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Neural Network for Positioning Space Station Solar Arrays

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NEURAL NETWORK FOR POSITIONING SPACE STATION SOLAR ARRAYS

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ABSTRACT

As a Shuttle approaches the Space Station Freedom for a rendezvous, the Shuttle's reaction control jet firings pose a risk of excessive plume impingement loads of Freedom solar arrays. The current solution to this problem, in which the arrays are locked in a feathered position prior to the approach, may be neither accurate nor robust, and is also expensive. An alternative solution is proposed here: the active control of Freedom's beta gimbals during the approach, positioning the arrays dynamically in such a way that they remain feathered relative to the Shuttle jet most likely to cause an impingement load. An artificial neural network is proposed as a means to determining the gimbal angles that would drive plume angle of attack to zero. Such a network would be both accurate and robust, and could be less expensive to implement than the current solution. A network was trained via backpropagation, and results, which compare favorably to the current solution as well as to some other alternatives, are presented. Other training options are currently being evaluated.

NOMENCLATURE

Name	Description	Units
E	body-to-inertial matrix	-
F	external force	force
P	vector from CG	length
R	distance from earth center	length
d	closure distance	length
m	spacecraft mass	mass
r	closure rate	length /time
x, y, z	relative position	length
α	plume attack angle	rad
η	approach cone ang.	rad
ω	orbit rate	rad /time

INTRODUCTION

The electrical power system of Space Station Freedom (SSF) draws power from the Sun by means of photovoltaic

solar arrays. Beta gimbals rotate these arrays about their masts, enabling the arrays to maintain position relative to the sun or to reach some commanded orientation.

Berthing of the Shuttle with Freedom is accomplished by maneuvering the Shuttle within a small distance of the station, as illustrated in Figure 1. During this maneuver, Shuttle attitude and approach closure rate are corrected by its Reaction Control System (RCS) jets. It is possible at times for certain RCS jets to fire in the general direction of an array. The plume of a jet firing, illustrated in Figure 2, would in such a case induce a structural load on the array. NASA's concern was that an excessive load from a plume impingement could cause a failure of the array mast near the beta gimbal.

The baseline solution to the problem of excessive plume loads is array feathering — the positioning of arrays prior to the approach such that their surfaces are parallel to the direction vector of a critical plume, and the subsequent locking of the gimbals. The locking mechanism design limits error margin in feathered position. The structural redesign also means a large cost increase to be incurred by the Space Station program, as is the case with most redesigns [1].

An alternative to this baseline solution is proposed: leave the beta gimbals active during approach, use their control systems to dynamically increment the feathered position of the arrays, and use an artificial neural network (ANN) to generate commanded gimbal angle. Active gimbal control allows for greater error margin in feathered position than do locked arrays, and active control also enables the gimbals to reject disturbances within the capability of their motors.

A neural network design is proposed that will provide gimbal commands that drive the angle of attack of plumes on the arrays to near zero. The network was trained via backpropagation, using as an objective function the error between optimal and actual beta gimbal commanded angle. The resulting proposed control architecture is shown by block diagram in Figure 3.

APPROACH MODEL

During approach, the Shuttle astronauts will keep the closure velocity somewhere near a defined function of the closure distance. Experimental work done in this area [3] led to the adoption of the so-called "0.1% Rule," which is achieved by controlling the closure rate to near 0.1 per cent of the closure distance, given like units.

The astronauts have a second goal: that of maintaining the line of sight (LOS) within pre-set limits. This is done (1) to enable the Shuttle to remain aligned with the target with as few lateral RCS firings as possible, and (2) to minimize the effects of LOS rates on the astronauts' perspective of the target [5]. These objectives lead to the recommendation that the astronauts maintain position within an "approach cone," (as shown in Figure 2) with vertex at the berthing point of the target and predetermined half-angle.

The SSF and the Shuttle are both modeled as a single rigid body with six degrees of freedom. The relative motion of the two bodies is controlled by the Shuttle RCS, and follows the 0.1% Rule and stays within a 5-degree approach cone. The equations of approach dynamics are in Shuttle body-fixed coordinates.

