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Autonomous Spacecraft Guidance and Control

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Abstract

By the next decade, spacecraft will be highly miniaturized and automated to realize much lower life-cycle costs in comparison to todays counterparts. These small spacecraft will have highly autonomous control systems for spacecraft attitude, maneuver, and orbit control. They will have the capability to sense disturbance environments, accept goal level commands, and make implementation decisions. Highlighted in this paper are the key enabling technologies of intelligent control, inducting neural-fuzzy control, and model-based robust reconfigurable control.

Introduction

"1'0 achieve future low-cost missions will require a radical change from the current dependence on real-time, trends-on ground support in mission operations. Low operational costs can be realized through greatly increased onboard autonomy and reliance on the adaptability built into control systems. Missions to explore planets, comets, and asteroids will emphasize fast-flying, agile. spacecraft that are capable. of insuring mission success in the face of a wide range of uncertainties, both on-board and in the external environment.[1,2]

Technology development of new methods> architectures, algorithms, and modular flight software that will enable the autonomous on-board functionality of an integrated spacecraft Guidance and Control subsystem, as well as the monitoring and management of spacecraft health, power, fuel, and computation resources is underway for future deep space missions. Important new capabilities for On-Board Task Planning and Command Sequence Generation to autonomously carry-out the baseline mission are also incorporated. This is shown in Figure 1 in compariso n with the past traditional approach.

In contrast to conventional feedback control, where the error signal is the main way to assure control stability and performance, *Intelligent Control* offers autonomy through self learning, self reconfigurability, approximate reasoning, planning and decision making, and the ability to extract the most valuable information from unstructured and noisy data. These attributes may be realized by the merger of *neural networks* and *fuzzy logic* in support of *uncertainty-tolerant robust control systems*. The *autonomous intelligent* spacecraft control systems of the near future will integrate these techniques to achieve robust reduced cost operability.[3]

Fuzzy Logic for Autonomous S/C Functions

Presently, on-board computers use *floating point variables, integer variables, Boolean variables*, (and sometimes *complex variables*). While such data types are inherently precise, they restrict the spacecraft to purely preprogrammed actions. This lack of real autonomy has linked past spacecraft closely to ground operations.

The next generation of spacecraft will have *linguistic variables* in the. flight software. This enhancement is essential for infusing intelligence and approximate reasoning capabilities. The fundamental knowledge representation unit in the theory of approximate reasoning is the notion of a *linguistic variable*.[4,5] The formal definition of a linguistic variable involves set-theoretic issues. " There is a great deal to be gained from using linguistic representations, while at the same time ensuring that no previous capability is compromised since Boolean logic is a special case of Fuzzy logic.

