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Reconfigurable Control Allocations for the Next Generation of Robust Reusable Launch Vehicles

5 August 2005

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VOLPE NATIONAL TRANSPORTATION SYSTEMS CENTER
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16. Abstract
The Aerospace Corporation was tasked by the Volpe National Transportation Systems Center to provide technical support to the Federal Aviation Administration, Office of Commercial Space Transportation (FAA/AST), in performing a study of the existing literature on reconfigurable control allocations for the next generation of robust reusable launch vehicles (RLVs) and determining the feasibility of deriving hierarchical control allocations and reconfiguration architectures that extend the safe ascent and descent operational envelopes of RLVs, in general.

Recent interest to develop technology that will enable RLVs to land autonomously and recover from failures or damage has fueled research in integrated adaptive guidance and control. The new technologies usually involve reconfigurable control and trajectory reshaping. Trajectory reshaping is performed in real time as follows: A database of pre-computed reference trajectories is used to select a feasible trajectory for a given failure, while an adaptive guidance system makes corrections for errors and disturbances. The advantage of this approach is that there is no need to consider every possible control failure to generate the trajectory database. It is enough to capture the effect of control failures with a few parameters such as the total variation in lift and drag.

The purpose of this study was to provide technical support on advanced guidance and control methods that may have significant potential to increase the safety and reliability of future RLVs and to reduce the cost of performing trajectory guidance, navigation and control analysis. Management of emergency situations arising from control surface degradation or actuator failure, using other available operating mechanisms and a reconfigured adaptive control strategy, may improve safe mission return or abort scenarios. The problem is generic, widely affects the general class of RLVs, and is of great importance from a safety perspective.

In addition to a thorough survey of current guidance, navigation and control (GN&C) reconfiguration strategies for RLVs, the results of this investigation can be construed as a comprehensive tutorial on the subject. Furthermore, Aerospace's evaluation by simulation of control allocation and adaptive control via (1) linear programming and (2) neural networks, two of the most promising methodologies, has demonstrated that those techniques are quite accessible to the GN&C practitioner.

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Abstract

The Aerospace Corporation was tasked by the Volpe National Transportation Systems Center to provide technical support to the Federal Aviation Administration, Office of Commercial Space Transportation (FAA/AST), in performing a study of the existing literature on reconfigurable control allocations for the next generation of robust reusable launch vehicles (RLVs) and determining the feasibility of deriving hierarchical control allocations and reconfiguration architectures that extend the safe ascent and descent operational envelopes of RLVs, in general.

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In addition to a thorough survey of current guidance, navigation and control (GN&C) reconfiguration strategies for RLVs, the results of this investigation can be construed as a comprehensive tutorial on the subject. Furthermore, Aerospace's evaluation by simulation of control allocation and adaptive control via (1) linear programming and (2) neural networks, two of the most promising methodologies, has demonstrated that those techniques are quite accessible to the GN&C practitioner.

Acknowledgments

Mr. Miguel A. de Virgilio and Mr. Robert W. Seibold served as Principal Investigator and Program Manager, respectively. Mr. Damian M. Toohey was a main contributor to the control allocation and adaptive autopilot section. Dr. Ahmed Omar-Amrani contributed to the guidance section. Dr. Jeffrey Caplin acted as a consultant in the control allocation task and provided models for the simulations.

Gratitude is extended to Mr. Pradipta Shome at the Office of the Associate Administrator for Commercial Space Transportation, Federal Aviation Administration, for valuable guidance on FAA/AST regulatory and licensing needs. Special acknowledgement is deserved for his valuable input in steering our investigation toward the use of neural networks. The authors also wish to thank Mr. John J. Sigona, who served as the Contracting Officer's Technical Representative (COTR) at the Volpe National Transportation Systems Center and provided valuable insight on government needs and regulations.

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1. Introduction and Background

1.1 Introduction

The Aerospace Corporation was tasked by the Volpe National Transportation Systems Center to provide technical support to the Federal Aviation Administration, Office of Commercial Space Transportation (FAA/AST), in performing a study of the existing literature on reconfigurable control allocations for the next generation of robust reusable launch vehicles (RLVs), and in determining the feasibility of deriving a hierarchical control allocation and reconfiguration architecture that extends the safe ascent and descent operational envelopes of RLVs, in general. The Aerospace Corporation is pleased to submit this final report, in accordance with the requirements delineated in Section F, Deliveries or Performance, of Volpe Center Contract No. DTRS57-99-D-00062.

The purpose of this study was to provide the Volpe Center and FAA/AST with technical support needed to understand advanced guidance and control methods that may have significant potential to increase the safety and reliability of future RLVs, as well as to reduce the cost of performing trajectory guidance, navigation and control analysis. Management of emergency situations arising from control surface degradation or actuator failure, using other available operating mechanisms and a reconfigured adaptive control strategy, may improve safe mission return or abort scenarios. The problem is generic, widely affects the general class of RLVs, and is of great importance from a safety perspective.

The delivered product is this final report summarizing (1) the current technology of reconfigurable control methods applicable to RLVs, in general, and (2) the development of general guidelines for application of reconfigurability for control allocations to enhance the safety attributes of RLVs. This task was organized into six subtasks:

1. Perform literature survey.
2. Evaluate most promising control allocation algorithms.
3. Evaluate adaptive guidance laws.
4. Evaluate optimum trajectory reshaping methods: (a) off-line trajectory database generation, and (b) on-line trajectory reshaping.
5. Perform limited simulation verification of the above using Aerospace's RLV six-degrees-of-freedom (6-DOF) simulation tool.
6. Develop general guidelines for application of reconfigurability for control allocations to enhance RLV safety attributes.

