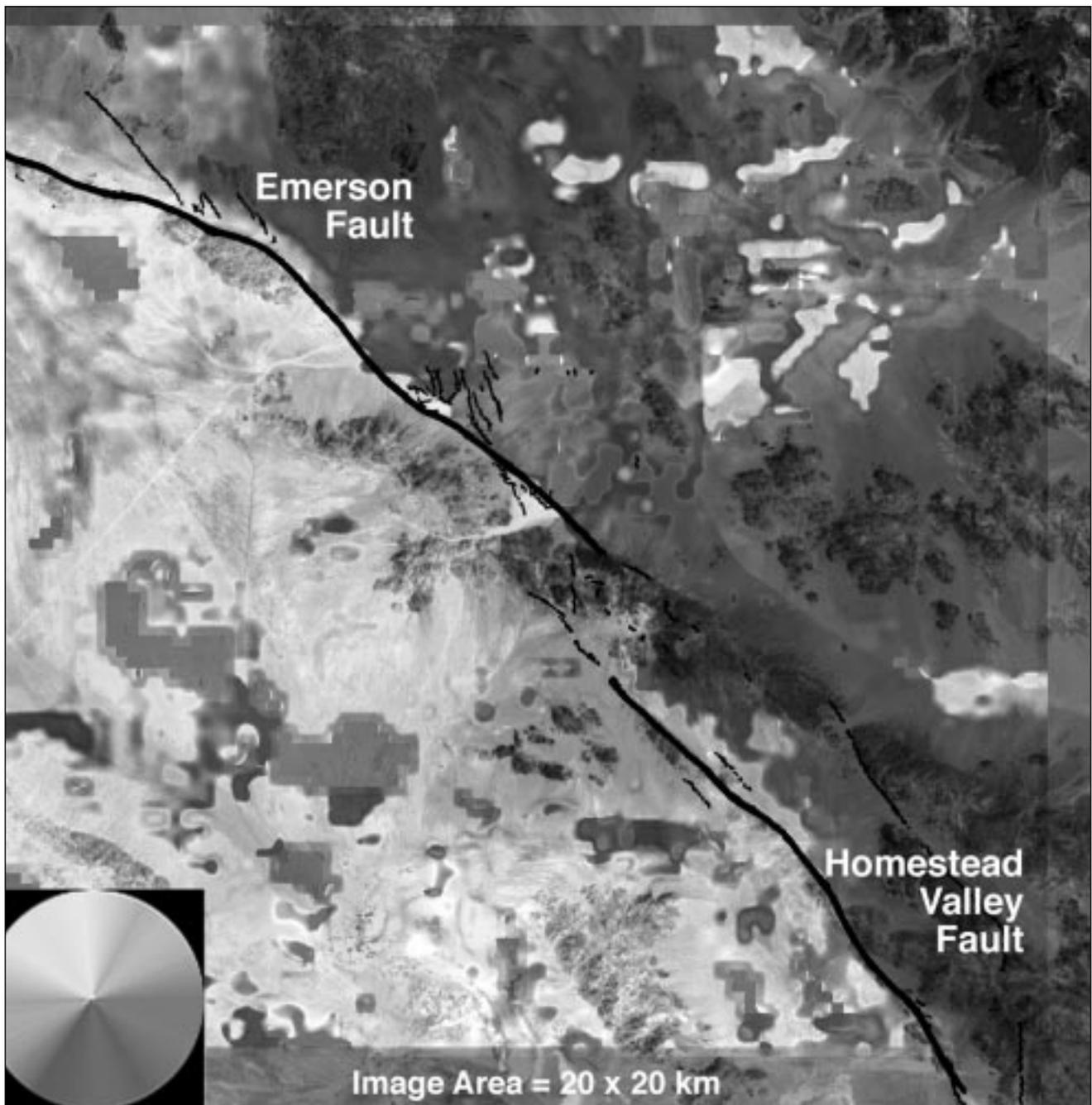


Figure 8. Ground-Displacement Map for Landers Earthquake Region Generated Using Statistical Learning Techniques.