* AIAA senior member

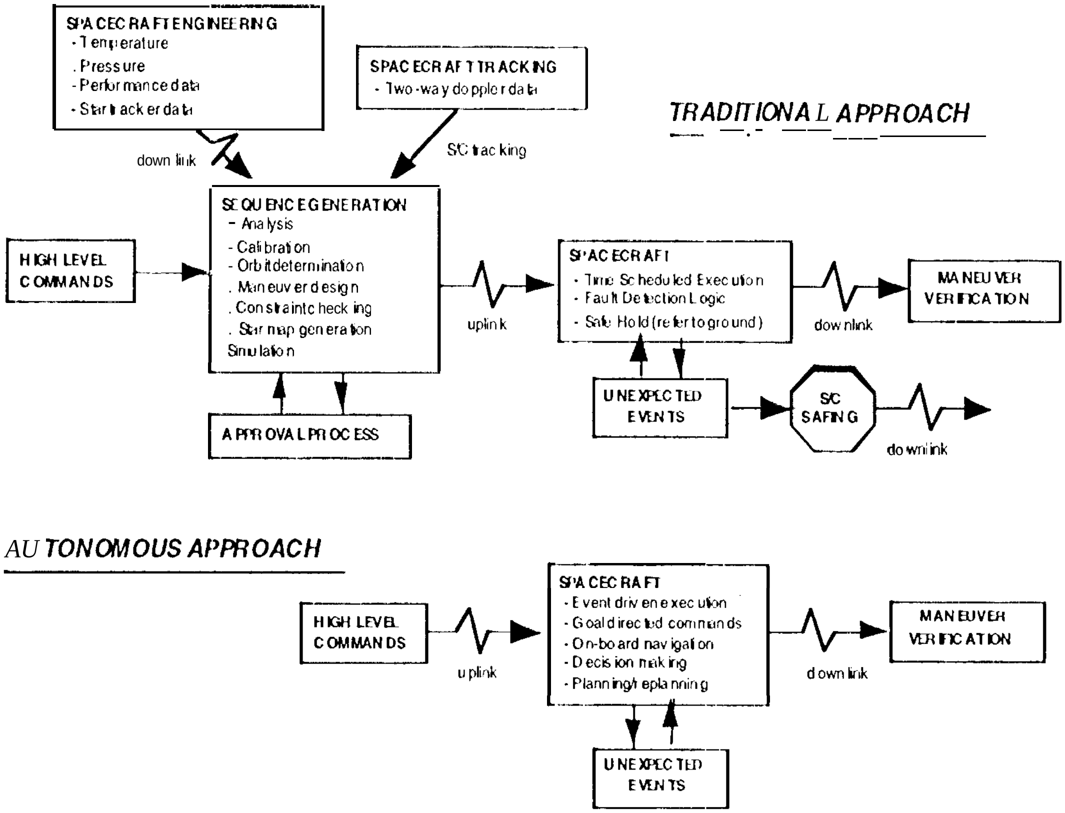

Figure 1. Future Autonomous Spacecraft Flight Operations

Certain special attributes of Fuzzy logic make it ideal for developing such autonomous spacecraft control and are depicted in Figure *2 keyed* to the autonomous functions which they best support.

1. Fuzzy Inference provides a well established basis for Expert System Diagnosis and Decision Making.[7]

?. Fuzzy representations allow smoothed/interpolated switching among several candidate models, controllers, estimators, etc.[8]

3. Fuzzy parameterizations arc. Universal Approximators useful for modeling nonlinearities, and can be adapted in real time for improved performance.[9,10,11]

4. Fuzzy models and representations simultaneously handle both numerica 1 data and linguistic knowledge.[12]

Autonomous Control Architecture

A candidate functional architecture for an autonomous spacecraft control system is depicted in Figure 3. Specific roles for Fuzzy logic to support the *Planning, Modeling, Executor and Monitor* functions arc outlined below.

Planner

As a specific example, consider a plan for an attitude maneuver. In this case, y_d represents the desired quaternion, rate, and acceleration profile.s. The calculation of y_d may involve constraints such as maximum S/C rates, maximum allowable torques, thruster profiles, and in addition, geometric constraints may be imposed which forbid science instruments, cameras, etc. to lie within certain cone angles of the sun, or restrict such excursions 10 be of limited time duration. la the case of orbit correction maneuvers, y_d is a specified sequence of attitude maneuvers and thrust vector profiles 10 achieve a desired Delta-V. la a similar manner, most other spacecraft control systems require planned profiles.

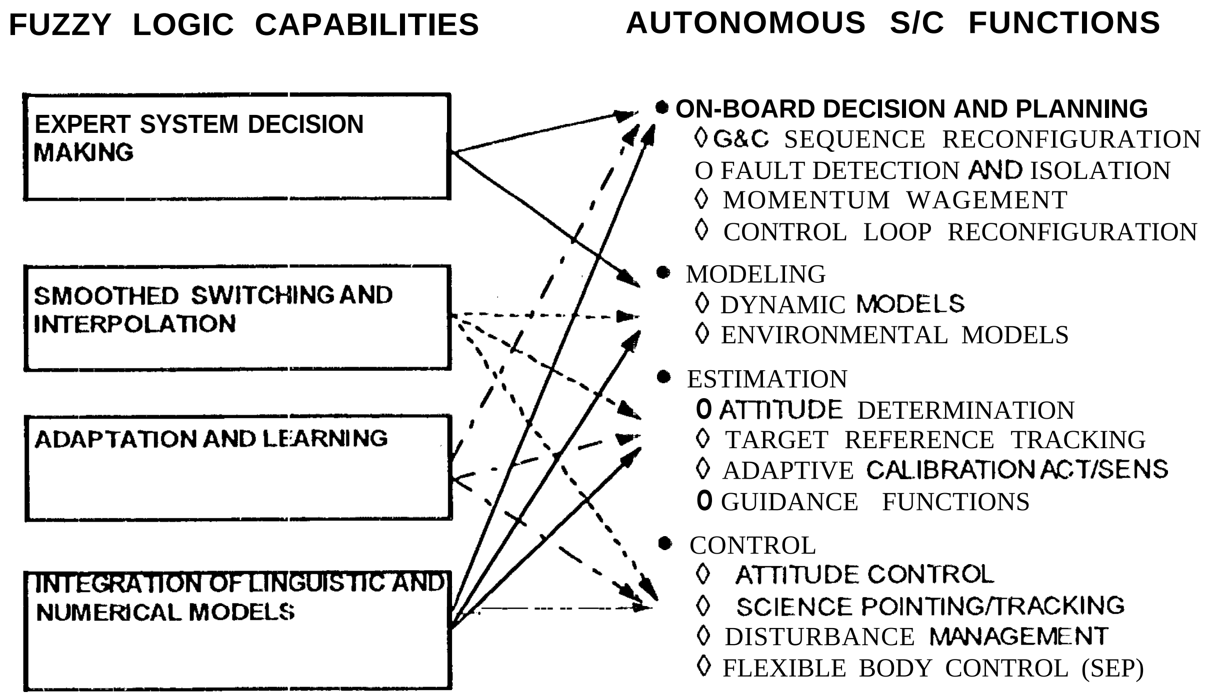

Figure 2. Fuzzy Logic Attributes for Autonomous Microspacecraft

The determination of the optimal plan typically involves solving an optimization problc.in, where the goal is introduced through the choice of objective function, and inequality constrains arc impose.ci based on spacecraft dynamics, hardware limitations, and other desired or competing physical constraints.