The equation for motion in the nadir direction is

$$\begin{aligned} \frac{F_{xs}}{m_s} + \frac{F_{xp}}{m_p} \\ = \frac{d^2x}{dt^2} - 2\omega \frac{dx}{dt} - \omega^2 x \end{aligned} \quad (1)$$

and for motion tangential to the orbits,

$$\begin{aligned} \frac{F_{ys}}{m_s} - \frac{F_{yp}}{m_p} \\ = \frac{d^2z}{dt^2} + 2\omega \frac{dx}{dt} \end{aligned} \quad (2)$$

and for out-of-plane motion,

$$\frac{F_{ys}}{m_s} - \frac{F_{yp}}{m_p} = \frac{d^2y}{dt^2} \quad (3)$$

The motion between two berthing points, one on each body and separated from their respective CGs by a vector (P_s and P_p), is given by

$$\begin{aligned} \frac{d\mathbf{v}}{dt} \Big|_{s/r} &= \left[\frac{d^2x}{dt^2} \quad \frac{d^2y}{dt^2} \quad \frac{d^2z}{dt^2} \right]^T \\ &+ \frac{d\omega_s}{dt} \times P_s + \omega_s \times (\omega_s \times P_s) \\ &- \frac{d\omega_r}{dt} \times P_r - \omega_r \times (\omega_r \times P_r) \\ &= \left[\frac{dv_x}{dt} \quad \frac{dv_y}{dt} \quad \frac{dv_z}{dt} \right]^T \end{aligned} \quad (4)$$

The critical parameters in proximity operations analysis are those that pertain to the 0.1% Rule and the approach cone. The closure rate is given by

$$x = \int_0^t \frac{dv}{dt} \Big|_{s/r} dt \quad (5)$$

and closure distance is given by

$$\begin{aligned} d &= \int_0^t x dt \\ &= [d_x \quad d_y \quad d_z]^T \end{aligned} \quad (6)$$

Angular position within the approach cone is given by

$$\begin{aligned} \eta_x &= \tan^{-1}(d_x / d_z) \\ \eta_y &= \tan^{-1}(d_y / d_z) \end{aligned} \quad (7)$$

Attitude and position control of the Shuttle is provided by 44 RCS jets, of which the first 38 have thrust capabilities ranging from about 690 to about 880 lbf. The other six offer 25 lbf of thrust and are automatically controlled during proximity operations.

A simple controller was used to simulate the behavior of the perfect astronaut. It wasn't important for this study that flight data be matched exactly — the goal was to create training data that gave "optimal" gimbal angles for various combinations of the six available inputs.

Of six RCS firing combinations observed, as shown in Table 1, only three had any chance of causing an impingement on an array: jets used for braking (9-29-32) and those used for out-of plane motion (5-22 or 7-25). Flight data indicates a transition of plume risk from one type of firing to the other as closure distance decreases.

Plume impingement force is a function of angle of attack and closure distance, which indicates that plume angle of attack (over which the beta gimbals can have some authority) and closure distance are two fundamental parameters to consider in minimizing impingement force.

Feathering suggests that plume angle of attack can be minimized throughout the maneuver. Simulation shows that zero angle of attack can be achieved if the arrays are slewed about ten degrees during the maneuver, and if the approach cone is scrupulously followed during the transition period from braking to out-of-plane plume damage risk.

Both the SSF and the Shuttle are actively controlled during this maneuver. For each of the two craft, high-fidelity attitude control system models were employed. Attitude control for Freedom [9] is accomplished through the use of seven RCS jets, pulsing in groups of three.

The beta gimbals consist of direct-drive motors and are controlled via a PID algorithm. The beta gimbal control law allows for parameter uncertainty in electric motor dead zone [10] and in gimbal bearing friction [11]. The beta gimbals are active here for dynamic feathering.

NEURAL NETWORK SOLUTION

An artificial neural network, such as shown in Figure 4, has as in its simplest forms the following ingredients: neurons (or nodes), which themselves consist of a weighted summer, a linear transfer function and a non-dynamic nonlinear limiting function; inputs and outputs based on the physics of the problem; and a learning mechanism that takes advantage of known data, which is readily available here.

This problem appears to be well-suited to a neural network solution in that it takes advantage of well-known characteristics both of the beta gimbals and of Shuttle proximity operations. Hunt et. al. [16] lists properties of ANNs that are suitable for control applications:

- o Theoretical ability to approximate arbitrary nonlinear mappings;
- o Directly suitable to parallel processing architecture.
- o Directly applicable to multivariable systems.

Kohonen [17] points out that "...one category of problems which is sometimes believed to be amenable to 'neural computing' consists of various optimization tasks" [emphasis mine], and this task certainly falls into that category.