1.2 Background

In recent years, significant efforts to develop new technologies for the next generation of RLVs have been undertaken by the National Aeronautics & Space Administration (NASA), Department of Defense (DOD), and by the civilian sector as well. The aging shuttle fleet will be replaced in the future by new manned and autonomous space vehicles. These new vehicles will benefit from advances in computer technology and also from the new more capable and adaptable flight algorithms currently being developed. Adaptive guidance and control re-allocation can be used effectively to land autonomous space vehicles safely. Autonomous vehicles, unlike manned ones, do not have the advantage of a pilot in the loop to compensate for failures.

The use of intelligent systems to compensate for failures is attractive but is no substitute for intelligent design of the space vehicle itself. The aim is rather to augment the reliability of existing control systems. Redundancy is commonly used for aircraft but not always for space vehicles because of penalties in weight, cost, and complexity. Some redundancy of the control effectors is desirable to retain full control authority, but if it is not possible, the RLV will be restricted in its operation and the flight path will have to be altered by the combined effect of adaptive guidance and control to save the mission.

A failure can occur at anytime during reentry; in addition, the nature of the failure varies and they are not easily recognizable without an active fault detection and isolation (FDI) system. However, all failures alter the aerodynamic characteristics of a given RLV, which can be expressed as total variation in lift, drag, and aerodynamic moments. Consequently, it is sufficient to know the effect of a failure to devise a course of action to compensate for it. This course of action may include on-board trajectory optimization when needed.

2. Approach

2.1 Principal Philosophy

The current Space Shuttle guidance, navigation, and control (GN&C) reconfiguration strategies following effector (e.g., flaps, actuators) failures were reviewed to identify areas of study for improvement. Currently, intensive preflight trajectory and GN&C analyses must be performed. This results in intensive computational requirements and development costs.

A preliminary literature survey (over 30 reports) was conducted to assess the state-of-the-art in this area. Key documents that were reviewed are listed in the References and Bibliography section. In the most general case, the reconfiguration capabilities for RLVs may employ the following elements:

- Failure identification
- Inner loop control reconfiguration
- Outer loop guidance adaptation
- Onboard trajectory command reshaping

An overview of system architecture with trajectory shaping is depicted in Figure 2-1.

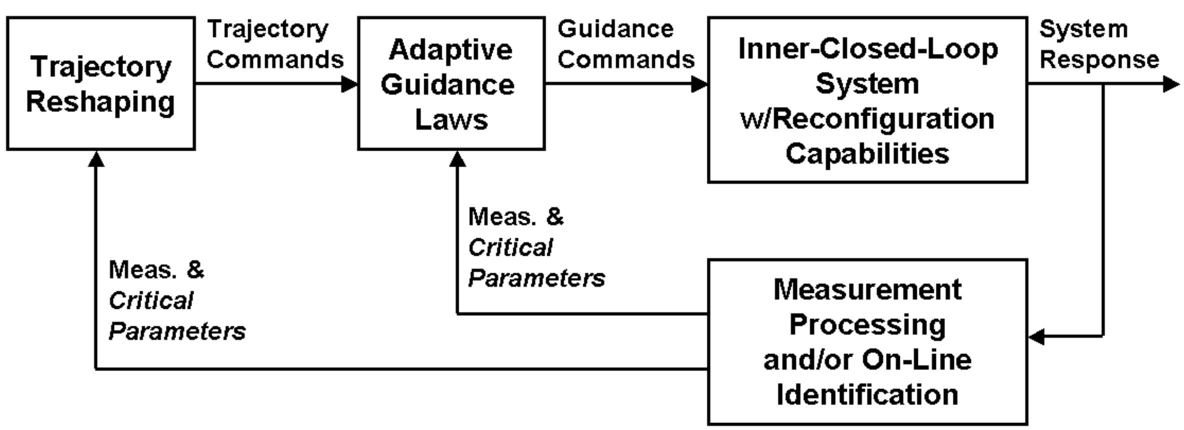


Figure 2-1. System Architecture with Trajectory Shaping

Following is an outline showing the key sub-elements of the first two of the four above-listed elements.

- <u>Failure Identification</u>:
    - o Failures may be of three types:
        1. Actuator failures
            - Reduced range, hard-over
        2. Internal failures
            - Only part of the plant fails
                - – <u>Example</u>: A coil failure will result in a sluggish response but provide the same steady state effectiveness
        3. Sensor failures

- Some measurements become unavailable, incorrect, or noisy

- Inner Loop Control Reconfiguration (Figure 2-2):
  - Involves four blocks:
    1. Reference model
    2. Proportional-plus-integral (P+I) controller (or equivalent compensator)
       - Possible learning neural network adaptation
    3. Dynamic inversion to generate desired command rates
    4. Control allocation algorithms
       - Pseudo-control hedging to modify reference model if actuator is saturating