A method for resolving this conflict is use of Fuzzy objective functions. [13] Fuzzy Objective Functions have been considered in Zak. [14] This approach gives weighted consideration to all important factors, emulating the approach previously taken by Human experts on the ground. Other examples include rc.source allocation (i.e., fuel for maneuvering, fuel for orbital corrections, memory for data storage, power, computational resources, etc.) for which competing needs must be prioritized and met.

Once an objective function is clarified, an optimization problem must be solved. Several alternative approaches exist based on Expert Systems, AI methods, anti Mathematical Programming approaches. A conceptual example of this approach is shown in Figure 4, which depicts the situation involved in planning a spacecraft maneuver. Here, one is working on the celestial sphere, (i.e., 3-axis rotations) where constraints (i.e., instruments which should not point into the sun, etc.) are shown as darkened regions on the surface of the sphere. An important advantage of using Fuzzy logic here is that heuristics for solving the problem can be embedded systematically into the search algorithms.

Modeler

The *Modeler* is supported by models contained in the Knowledge base, and is essentially a simulation/prediction function which can play out "what-if' scenarios by propagating differential equations, algebraic relations, sequential logic, etc. to assess tbc quality of a candidate plan. In particular, Fuzzy modeling is most advantageous when

1. Complexities or uncertainties arc beyond what can be modeled easily or- precisely with mathematical models alone.

2. The model can benefit from including linguistic in for mation, obtained from experts

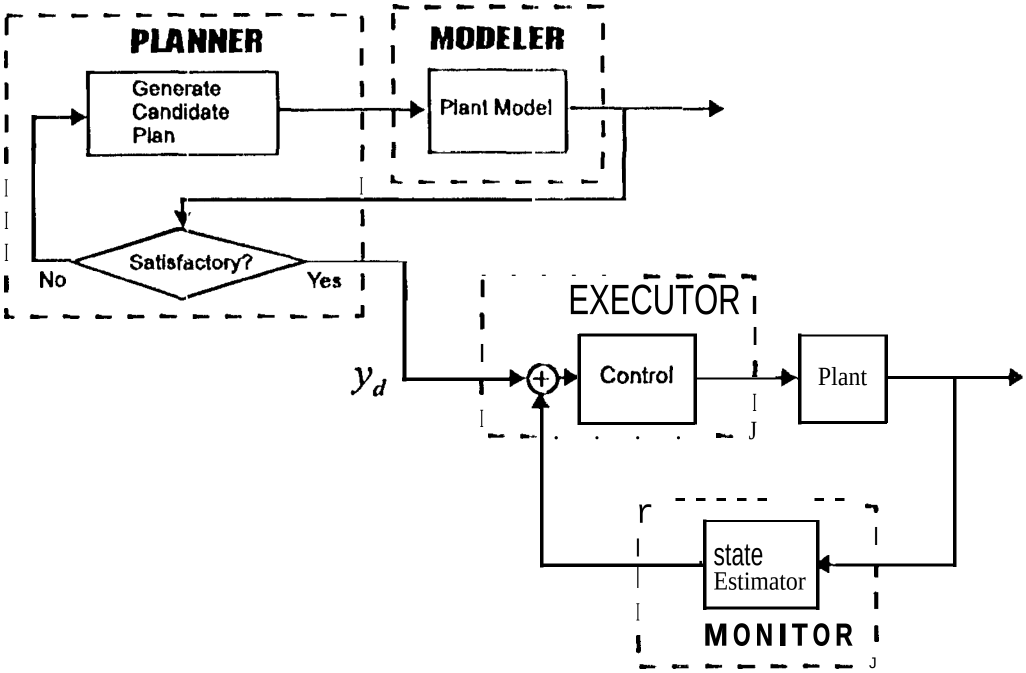

Figure 3. Autonomous Control System Architecture

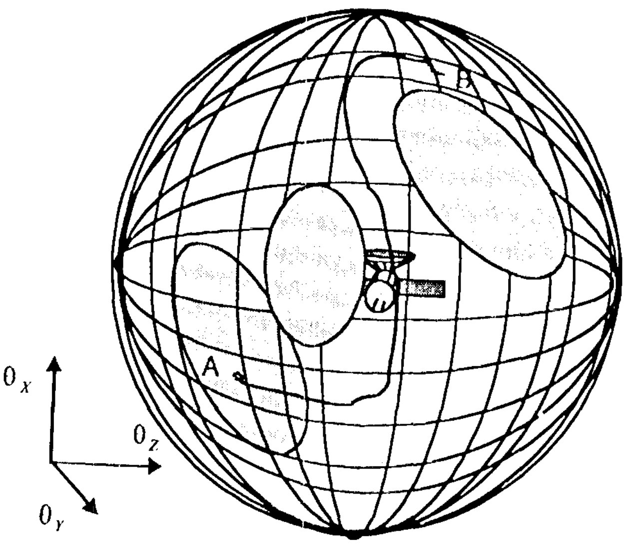

Figure 4. Spacecraft Autonomous Maneuvering Problem

3. The model has widely varying dynamic characteristics and is best modeled by several models, each optimized for a particular operating range, In this case, switching and interpolation between models can be done smoothly and systematically using Fuzzy logic.