Desirable features of a neural network for this problem include:

- o Simplicity
- o Cost effectiveness
- o Large amount of data
- o Design stage not time-critical
- o Smooth motion commands

Characteristics of this problem which may be exploited are:

- o Astronaut behavior
- o Beta gimbal behavior
- o Jet firing behavior
- o Attitude control behavior
- o Ground command behavior
- o Complete availability of input data

Clancy et. al. [18] opted for a single hidden layer, and the use of radial basis functions (RBFs) as the neuronal activation functions. The advantage of RBFs for a problem such as this is that they can be used to classify inputs wherever they fall in the input space. Clancy's work yielded a large hidden layer, although his results were otherwise encouraging.

The network design used for proof-of-concept was trained via backpropagation [19]. The inputs used here are as follows:

- o closure distance
- o closure rate
- o approach cone position (two values)
- o approach cone rate (two values)

The nonlinearity must be continuously differentiable. If the inputs are known to vary between zero and one, Rumelhart and others suggest the use of a sigmoid function — in this case, the inputs may be of either sign, so a hyperbolic tangent function was used.

Of the various learning methods available, backpropagation is commonly used in practice. It is efficient (depending on the problem), relatively simple to understand, and readily available in various algorithms via shared software.

The training data for this problem was selected with the following assumptions:

- (1) Data taken from simulations of approach, using "ideal" astronaut behaviour.
- (2) Data from simulations sampled every 1 second of approach, for 500 data points per simulation run.
- (3) Runs chosen on the basis of initial conditions of x and y closure position and x, y and z closure rate, with two parameters varied from nominal for each run. This procedure produced 21 simulation runs (for a total of 10500 data points), described by Table 1.

There is a constant difference in geometry between the two beta gimbals only, and the resulting weights show that the same feature in the error surface should impact both gimbal commands in approximately the same way. The network error is plotted as a function of 1000 passes through the training data in Figure 5.

After 24000 passes through the training data, the network achieved very slow convergence, taken for this study as a minimum. The resulting weights were tested in the approach simulation, with the following results, in terms of how the network error was divided among the 21 training scenarios, as shown in Table 2.

The term "target switching" indicates that the primary jet the array is being feathered for is switching from z-braking to one of the two out-of-plane jets, or vice-versa. For some of the training scenarios, particularly those in which initial conditions had the approach offset out-of-plane, one would expect a great deal of switching back and forth between braking and out-of-plane firings, and the determination of optimal commanded gimbal angle reflects this effect. In fact, this is exactly the effect that the neural network must be designed to achieve: some tradeoff between feathering for braking firings and out-of-plane firings. As one might guess, the network performs much better for training runs in which there is little or no switching, and not as well when there is a great deal of switching. The network tries to fair a curve somewhere between feathering for braking and for out-of-plane firings, which may be sufficient for the problem, since such a curve would probably reduce the angle of attack of a plume from either jet to within one degree.

Perhaps more important is the idea that the optimal beta gimbal angle for following even a single jet sweeps through several degrees during the 500 seconds of approach examined here. That means that the solution involving locked gimbals is very restrictive, in that the angle of attack will at some point in the approach exceed the accuracy afforded by the locking mechanism.

CONCLUSIONS

The gimbal lock solution can achieve as its best accuracy the angle between adjacent locking points. This accuracy, however, only represents two locking points — which of course assumes the optimal locking point is chosen. The locking mechanism is a much coarser solution otherwise.

#	Initial Conditions (in or in/s)				
	x	$\frac{dx}{dt}$	y	$\frac{dy}{dt}$	$\frac{dz}{dt}$
1	0	.0	0	.0	.3
2	30	-.1	0	.0	.3
3	0	.0	30	-.1	.3
4	30	.0	0	.0	.4
5	0	-.1	30	.0	.3
6	0	.0	0	-.1	.4
7	-30	.0	-30	.0	.3
8	0	.1	0	.1	.3
9	0	.0	-30	.0	.2
10	-30	.0	0	.1	.3
11	0	.1	0	.0	.2
12	30	.0	0	.1	.3
13	0	-.1	0	.0	.2
14	-30	.0	30	.0	.3
15	0	.1	0	-.1	.3
16	0	.0	-30	.0	.4
17	-30	.0	0	.0	.4
18	30	.1	0	.0	.3
19	0	-.1	-30	.0	.3
20	0	.0	30	.1	.3
21	0	.0	0	-.1	.2

Table 1. Training data sets.