Direction of ground displacement is indicated in grey-scale wheel at left.

problem of automatically detecting and cataloging important temporal processes in massive data sets. In general, this task is one of overwhelming scale that has so far eluded automation for the great majority of scientific problems. Historically, careful manual inspection of images by highly trained scientists has been the standard method of extracting

important scientific information from even high-resolution images. This process is time consuming and extremely expensive. In a collaboration between the MLS group and the Terrestrial Science Element at JPL, the QUAKEFINDER system was developed and implemented as a prototype data-mining system that dramatically speeds up this process

(Stolorz and Dean 1996). It tackles the problem of analyzing the earth's crustal dynamics by enabling the automatic detection and measurement of earthquake faults from satellite imagery. The system has been used to map the direction and magnitude of ground displacements that resulted from the 1992 Landers earthquake in southern California over a spatial region of several hundred square kilometers at a resolution of 10 m to a (subpixel) precision of 1 m. Figure 8 shows this ground-displacement map. The grey-scale wheel at the bottom left indicates the direction of inferred ground movement. The fault itself is clearly shown by the discontinuity in the ground movement. This calculation is the first to have been able to extract area-mapped information about two-dimensional tectonic processes at this level of detail. It is accomplished using a combination of statistical inference (entropy minimization-style learning), parallel computing, and global optimization techniques.

Although applied initially to the specific problem of earthquake fault analysis, the principals used by QUAKEFINDER are broadly applicable to a far more general class of calculations involving subtle change detection in high-resolution image streams. Success in this domain points the way to a number of such data-mining calculations that can directly and automatically measure important temporal processes to high precision from massive data sets such as problems involving global climate change and natural hazard monitoring as well as general image-understanding tasks involving target detection and identification in noisy image streams. Efforts are now under way to use QUAKEFINDER to analyze possible activity on the ice-covered surface of Jupiter's moon Europa and search for sand dune activity on Mars. There are also a number of potential applications in the biomedical imaging field.

In a collaborative effort with Caltech astronomers, machine-learning techniques have also been applied to a problem in the area of large-image database analysis. SKICAT (Weir, Fayyad, and Djorgovski 1995; Fayyad, Djorgovski, and Weir 1996a, 1996b) integrates image processing, high-performance database management, and AI classification techniques to automate the reduction of the second Palomar Observatory sky-survey image database. Image-processing routines first detect sky objects and measure a set of important features for each object, for example, brightness, area, extent, and morphology. These features are used to classify

sky objects using the machine-learning component of our system. The JPL learning algorithms GID3*, O-B TREE, and RULER have been used to produce decision trees and classification rules from training data consisting of astronomer-classified sky objects. These classifiers are applied to new survey images to obtain the classifications needed for a complete northern celestial hemisphere survey database containing on the order of 5×10^7 galaxies, 2×10^9 stars, and more than 10^5 quasars.

One notable success of the SKICAT system is its use by Caltech astronomers, with color and classification information, to select quasar candidates at red shifts of $z > 4$ (Kennefick et al. 1995). This approach was 40 times more efficient in terms of the number of new quasars discovered for each unit of telescope time than the previous survey for such objects done at Palomar. To date, some 24 new quasars at these high red shifts have been found and have been used to constrain the evolution of their luminosity function, indicating the epoch of quasar and, probably, galaxy formation. They have also been used by many other groups of astronomers to probe the early universe and the early intergalactic medium.

SKICAT is now being extended to perform unsupervised clustering on the roughly 40-dimensional feature space produced by the initial image-processing software. Probabilistic clustering methods are being applied to systematically explore the parameter space of object measurements in an unbiased fashion to search for possible previously unknown rare groupings. It is quite possible that in a data set this large, some previously unnoticed, new astronomical type of objects or phenomena can be found by suitable outlier searches. This result would be major and path breaking, both displaying scientific interest and demonstrating the power of machine-assisted discovery in astronomy.

Although much of the focus of the work at JPL is focused outward toward the planets and beyond, there are many important unanswered scientific questions concerning the earth's geology and climate, which are also under investigation. The MLS group is developing novel spatiotemporal data-mining techniques and tools for tapping the vast resources of earth-observed data. One example is our ongoing analysis of low-frequency variability in the upper atmosphere, specifically spatial grids of 700-megabyte geopotential height records taken daily since 1947 over the Northern Hemisphere (available from the National

The volume of image data collected by spacecraft has reached a level that makes the traditional approach of manually examining each collected image infeasible.