4. The model has nonlinearities which are not easily characterized using standard modeling methods, but which can be systematically represented by the Universal Approximation properties of Fuzzy basis functions [10][11][12].

5. In-flight learning is required to improve model fidelity due to either the time-varying dynamics, or performance sensitivities to model uncertainty.

Two fuzzy modeling concepts support the *Modeler* function. The first concept is *Fuzzy Human Inference Models*, and is motivated by situations 1 and 2 above.. The second concept is *Fuzzy Switched-Interpolated Models,* and is motivated by situations *3,4,5 above.*

The basic concept behind Fuzzy Human Inference Models is to incorporate *linguistic information* into the models using a Fuzzy Logic formalism. Three types of Fuzzy modeling can be defined based on the amount and nature of the information:

- *Expert Based*: *Uses* linguistic information exclusively
- *Model Based*: Integrates both linguistic rules and numerical data.
- *Model Free*: Generates model from "watching'" tbc phenomena over a period of time and learning the observed input-output mapping.

Expert Based Approach

Here models are composed exclusively from linguistic information supplied as sets of Fuzzy rules obtained by polling experts. Expert based models stored in the spacecraft Knowledge Base would be essential for handling emergencies, anomalous behavior, as well as reacting to special situations. For example, when present spacecraft get into trouble they switch into safing modes such as: *find Sun--find Earth--call Home.*

In contrast, an autonomous spacecraft must solve problems by itself. In this case, it is essential for knowledge obtained from experts on the ground to be stored and maintained onboard. These models would be particularly useful to support the following autonomous spacecraft functions:

- Fault Detection, Isolation and Recovery
- Resource Management (fuel, power/battery, thermal, momentum, data storage, etc.)
- Target Selection rules for Optical Navigation
- Serendipitous Science/Targets

Model Based Approach

In this approach, ***objective*** information is incorporated using mathematical models, whereas subjective information is incorporated using linguistic statements, The linguistic statements are converted to rules which are quantified using the Fuzzy Logic formulation, and integrated with the mathematical models.

The Model-Based approach allows a ***hybrid*** methodology which incorporates linguistic information while retaining full use of available physical models. This is important in spacecraft applications where critical information must be retained in the form of rigid-body dynamics, orbital mechanics, celestial body ephemerides, environmental disturbance models, etc. The Fuzzy Logic approach allows one to blend fuzzy notions of *Smoothness, Closeness, Correlatedness, Coincidence*, etc. into models and knowledge bases, Specific spacecraft applications would include models for

- Attitude Determination and Control
- Orbit Determination and Correction Maneuvers
- Autonomous Target Tracking
- Autonomous star/planet ID
- Imaging Sequence Design
- Actuators and Sensors
- External Torques and Disturbances
- In-Flight Calibration of Instruments and Sensors
- Thermal Control

Model Free Approach

In the *Model Free* approach, rules are determined directly by analyzing data, and then enhancing this information with linguistic rules and intuitive guidance typically obtained from experts. Both steps are quantified and integrated into a learning process using a Fuzzy Logic paradigm.

Typically, the *Model-Free* approach is used for characterizing behavior which is so complex and elusive, that mathematical representations are either unavailable or infeasible. Using this approach, it is possible to develop a new class of spacecraft controller from input-output mappings of the Human operators. Specific spacecraft applications would include models for

- Propellant Slosh, Fluid/Cryogen motion
- Gas Thrusters, Momentum Pulse Calibrations
- Calibration of Instrument Nonlinearities
- Environmental Torque and Disturbance Sources
- Comet Outgassing Disturbances

An important property of Fuzzy Basis Functions is their ability to approximate arbitrary nonlinear functions. For instance, a curvilinear function can be approximated by a weighted sum-of-products of Gaussian type pulses. For each pulse, the placement of the pulse, the pulse width, and the pulse height are determined by a linear parameter set which is tuned on the ground using both experimental data and expert linguistic information. Once in flight, the linear parameters can be updated using standard recursive least squares algorithms. In this manner, the ground based information is used to provide a foundation for tuning in-flight, and the required adaptation laws for in-flight learning are kept simple and linear in the parameters.