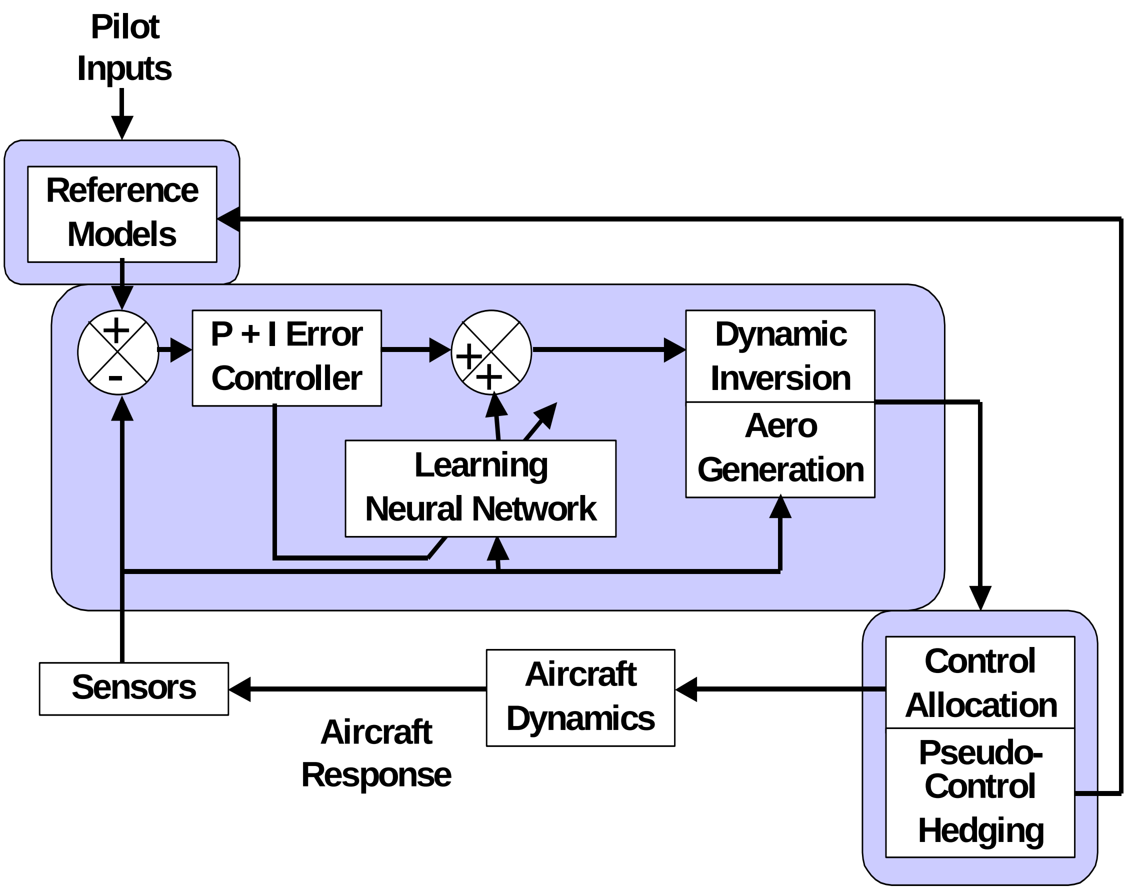


Figure 2-2. Inner Loop Architecture

2.2 Subtasks

The most promising control allocation algorithms were reviewed, and among them, linear programming was evaluated in detail via simulation (Section 3). A subtask not initially included in Aerospace's proposal was added to this study. This new subtask, a study of the use of neural networks for adaptive control, suggested by P. Shome, FAA/AST, was extensively researched.

Aerospace's simulation results for this approach are reported in Section 4. A review of adaptive guidance and control and resulting recommendations are reported in Section 5. General guidelines for application of reconfigurability technologies, along with recommendations for future work, are reported in Section 6.

3. Control Allocation

Control allocation algorithms were evaluated, along with linear programming, and conclusions were drawn.

3.1 Evaluation of Control Allocation Algorithms

Control allocation algorithms were evaluated using the approach reported by C. Reagan in Ref. 1. An outline of this evaluation follows. Vector entries are shown in **bold** font.

C: Effectiveness Matrix **v**: Commanded control **u**: Control deflections $\mathbf{W_u}$: Weighting matrix $\mathbf{u_p}$: Trim value of **u** **x**: State vector *k*: Current sampling time *lb*: Lower effector limit *ub*: upper effector limit

- Problem Statement:
  - Given a control command, **v**, and control effectiveness matrix, **C**, find the "best" admissible combination of control deflections, **u**.
  - Solve for $\mathbf{u}^{(k+1)}$: $\mathbf{C}(x,u)\mathbf{u}^{(k+1)} = \mathbf{v}$

    Bound to: $lb < u < ub$
- Various Methodologies:
  - Weighted Pseudo-inverse
    - $\mathbf{u} = \mathbf{W}_u^{-1}\mathbf{C}^T\left(\mathbf{C}\mathbf{W}_u^{-1}\mathbf{C}^T\right)^{-1}\left(\mathbf{v} - \mathbf{C}\mathbf{u}_p\right) + \mathbf{u}_p$
  - Daisy-Chain
    - Implemented as a multiple pass pseudo-inverse where effectors are prioritized. Primary surfaces used for normal flight maneuvers. Secondary surfaces handle commands unattainable by primary surfaces.
  - Linear Programming (LP)
    - $$J = \min_x f^T\mathbf{x} \quad \text{such that} \quad \begin{matrix} A \cdot x \le b \\ Aeq \cdot x = beq \\ lb \le x \le ub \end{matrix}$$

      Where: J = cost function
      A = Inequality constraint matrix
      b = Inequality constraint
      Aeq = Equality constraint matrix
      beq = Equality constraint
  - Quadratic Programming (QP)
    - $$J = \min_x\left(\frac{1}{2}\mathbf{x}^T\mathbf{H}\mathbf{x} + f^T\mathbf{x}\right) \quad \text{such that} \quad \begin{matrix} A \cdot x \le b \\ Aeq \cdot x = beq \\ lb \le x \le ub \end{matrix}$$
  - Sequential Optimization
    - Using either LP or QP, sequential optimization attempts to first minimize the error between commanded control and achievable control. If the error is zero, it then attempts to minimize the control effort.
  - Mixed Optimization

        - Similar to sequential optimization, except that the cost function is a combination of minimizing control effort and control error.
- Pros and Cons of Above Methodologies:
    - Weighted Pseudo-inverse
        - Does not allow for control effector limits
        - Does not take advantage of entire admissible moment set (AMS)
    - Daisy Chain
        - Allows for control limits by implementing multiple passes of pseudo-inverse
        - Does not cover entire AMS
    - Linear/Quadratic Programming
        - LP and QP cover the entire AMS
        - Both LP- and QP-based methods distribute more control to the most effective surfaces
        - QP based methods distribute input commands among all available control surfaces, whereas linear programming methods are more restrictive.
        - Computational time may be an issue for quadratic programming.

3.2 Evaluation of Linear Programming

A stand-alone MATLAB/Simulink simulation using a linear model for the plant was developed in order to investigate the various control allocation methodologies. The RLV control architecture used in this evaluation is presented in Figure 3-1. In this figure, AoA is angle of attack, $\dot{q}_C$ is attitude rate command, and K_{EQ} is attitude rate gain.