Run #	%Error	Comments
1	3.78	
2	2.90	Benign case
3	6.34	Target switching
4	2.98	Benign case
5	6.39	Target switching
6	4.64	
7	6.43	Target switching
8	6.53	Target switching
9	3.37	
10	6.60	Target switching
11	3.33	
12	3.54	One target switch
13	3.36	
14	7.57	Max. switching
15	5.93	Target switching
16	5.78	Target switching
17	3.88	
18	2.77	Benign case
19	6.17	Target switching
20	4.19	One target switch
21	3.54	One target switch

Table 2. How error was parceled to training data.

The accuracy needed in plume angle of attack must be determined both by proximity operations and loads specialists, since it involves both geometry and structural dynamics.

The baseline design falls short in the following areas:

- o It depends too heavily on a priori knowledge to get the right feathering angles.
- o It is not simple, as the structural/mechanical redesign affects too many other components.
- o It is not robust with respect to Shuttle motion.

The neural network proposed here could be trained and retrained as necessary. It can solve the optimization problem to (for practical purposes) whatever accuracy is needed. It is simple, in that only the beta gimbals are involved -- just as in the baseline solution, only without a mechanical redesign. And it is robust, as the neural network can be trained to respond to whatever relative motion combinations are of interest.

Any structural design change in Freedom may add several million dollars to the Station's overall price tag. Software design changes are also expensive, but depend on the order and accuracy of the algorithm to be implemented.

Any solution to be adopted must minimize engineering design and manufacture time. A structural redesign may delay other aspects of the structure, e.g. modal testing and component qualification. A software design solution may require training of engineering personnel and astronauts.

The network design proposed here was the result of training essentially by trial and error. It may be that too much attention was paid to avoiding local minima, and that the error surface is in reality flat (or gently sloped) and rough (based on target switching). Researchers must decide whether this caution is critical or not, and if it is, decide whether to proceed by trial and error or to automate the process, via simulated annealing or perhaps a "Monte Carlo" approach with a large number of starting points. The approach taken here led to a design in an acceptably timely manner, and without using excessive CPU, for proving the neural network concept.

Backpropagation learning is in this case slow. Again, if the network design is not time-critical, a designer could realize several different designs that work. This may not, however, be acceptable in training a final network design for software coding at the ground station. Backpropagation is in wide enough use that variants of the algorithm that run much faster than the original may be found via anonymous file transfer protocol at computer sites all over the world.

Alternatively, an approach such as Clancy's could be adopted -- a radial basis function neural network. The problem with the radial basis function approach is that the complexity of these networks goes up drastically as inputs are added, or as the error surface takes on more features. This tends to be true to some extent even when nodes are not selected randomly: Clancy estimated over 40 neurons in the hidden layer, with a design based on fewer training runs than were employed here.

The existing problem of risk of excessive Shuttle RCS jet plume loads on Space Station Freedom solar arrays during approach has been examined. The baseline solution to the problem, locking the arrays in a feathered position, is considered here to be neither accurate nor robust, and is very expensive. A proposal is made to replace the baseline solution with one in which the arrays are positioned dynamically during approach, using the existing beta gimbals. The gimbal commanded angles would be

provided via a ground-implementable artificial neural network, a solution that provides greater accuracy and robustness, and is likely to do so at less cost.

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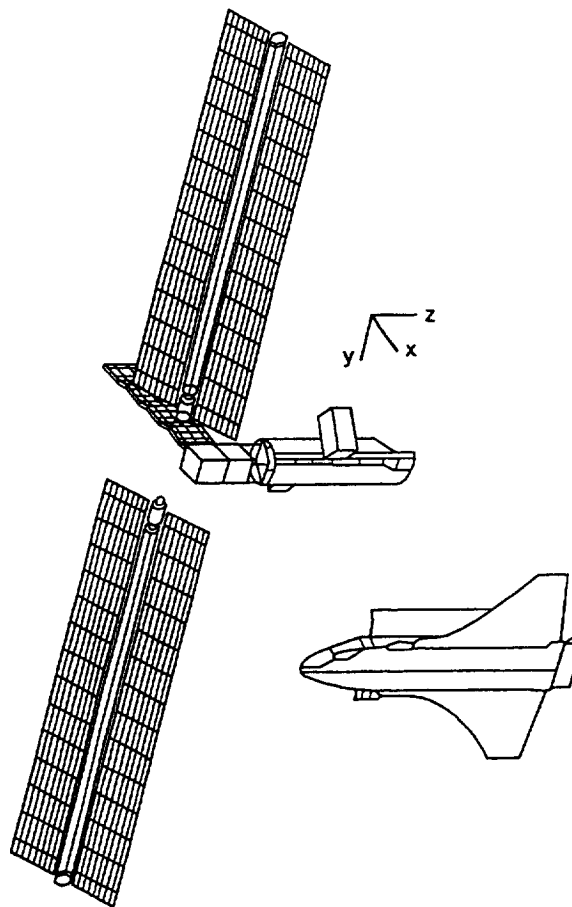


Figure 1.—Shuttle approach to SSF stage configuration SC-2.