Fuzzy Switched-Interpolated Models

The *Fuzzy Switched-Interpolated Modeling* concept is depicted in Figure 6. The basic idea is to switch smoothly between several alternative models, each designed to be optimal for a different operating regime. This concept is useful for phenomena whose parameters vary in time and for which no single model will suffice. In addition, expert knowledge, and feedforward information (e.g., a gain scheduling variable) can be included to improve modeling performance. Specific spacecraft applications would include models for:

- Propellant Slosh and Fluid/Cryogen Motion
- Gas Thrusters
- Spacecraft Distortion Under Thermal Loads
- Euler Equations/Attitude Dynamics
- Flexible Body Dynamics

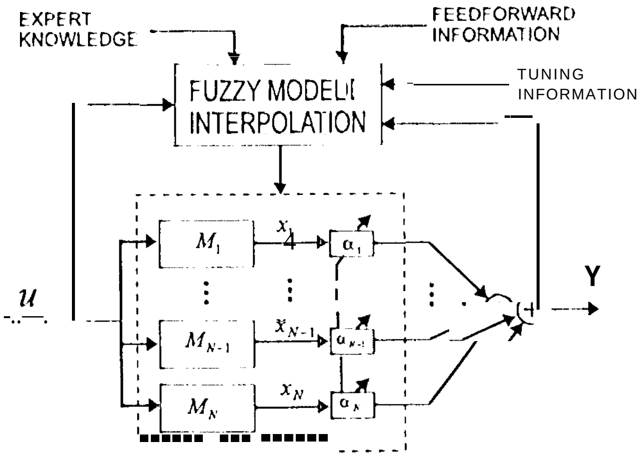

Figure 6. Architecture for Fuzzy Switched-Interpolated Models

The modeling of propellant and cryogen slosh is particularly challenging since its dynamics and disturbance to the spacecraft can vary widely over a mission as a function of fuel mass fraction, g-level from thrusters or rapid maneuvers, and tank fill ratio.

Executor

The *Executor* function executes the final plan of action determined by the *Planner*. All space.c[af(control loops are in the domain of the *Executor*, which is responsible for driving the hardware. The *Executor* utilizes feedback information from the *Monitor* in the form of processed sensor information , or estimates of the dynamic state, to best accomplish its goals.

There are two fuzzy control design concepts which are appropriate for supporting the *Executor* function. The first concept is the *Multi- Window Fuzzy Control* design. The second concept is *Fuzzy Switched Control* design. These designs arc. dc.scribed briefly below.

Multi- Window Fuzzy Control

Multi- Window Fuzzy Control is a recent concept which has demonstrated breakthrough improvements over conventional Fuzzy control designs. In order to appreciate the new approach, it is necessary to give a brief review of previous conventional Fuzzy designs.

Most conventional Fuzzy logic control designs to date. have been based on *phase-plane partitions*. Such controllers are designed using phase-plane (time-domain) analysis, passivity theory, or proportional, integrative, and derivative (PID) controller modifications. It is seen that the.sccrmlro]lcrsarc implemented by partitioning the phase plane into regions having different feedback gains. This is simply a generalization (to "soft" partitions) of classical methods which use hard partitions of thcJ)llasc-plane (i.e., switching lines, surfaces, etc.).

1a contrast, the new *Multi- Window Fuzzy Controller* is based on *magnitude -frequency plane* partitions as shown in Figure 7 which or-tray ys linguistic variables in a graphical IF-THEN statement relationships, where, NB= Negative Big, NM= Negative Medium, NS= Negative. Small, Z= Zero, PS= Positive Small, PM= Positive Medium, and PB=Positive Big . Then the fuzzy controller operation can be described as follows.

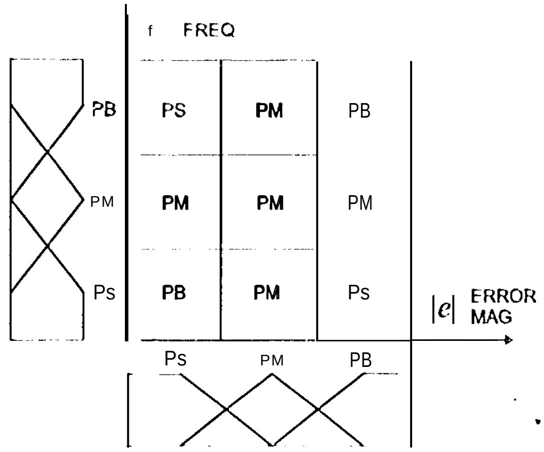

Figure 7. Multi-Window Fuzzy Control Based on Magnitude-Frequency Partition

When |e| is large, the system is in a transient phase, where the actuator is typically saturated. Here, we predominately use a velocity-lypc feedback gain to promote switching and hence approximate the time-optimal response which would be of the bang- bang type. In contrast, when |e| is small, the transient response is near completion and we increase the. contribution of the integral gain to improve steady-state performance. The moderate gain values at intermediate frequencies and also for moderate size |e|, arc used to help smooth the transitions between the operating regimes, which might otherwise be too abrupt to ensure smooth and efficient operation.