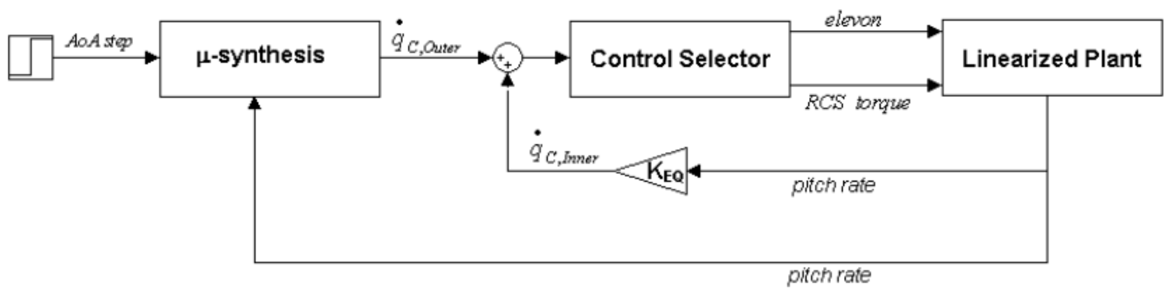


Figure 3-1. RLV Longitudinal Architecture

Current studies focus on a linearized RLV model perturbed by an angle-of-attack step input. In order to force the aerodynamic flaps into saturation, the vehicle plant model was linearized around a low dynamic pressure flight condition (12 psf) representing an altitude of 250,000 ft. The inner-loop controller uses pitch rate and angle-of-attack feedback, while µ-synthesis is employed for the outer loop compensator. Given a reference angle-of-attack and the feedback states, the commanded pitch acceleration is generated to meet the desired performance. The control selector then uses dynamic inversion to compute the necessary effector usage.

Previously, when the Aerospace RLV six-degrees-of-freedom (6-DOF) simulation was first developed, its control selector employed the daisy chain methodology. That technique put total priority on the aerodynamic surfaces in an attempt to avoid using the reaction control system (RCS) and expending thruster propellant. Only after elevon deflection commands became saturated were the RCS thrusters utilized.

While the daisy chain approach has proved successful in the past, greater flexibility may be achieved by introducing the linear programming method. This latter technique attempts to find an optimal combination of control effector contributions by minimizing a cost function. For instance, if the goal is to minimize fuel consumption, RCS thrusters are given a higher cost to discourage their use.

A control selector that utilizes the linear programming method was therefore introduced to the RLV simulation. The new algorithm was validated through simulation by examining a simple test case that uses the following cost function:

$$z = c_1 \left| \dot{q}_{elevon} \right| + c_2 \left| \dot{q}_{RCS} \right|$$

The elevon deflection rate, $\dot{q}_{elevon}$, and the equivalent RCS deflection rate, $\dot{q}_{RCS}$, are chosen such that they satisfy the desired input command while at the same time attempting to minimize z. In this simple case, the cost coefficients, c_1 and c_2, are set as constants. If $c_1 < c_2$, an incremental change in elevon deflection will always be "cheaper" than firing the RCS thrusters. Therefore, it should not be surprising that this particular cost function will mimic the daisy chain method. Figure 3-2 displays the control effort of the system after being perturbed by an angle of attack step input. Due to the low dynamic pressure, the initial commanded acceleration was larger than what the elevon flaps could provide, so RCS contribution was required. The simulation currently uses an idealized RCS thruster model that allows for variable thrust. A more realistic model that incorporates thruster pulse width modulation is currently under development and could be used in subsequent analyses.

The next step in the control allocation study would have been to develop more refined cost function weighting factors for the elevon deflections. For instance, to avoid slamming against stops, the cost may increase significantly as deflections approach their maximum values. Similarly, varying costs can be used as actuator rate limiters. Another task would have been to implement the optimal control allocation algorithm into the non-linear RLV simulation. Doing so would have allowed us to examine the effects on performance as the vehicle negotiates through varying flight regimes, but this could not be completed within the scope of this task.

3.3 Control Allocation Conclusions

Our limited study involved only two control effectors (elevon deflections and RCS). For this case, there was no real difference between daisy chain and linear programming performance.

The advantages of linear programming over daisy chain will become more apparent as more refined cost functions are employed.