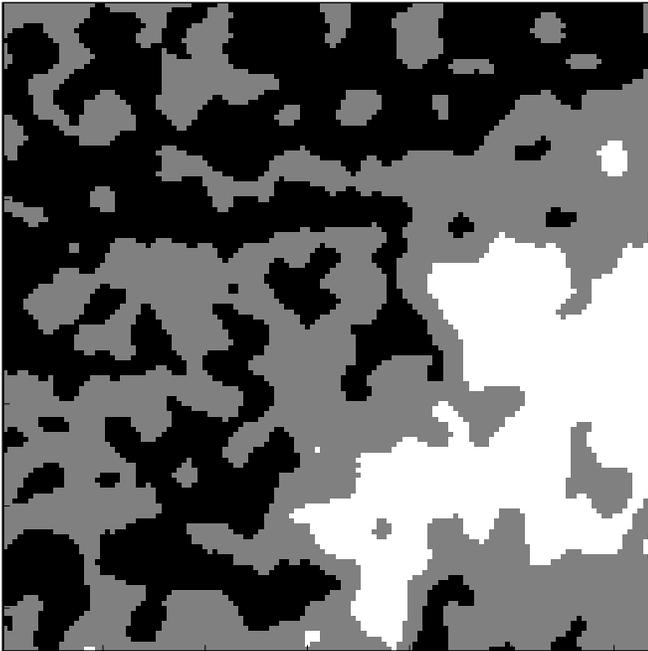
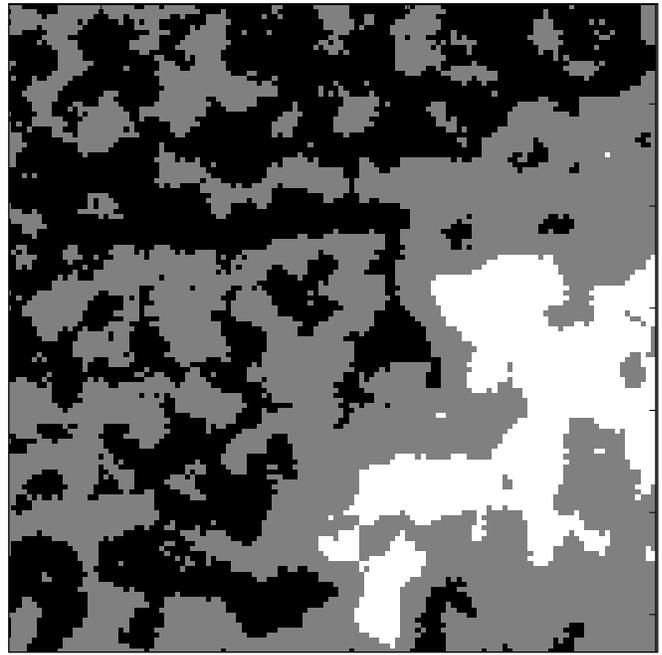
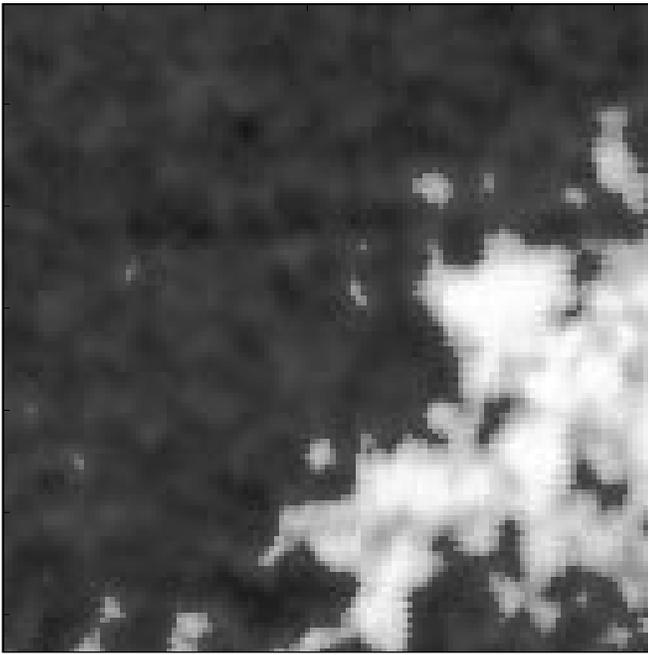


Figure 9. Automatically Classified Solar Image.

Top Left: Raw solar image. *Top Right:* Threshold-derived classifications. *Bottom Left:* Markov random field-derived classification.