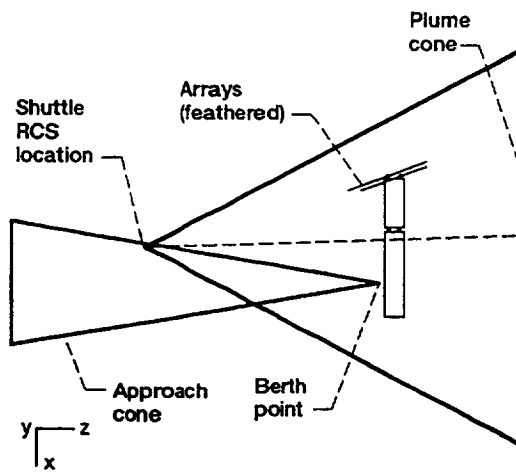


Figure 2.—Geometry of plume impingement.

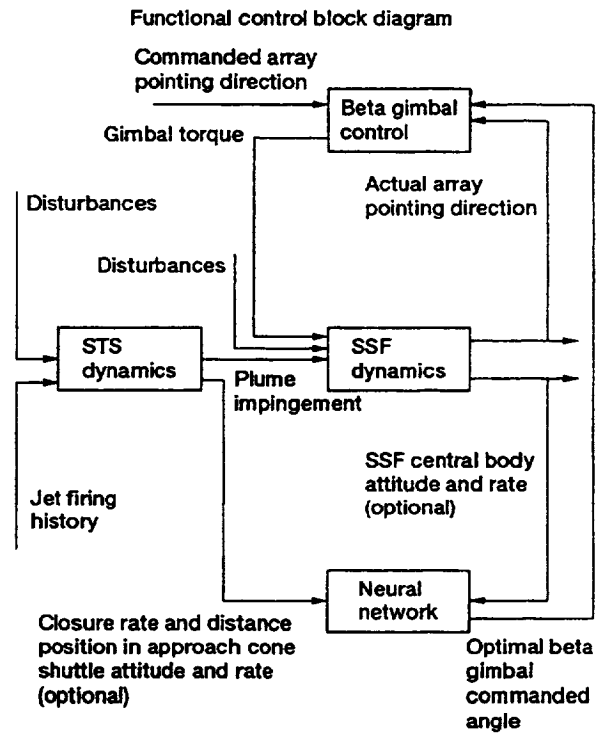


Figure 3.—Block diagram of proposed feathering control.

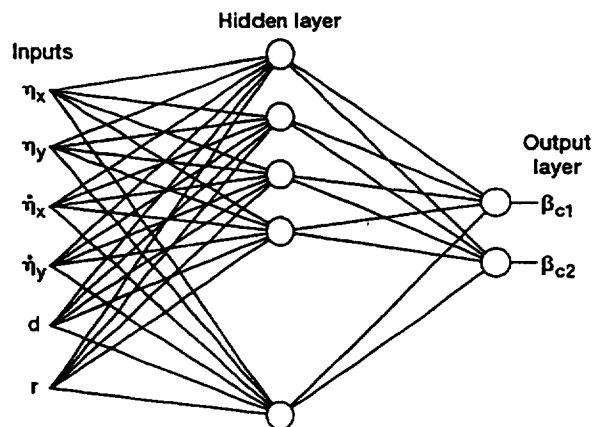


Figure 4.—Artificial neural network.

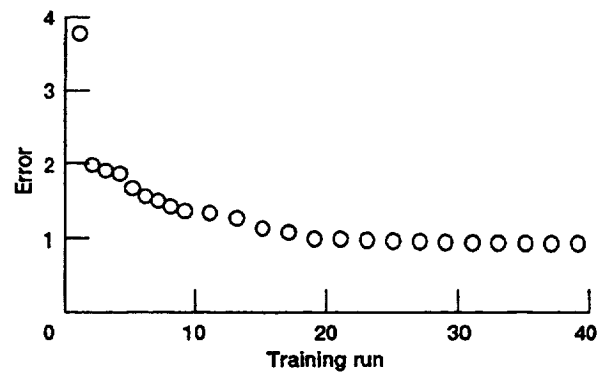


Figure 5.—Network error as a function of training run.

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