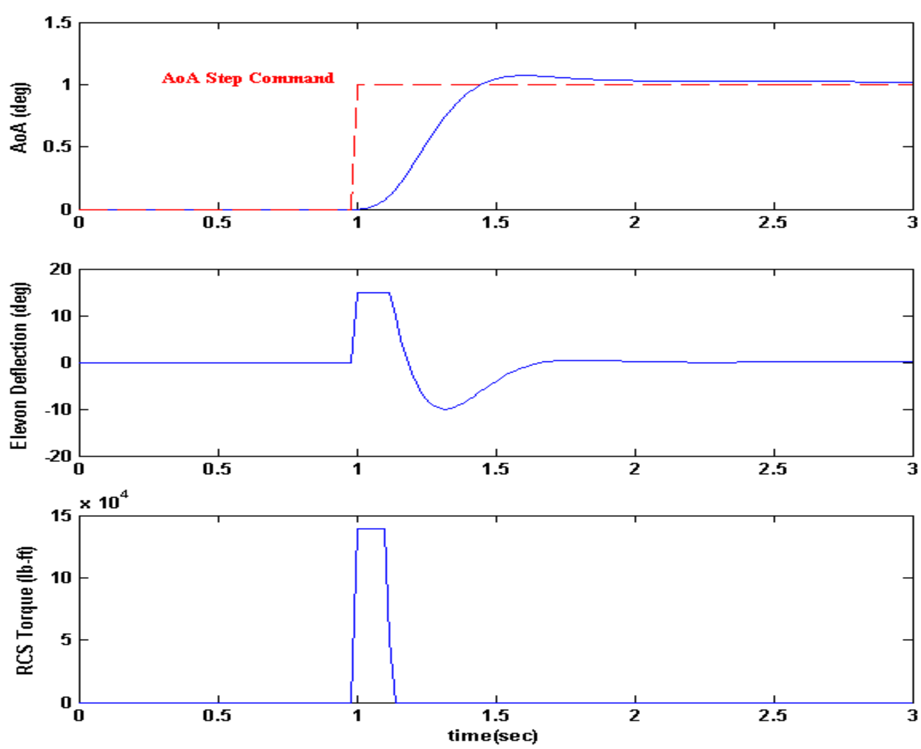


Figure 3-2. Simulated RLV Response to AoA Step Input Using Linearized Plant

4. Adaptive Control Using Neural Networks (NN)

Conventional adaptive control requires modeling of the plant by differential/difference equations, with certain parameters required to be estimated in flight. In real life, the plant and its environment may be difficult to model. Conventional adaptive control must rely on preliminary parameter identification, which may take longer than direct adaptation.

Unique properties of NN make them suitable for use in adaptive control applications. Examples of these properties are:

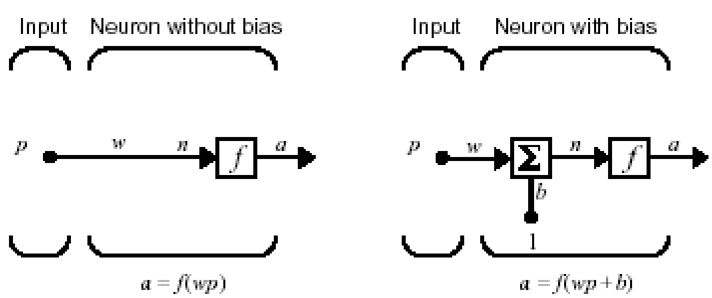
- Learning by experience: "human like"
- Ability to map similar input to similar outputs
- Ability to map nonlinear functions

4.1 Neural Network Fundamentals

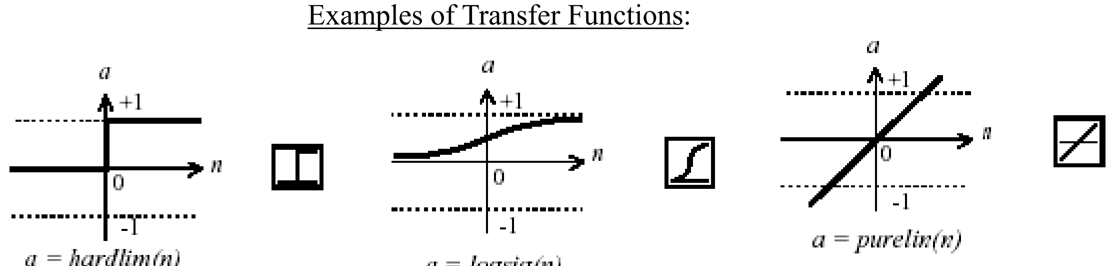
The material in this section was extracted from Ref. 2.

A simple neuron with single input is characterized by:

- Input (p)
- Bias (b)
- Weighting factor (w)
- Transfer function (f)
- Output (a)

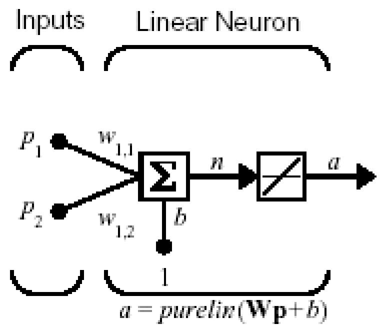


Examples of Transfer Functions:



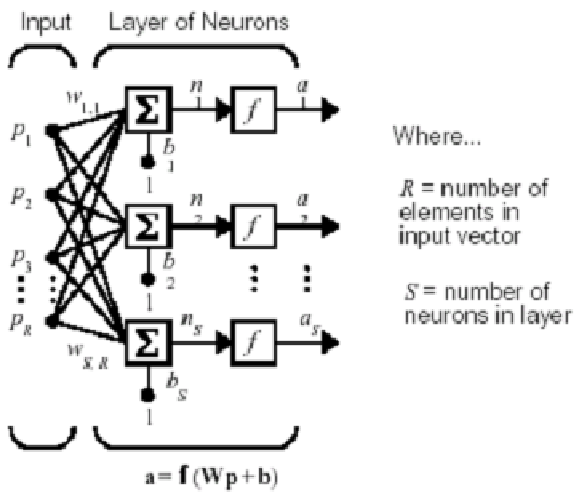
Hard-Limit Transfer Function   Log-Sigmoid Transfer Function   Linear Transfer Function

<u>Neuron with Input Vector</u>:

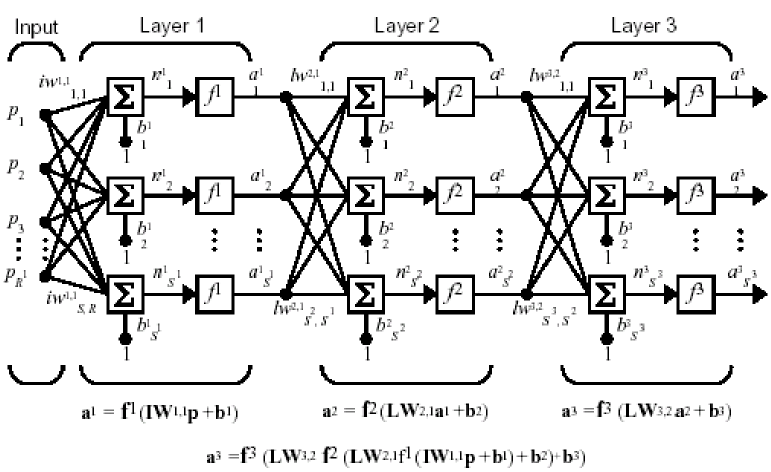


<u>A Layer of Neurons</u>:

A one-layer network with R input elements and S neurons is depicted.