Oceanic and Atmospheric Administration). A key scientific question is whether recurrent, stable regimes of climatic activity exist. We applied finite-mixture models to the data to see if we could discover the underlying cluster structure. Combining the cluster results in a novel

probabilistic method for determining the best number of clusters (Smyth 1996), we have provided the first objective proof of the existence of three distinct regimes in the earth's upper atmosphere. This result is significant from both a scientific and a methodological viewpoint: It has answered a long-standing open question in the field and is the first application of objective cluster-validation criteria in this area. Ongoing work is focusing on temporal clustering using generalized hidden Markov models and extensions to oceanic data and ocean-atmosphere modeling.

The MLS group is also developing statistical pattern-recognition methods leading to automatic and objective image-analysis systems for science data sets in astronomy and solar physics (Turmon and Pap 1997). The system allows scientists to label active regions on solar images and combine this information with domain-specific knowledge to train a pattern recognizer. Data sources include a 30-year database of ultraviolet intensity images taken each day on the ground and light images and magnetic field maps taken many times daily from the NASA-European Space Agency *SOHO* (solar and heliospheric observatory) satellite. Our existing recognition system incorporates information about pixel-level spatial continuity. Ongoing efforts will allow higher-level constructs describing active regions; also, we want to make an active-region database and correlate it with existing solar-irradiance data for climatological purposes. Figure 9 illustrates the data classification enabled by the statistical pat-

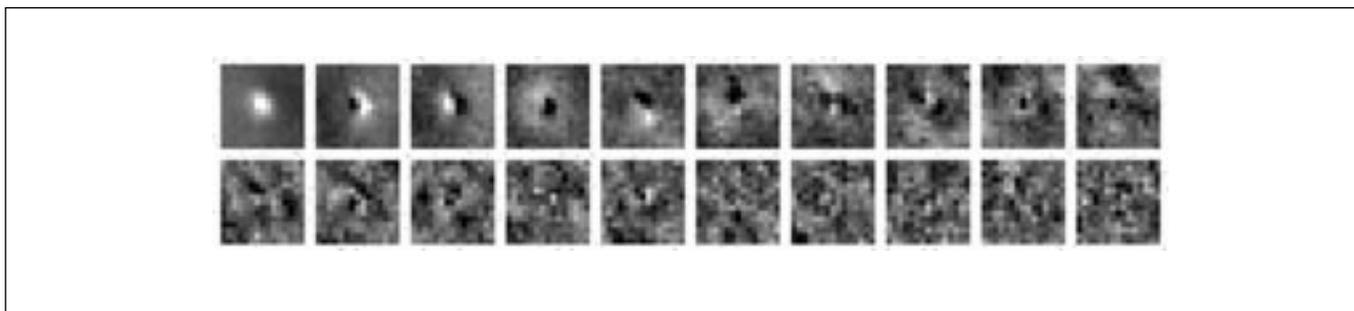


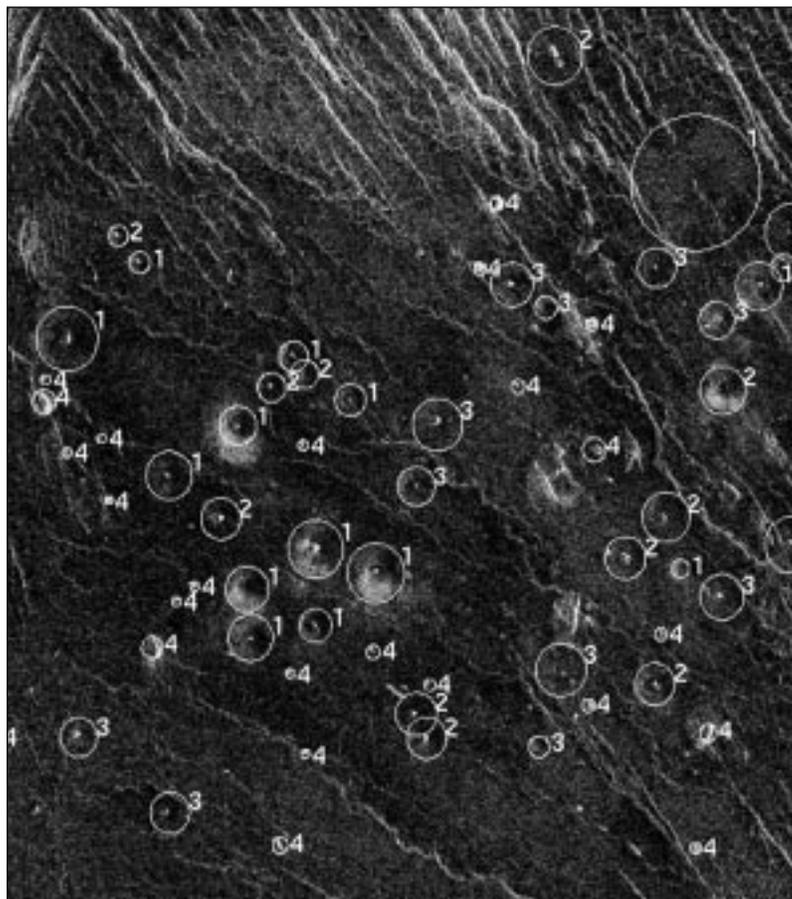
Figure 10. Volcanoes on Venus.