The *Multi- Window Fuzzy Control* approach has been applied successfully to Mats Global Surveyor despin control for s/c booster separation. This has important implications for future microspacecraft since it supports the use of launch vehicles with a spinning orbit injection stage. It also provides fast despin, and is robust (safe) for a wide range of possible initial conditions.

Fuzzy Switched Control

In the Fuzzy Switched Controller, one switches smoothly between several alternative controllers, each designed to be optimal for a slightly different operating regime. The basic concept is summarized in Figure 8. Switching is done in a smooth manner, by combining information gathered based on performance feedback, feedforward disturbance information, externally measured signals, as well as expert knowledge which has been embedded in the choice of operating rules.

The application of this approach to the precision pointing of imaging cameras using thrusters is of high interest. There is precedence for this approach on the Cassini spacecraft where separate low and high rate thruster controllers must be switched back and forth to achieve adequate performance over the range of conditions during the Titan flyby. [15] The improvements offered by this Fuzzy Control method are most relevant to future spacecraft for which thrusters are the primary attitude control actuator.

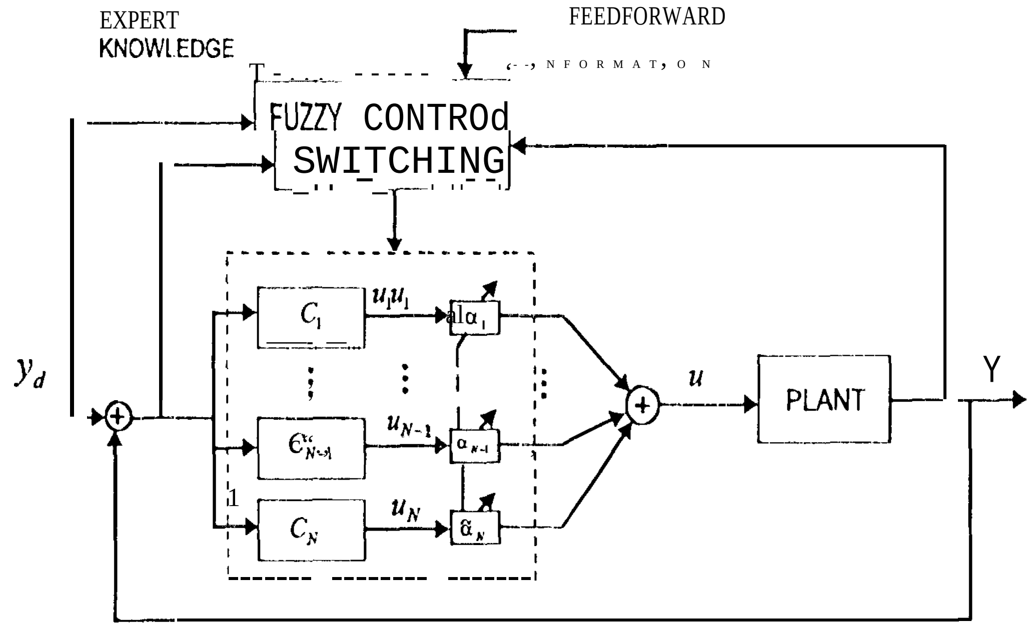

Figure 8. Architecture for Fuzzy Switched Control

Monitor

The *Monitor* accepts and processes measurement information from the sensors. The *Monitor* contains the Kalman filter for attitude determination, sensor fusion functions, and detection algorithms for fault protection and health monitoring. In the control system block diagram of Figure 3, the *Monitor* would be the state observer (for deterministic systems) or state estimator (for stochastic systems) which produces the state estimate.

The fuzzy estimation design example for supporting the *Monitor* function is the *Multiple Model Fuzzy Estimator* which can be tuned and incorporates expert knowledge. This concept is described below. A similar approach can also be applied to *Fuzzy Health Monitoring* to improve spacecraft Error Detection and Fault Analysis.

Fuzzy Multiple Model Estimator

The Fuzzy Multiple Model Estimator concept is shown in Figure 9. In this design, a bank of Kalman filters is propagated in parallel. The performance of each estimator in the bank is judged based on the prediction errors (i.e., how well each model predicts the actual sensor measurements). A Fuzzy figure-of-merit is used to choose the estimator. Such measures are typically some measure of correlation or magnitude of the prediction error. However, the fuzzy approach allows one to include other information about correlations, nonidealities, expected disturbances, etc., which can be described linguistically. in addition, each of the separate estimators can be Fuzzy, and can be parametrized by coefficients which themselves can be tuned using in-flight learning techniques. The Fuzzy Multiple Model Estimator can improve functionality for

- Rate Knowledge in Image Motion Compensation During Fly-bys, Encounters, etc.
- Disturbance estimation
  - Rigid body parameter estimation
  - Actuator and Sensor Estimation/Calibration