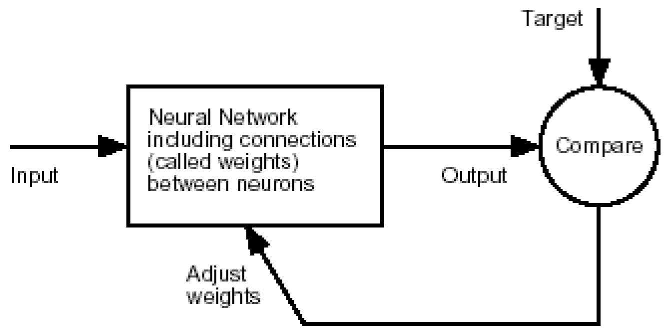


<u>Multiple Layers</u>:



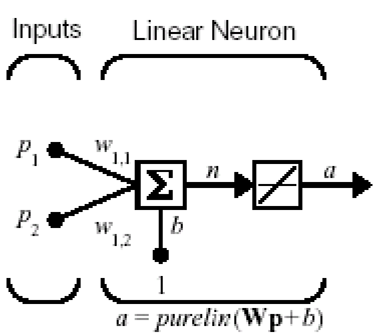
4.2 The Neuron as an Adaptive Filter

Neural networks are adjusted, or trained, so that a particular input leads to a specific output or target, as illustrated in the figure below:



4.3 Example of Neuron Training

Incremental training with a static network to represent a function of two variables is discussed. We use a single neuron model with two-component input vector (p_1 and p_2), and a single output target, a, where $a = 2p_1 + p_2$ and W = weighting matrix.



This problem can be solved in the MATLAB neural toolbox by providing:

4 sets of input pairs: $p_1 = \begin{bmatrix}1\\2\end{bmatrix} \begin{bmatrix}2\\1\end{bmatrix} \begin{bmatrix}2\\3\end{bmatrix} \begin{bmatrix}3\\1\end{bmatrix}$

and a set of 4 single targets:

$a_1 = [4]$, $a_2 = [5]$, $a_3 = [7]$, $a_4 = [7]$

by calling the ADAPT algorithm (a MATLAB adaptive algorithm), which uses the Withrow-Hoff learning algorithm.

The ADAPT algorithm sequentially computes the optimal weights and bias to match the targets. The weights and bias are updated each time a new pair (input, target) is presented. Eventually the error should be driven to zero.

The same set of 4 inputs and targets were presented 30 times to the ADAPT algorithm.

Every row below represents the error in matching each one of the 4 targets at each iteration step.

[4.0000]	[3.0000]	[1.0000]	[1.2000]
[-1.5200]	[0.2000]	[-0.3920]	[1.0240]
[-0.9696]	[0.0592]	[-0.0419]	[0.4739]
[-0.6641]	[0.0101]	[0.1324]	[0.2105]
[-0.5162]	[-0.0122]	[0.2108]	[0.0876]
[-0.4427]	[-0.0223]	[0.2443]	[0.0304]
[-0.4040]	[-0.0267]	[0.2569]	[0.0039]
[-0.3818]	[-0.0284]	[0.2597]	[-0.0083]
[-0.3672]	[-0.0288]	[0.2580]	[-0.0138]
[-0.3564]	[-0.0287]	[0.2543]	[-0.0161]
[-0.3474]	[0.0283]	[0.2497]	[-0.0170]
………………………………………………			
………………………………………………			
[-0.0992]	[-0.0082]	[0.0718]	[-0.0052]

4.4 Noise Cancellation Example

As a demonstration of the Widrow-Hoff learning method, a simple noise cancellation filter was examined. In this example, a random input signal is corrupted by a constant-frequency noise. An adaptive linear filter is used to restore the original signal. The filter attempts to find the optimal weighted combination of the neural network inputs that best reproduces the noise path filter.

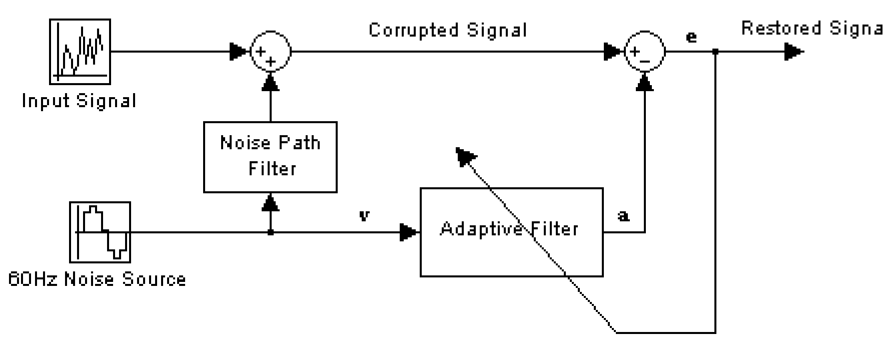


Figure 4-1. Noise Cancellation System

Figure 4-1 describes the system. In this figure, v = input to adaptive filter, a = output from adaptive filter, and e = error. The adaptive output, a(k) (where k = sampling interval), is subtracted from the contaminated signal to create the restored signal, which is then fed back into the neural network as the error. The Widrow-Hoff learning algorithm uses that error to update the network weights. A single layer network consisting of the noise input and a tapped delay is all that is required to sufficiently restore the signal. Figure 4-2 depicts the adaptive linear filter network, and Table 4-1 shows the Widrow-Hoff learning algorithm for the noise cancellation example.