Top: Volcano-appearance components (in decreasing strength). Right: A 75-kilometer x 75-kilometer region of Venus containing numerous small volcanoes labeled by experts.

tern-recognition methods. At the top left is the input solar data; the top right image is a classification produced by a simple thresholding algorithm. At the bottom left is the (improved) classification produced using the Markov random-field pattern-recognition techniques.

The volume of image data collected by spacecraft has reached a level that makes the traditional approach of manually examining each collected image infeasible. The scientists, who are the end users of the data, can no longer perform global or comprehensive analyses effectively. To aid the scientists, we have developed a trainable pattern-recognition system, known as JARTOOL (JPL adaptive recognition tool) (Fayyad et al. 1995; Burl et al. 1994), for locating features of interest in remote sensing data. The system has initially been applied to the problem of locating small volcanoes in *Magellan* synthetic aperture radar imagery of Venus. Scientists train the system by labeling volcano examples with a simple GUI. The system then learns an appearance model for volcanoes and uses this model to find other instances of volcanoes in the database. Figure 10 shows the radar-input image data at the left and volcano-appearance components at the right (in decreasing strength). It is particularly interesting to note that the first several appearance components correspond to descriptive features used by human experts, such as a pit at the summit and a shadow opposite the look direction of the radar.

The MLS group is also applying AI and pattern-recognition techniques to the problem of conducting on-board science analysis for



space missions. As spacecraft become highly autonomous, there are increasing opportunities for in situ analysis of scientific data, enabling real-time planning of scientific experiments in response to important events. In collaboration with planetary scientists at the Southwest Research Institute in Boulder, Colorado, a prototype system has been developed that performs automatic on-board detection of natural satellites in the vicinity of asteroids and planets (Stolorz et al. 1997).

The initial system deals with the case of static objects and is now being extended to

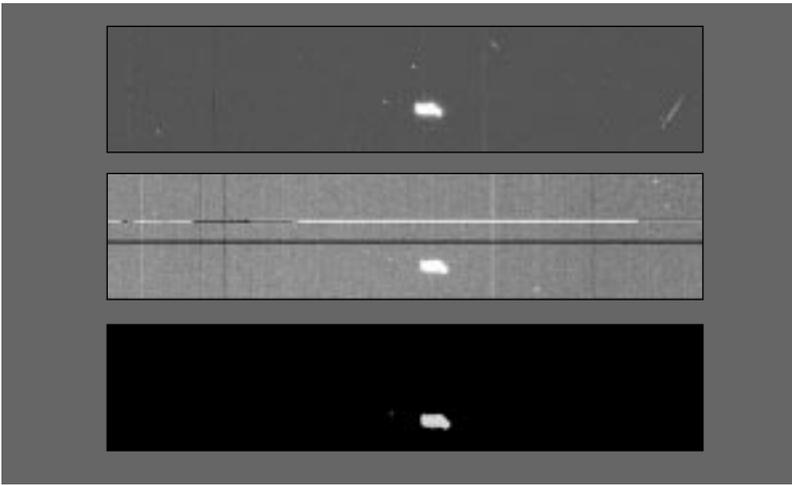


Figure 11. Automatic Satellite Detection.

Top: Raw-data input for infrared filter. *Middle:* Raw-data input for green filter. *Bottom:* Processed detection image for static satellite detection.

account for parallax effects that result from both spacecraft and satellite motion. Accounting for parallax effects involves the introduction of predictive methods in the presence of uncertainty as well as careful registration techniques. Images from a preliminary demonstration of the static satellite-detection capability are shown in figure 11. The top and middle images show two of the four raw-data input images (each taken with a different filter). The bottom image is the processed image used for satellite detection using the prediction and registration processing.