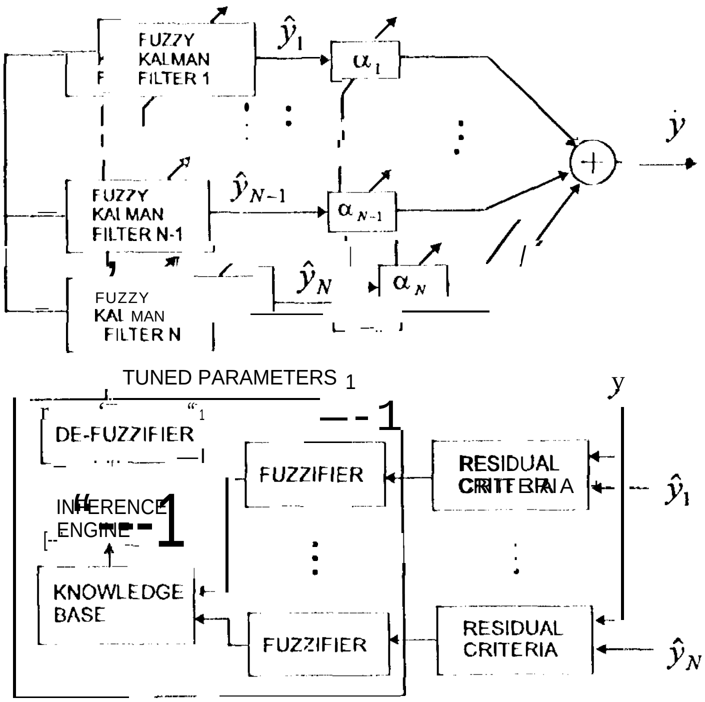

Figure 9. Architecture for Fuzzy Multiple Model Estimator

Autonomous Intelligent Robust Control Synthesis

Automated Modeling and Robust Control

The three generic design issues for any control system are stability, robustness to modeling uncertainties and performance. An new automated design method of Modeling and Control Synthesis (MACSYN) addresses these issues directly via a deterministic model-based approach.[16,17,18] Figure 10 shows the basic concept of MACSYN. This provides the technology for the *inner loop* (or first layer) of an *Intelligent Robust Control* architecture discussed later.

First, the plant input/output (1/0) data from prescribed excitations of the system are processed by system identification (ID) algorithms to generate a mathematical model of the multivariable plant and any disturbances. Based on system ID data, additive and multiplicative uncertainty models are created 10 capture system variations in rigid-body mass properties, flexible-body modal frequencies and damping, plant parameter drift, nonlinearities, noise, and disturbances. Finally, the plant and uncertainty mode.ls are passed to the robust control design algorithms to generate a controller (either H-infinity or LQG methods) that can perform robustly under the defined uncertainties and to the prescribed margins. This particular approach is referred to as a model-based design technique. MACSYN can provide *guaranteed stability and robustness* since identification and uncertainty modeling are true for in-flight conditions. During the mission, a fully automated onboard process would provide. periodic non-real-time self-tunins of the control system nominal design. in the event of equipment failures, MACSYN could also support autonomous reconfiguration of control loops for the best performance using the available control channels.

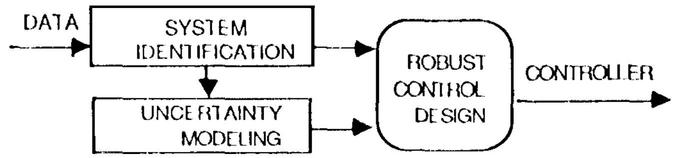

Figure 10. Modeling and Control Synthesis (MACSYN) Basic Concept

Autonomous Fuzzy-Neural Control

To probe more deeply into the issue of global robustness, we examined the possibility of using the robust, nonlinear, and intelligent control methods to enhance system robustness.. The technique proposed offers a means to integrate fuzzy logic-neural network control with modern robust control, where *global convergence* is handled by the rule-based fuzzy-neural network control law and *stability performance* is handled by the robust control law. The fuzzy -neural network merges the expert knowledge base and input-output data into a more effective intelligent control configuration. With the proposed fuzzy-neural network approach, qualitative knowledge can be used to enact control policy.[19,20,21]

Fuzzy-neural control adds a completely new dimension to control system capability. In combination with deterministic input-output mappings encoded by the. neural network, the fuz,zy-neural network provides a powerful technique in support of stabilization, identification, fault detection and adaptive control. This approach is capable of providing autonomy and precision control in the presence of disturbances, system uncertainties, and configuration changes. In addition, fault tolerance, health monitoring and reconfigurable control strategies are accommodated to ensure stability and an optimized reconfiguration of control and sensing channels in the case of malfunctions.

However, the *highly nonlinear* structure of fuzxy-neural control results in a system design that is hard to assess for stabilit y and robustness margins. Nor is it possible to provide a rigorous guarantee of these margins.