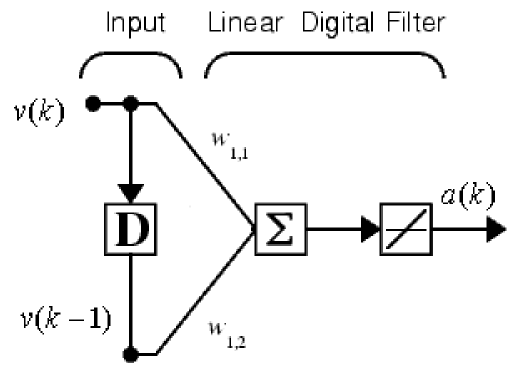


Figure 4-2. Adaptive Linear Filter Network

Table 4-1. Widrow-Hoff Learning Algorithm for Noise Cancellation Example

$a(k) = w_{1,1}v(k) + w_{1,2}v(k-1)$
$\mathbf{w}(k+1) = \mathbf{w}(k) + (2\lambda)e(k)\mathbf{p}^T(k)$
$\mathbf{p}(k) = [v(k) \quad v(k-1)]$ $e(k) =$ Error Signal $\lambda =$ Learning Rate

Note: It may seem counterintuitive that the restored signal is used as the error that drives the network. After all, since the function of the learning algorithm is to minimize the error, the neural network will attempt to drive the restored signal to zero. However, because an adaptive linear filter can only solve linearly separable problems, it will only reproduce the portion of the error signal that is correlated to the reference noise. Therefore, without knowing it, the neural network removes only the contamination and restores the original signal (Figure 4-3).

Figure 4-3 presents simulation results comparing the restored signal against the input signal. At time = 0, the network is not yet trained, and the weights are initialized to zero. As expected, much noise is initially present. The LMS learning algorithm adjusts the weighting function, and after time, the neural network weights settle near the ideal values, and the noise error is minimized (Figure 4-4).

In this example, a conservative learning rate was used to better illustrate the update process. Increasing its value will improve the network's response, but too large an increase will lead to instability. The learning rate acts as a gain to the neural network compensator. For any given system, design decisions will need to consider the tradeoffs between responsiveness and stability.

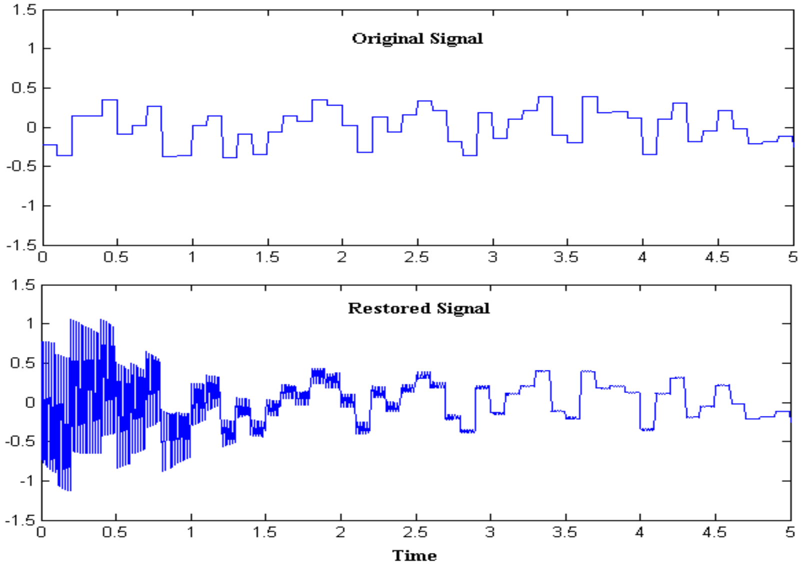
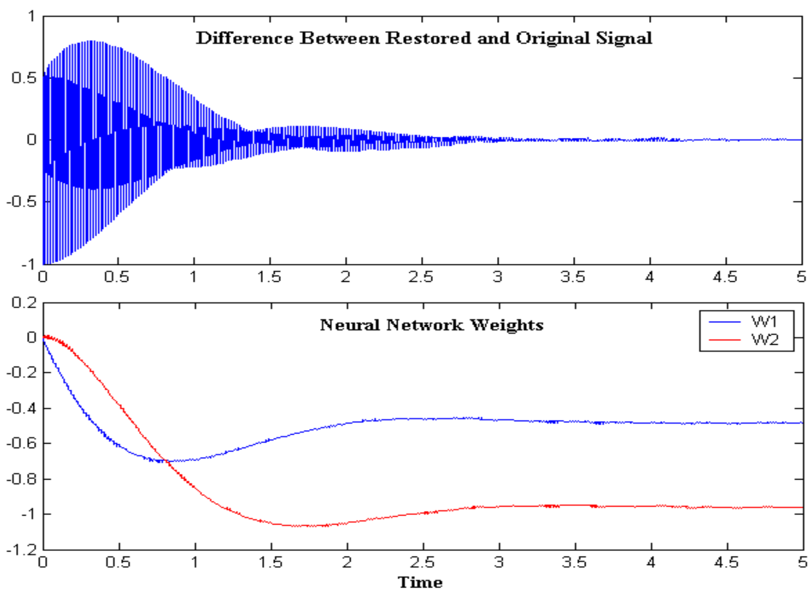