Another system deals with the automatic analysis of ultraviolet spectra to allow decision making about the optimal way to conduct a spectral experiment. By automatically identifying and removing the main chemical species present in a scientific target, such as a cometary tail, decisions can be made about the optimal data-taking mode, for example, whether to scan the spectrometer across portions of the tail in a survey mode or to concentrate on obtaining high-resolution data from one area where unexpected species might have been discovered.

We believe that in situ machine-learning applications such as these will have a dramatic effect on the range and quality of science that can be pursued by spacecraft missions in the future. They have immediate relevance to NASA initiatives such as JPL's New Millennium Program. They also tie in strongly with longer-term research and development projects. One of these projects is JPL's Remote Exploration and Experimentation Program,

which is designed to provide high-performance low-power multicomputers for spaceborne platforms. The intent is to provide a scalable family of computing platforms for a wide range of spacecraft. It is anticipated that autonomy applications developed by the MLS group will be used by science instrument principal investigators on future space missions. These autonomy applications will then, in turn, be major users of this future space-borne scalable computing capability.

Design Automation

Spacecraft design is a knowledge- and labor-intensive task with demanding requirements. Spacecraft must survive the most hostile environments, operating at great distances and with little interaction with earth-based personnel. In synthesizing a design, engineers must balance rigorous survivability and science requirements against mass, power, volume, and processor limits, all within reduced mission budgets. To assist spacecraft design engineers in this challenging task, the AI group has been developing and deploying technology in the area of intelligent optimization.

Spacecraft design optimization is difficult using current optimization methods because (1) current methods require a significant amount of manual customization by the users to be successful and (2) traditional methods are not well suited for mixed discrete-continuous, nonsmooth, and possibly probabilistic cost surfaces that can arise in many design-optimization problems. Of particular interest are the so-called black-box optimization problems in which the structure of the cost function is not directly accessible (that is, the cost function is computed using a simulation).

We are currently developing the optimization assistant (OASIS) (Fukunaga, Chien, et al. 1997), a tool for automated spacecraft design optimization that addresses these two issues. The goal of OASIS is to facilitate rapid what-if analysis of spacecraft design by developing a generic spacecraft design-optimization system that maximizes the automation of the optimization process and minimizes the amount of customization required by the user.

OASIS consists of an integrated suite of global optimization algorithms (including genetic algorithms, simulated annealing, and automated response-surface methods) that are applicable to difficult black-box optimization problems and an integrated intelligent agent that decides how to apply these algorithms to

a particular problem. Given a particular spacecraft design-optimization problem, OASIS performs a metalevel optimization to (1) select an appropriate optimization technique to apply to the problem and (2) automatically adapt (customize) the technique to fit the problem. This metalevel optimization is guided by both domain-independent and domain-specific heuristics that are automatically acquired through machine-learning techniques applied to a database of performance profiles collected from past optimization episodes on similar problems.

We have been applying the OASIS system to the problem of penetrator design. A *penetrator* is a small, robust probe designed to impact a surface at extremely high velocity with the goal of performing sample analysis. Specifically, we have been applying OASIS to design and simulation data from the New Millennium *Deep Space Two* Mission penetrator design in which the design variables are penetrator diameter and length. The *Deep Space Two* Mission consists of a pair of penetrators to be launched in 1998, impacting the planet Mars to perform soil analysis in 1999. Figure 12 shows optimization surfaces derived from impact simulations for candidate designs. Each of the three surfaces represents the predicted depth of penetration for a different soil consistency; in all three cases, the surface is highly discontinuous. The negative values represent physically unrealizable designs, and the zero values indicate cases in which the penetrator deflects on impact (catastrophic mission failure). The goal of the design problem is to produce a physically realizable design while it maximizes the chance of successful penetration over an expected distribution of soil consistencies and minimizes design cost

Summary

This article has described ongoing AI activities at JPL. Because of space, time, and coordination constraints, we were unable to fully cover all related areas of work at JPL (most notably, this article does not cover considerable robotics, computer vision, neural net, fuzzy logic, and pattern-recognition work). For further information on the projects described in this article, readers are invited to visit our web page at www-aig.jpl.nasa.gov/ or the JPL general web page at www.jpl.nasa.gov/ or to contact one of the following individuals at firstname.lastname@jpl.nasa.gov: Chester Borden, Operations Research Group; Dennis DeCoste, Monitoring and Diagnosis