Autonomous Intelligent Robust Control

To overcome the separate limitations of MACSYN and fu7.7y-neural control, a combined hierarchical scheme is proposed. Figure 11. shows a candidate architecture for Autonomous Intelligent Robust Control (IRC) technology.[22,23] The three-layer control system places guaranteed convergence, robustness, and stability within the reach of autonomous control. It also has the real-time capability of self tuning, self organizing, and time-critical contingency actions in dealing with unanticipated environments and mission events. One of the primary functions of control design is to ensure. the "robustness'" of the system to uncertainty. Typically, this requires considerable human interaction in the modeling and redesign processes. With IRC, substantial human effort can be saved, and that is an important motivation for autonomous spacecraft design.

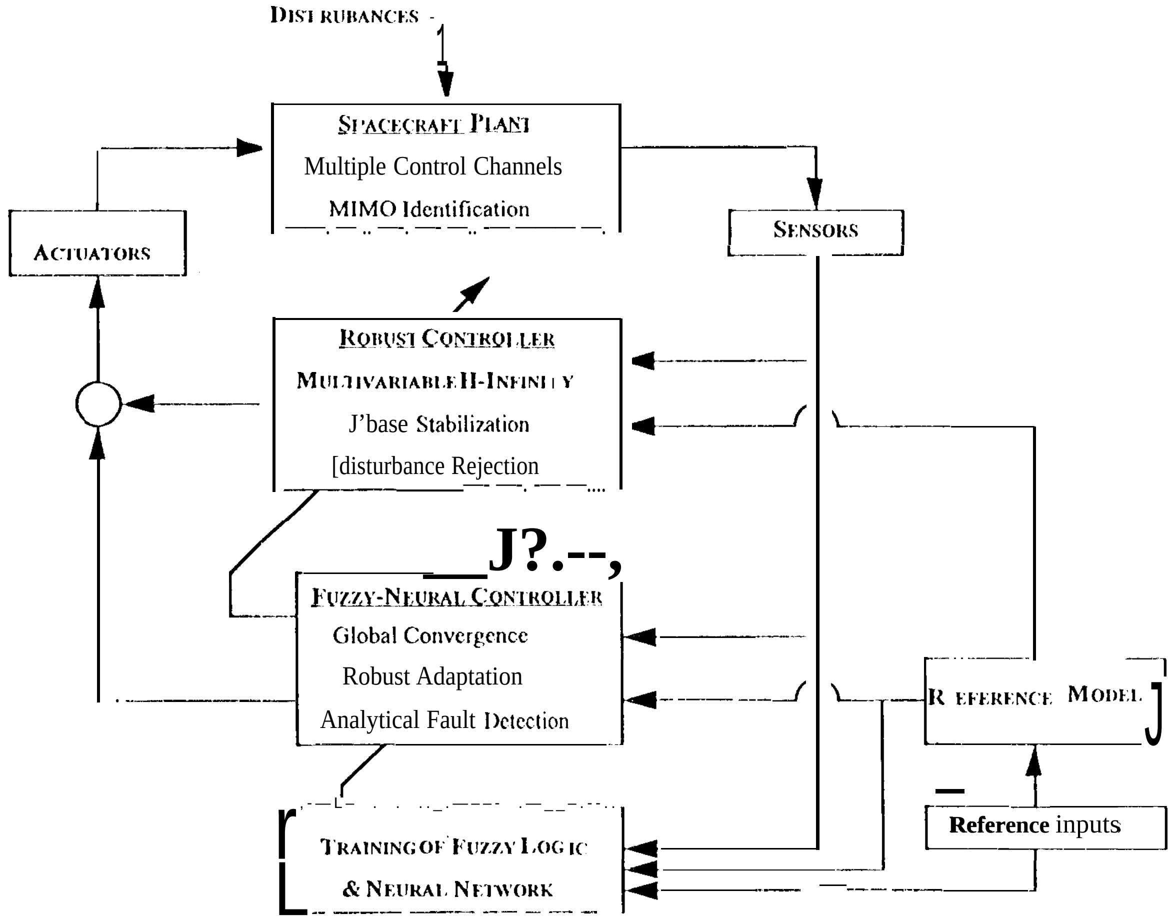

Figure 11. Autonomous Intelligent Robust Spacecraft Control Systems

Conclusions

NASA's future spacecraft will need to incorporate these advanced technologies so that scientifically ambitious deep space missions can also be affordable. This premise motivates the vision of small autonomous spacecraft equipped with decision and control authority to perform their mission without human intervention. The spacecraft will autonomously sense. and interpret its environment and execute its decision tasks to satisfy its mission plan. The flight system must be functionally robust and adaptable to a range of uncertainties and even unanticipated conditions. Advanced guidance and control functions are fundamental to this objective. Autonomous flight operations dictates control strategies that remain effective in the. presence of plant model uncertainties, equipment anomalies, sensing/perception constraints, and poorly-predicted exogenous inputs. The synthesis of advanced robust control and fuzzy-neural methods to form a new generation of autonomous intelligent spacecraft control lers is proposed in Ibis paper, and considered essential to achieving affordable and scientifically challenging missions in the next decade.

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