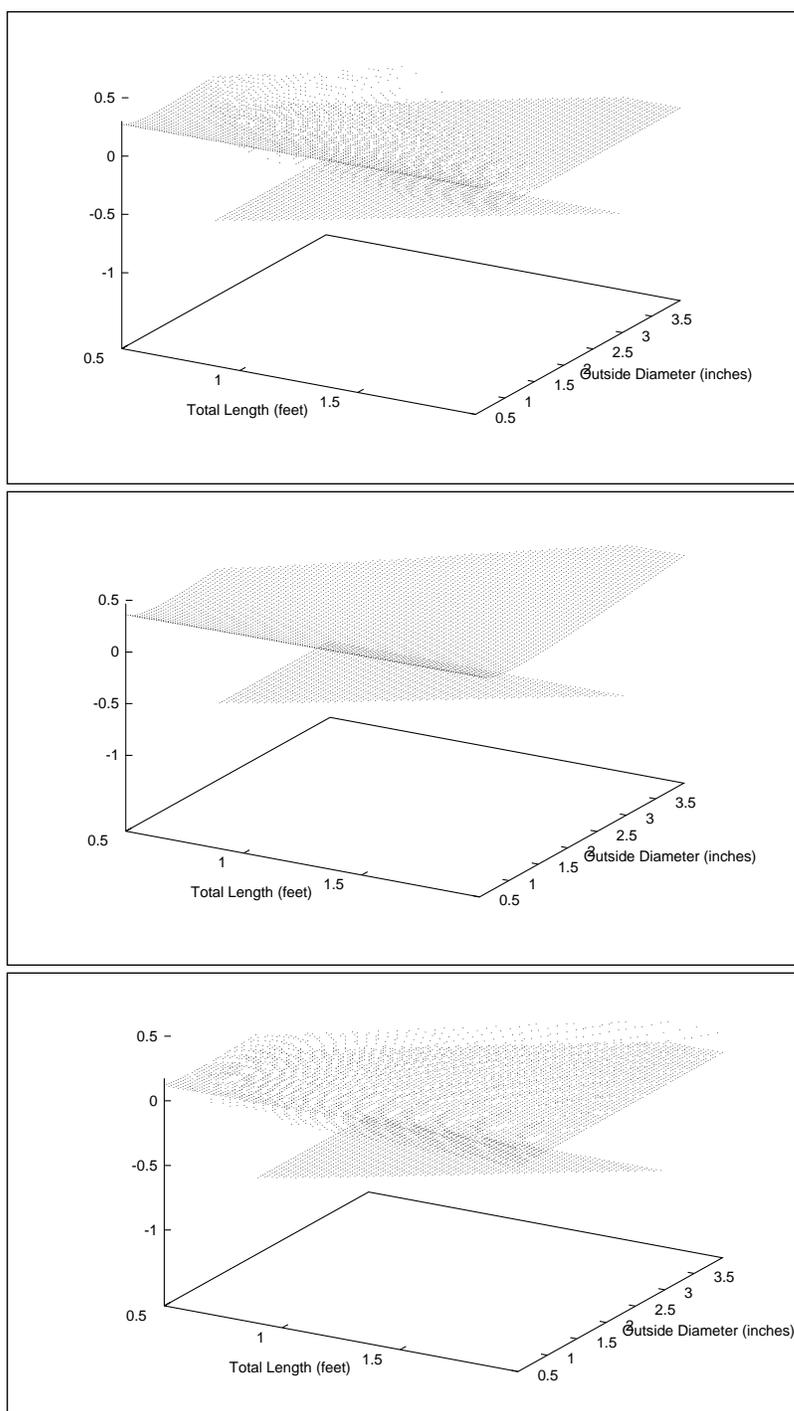


Figure 12. Optimization Surfaces for Impact Penetration Depth (Output) as a Function of Outside Diameter and Length of New Millennium *Deep Space Two* Mission Penetrator (Three Different Soil Densities).

Technology Group; Steve Chien, Artificial Intelligence Group; Sven Grenander, Sequencing Automation Research Group; and Paul Stolorz, Machine Learning Systems Group.

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