Figure 4-3. Original Signal vs. Restored Signal



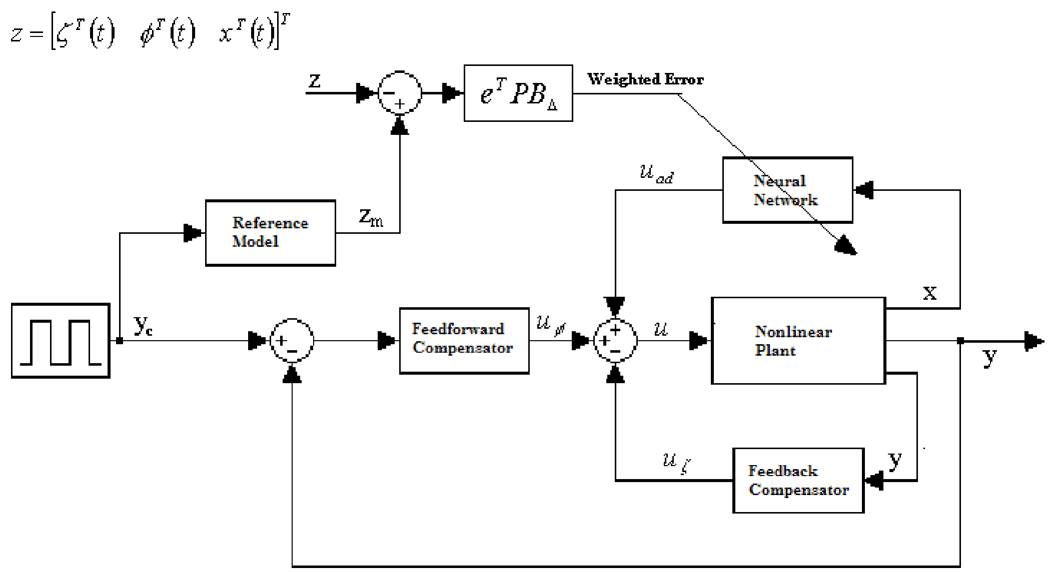
w_1 and w_2 = weighting factors

Figure 4-4. Noise Cancellation Performance

4.5 Adaptive Control

In many control applications, a controller is designed around a linearly approximated model of the actual system. Any nonlinearities or effects in the plant not predicted by the model will affect the performance of the control system and potentially lead to instability. Recent studies have demonstrated that neural networks may be used to augment linear controllers to compensate for these modeling errors.

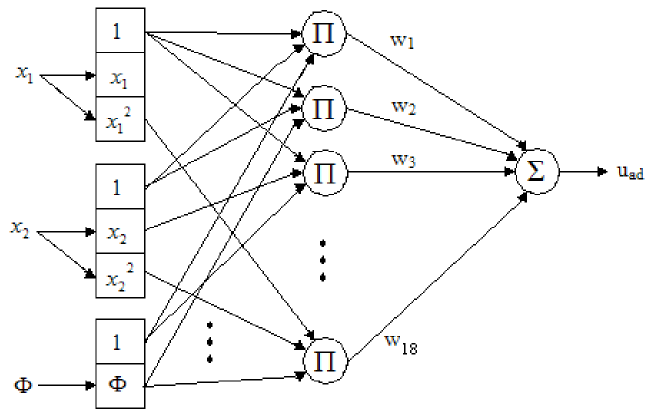
An example of such an adaptive control scheme is shown in Figure 4-5. A neural network augments the existing closed loop system to account for any plant characteristics not predicted by the model. The system's response is compared to a reference model, and the difference between the two is the error that drives the adaptation process. A weighted error is generated, which is then used to update the weighing function. According to the universal approximation theorem, there exist constant, ideal weights that allow the neural network to approximate the model error to an arbitrary accuracy, provided that the network contains a sufficient number of nodes or hidden layers.



ζ and ϕ are the states of the compensators

Figure 4-5. Adaptive Control System

A simple verification of this methodology was tested using the control system discussed in Ref. 3. For this demonstration, adaptive control was achieved using a single layer network consisting of 18 neurons (Figure 4-6). Figure 4-7 shows a comparison between the system response with and without neural network compensation. The error driving the network was based on the comparison between the reference model and actual system response. In order to ensure that the weights remain bounded, an error deadband was introduced to limit the weighting function update process once the error dropped below a specified value. Initial simulations did not include the deadband, which led to instability.



Π = multiplier

Figure 4-6. Neural Network Architecture

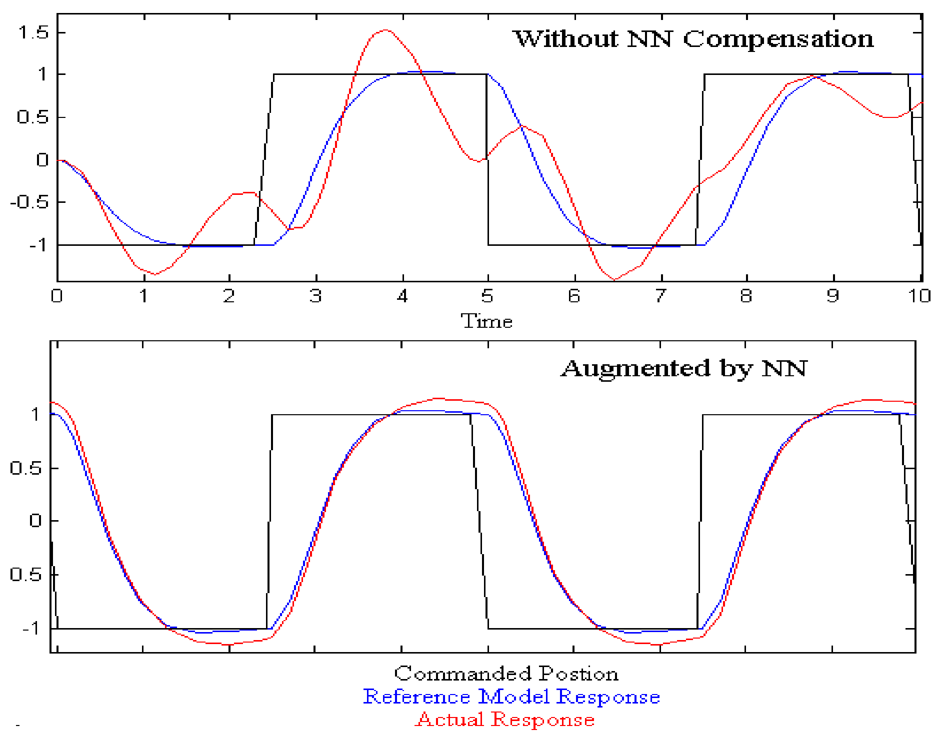


Figure 4-7. Adaptive Control Performance

There is great potential for adaptive control for reentry vehicles. However, any practical implementation must account for the fact that an RLV has limited controllability. In the adaptation example discussed above, full controllability was assumed. If a control effector is ever limited – for instance, when a flap reaches a hard limit – care must be taken to prevent the neural network from learning incorrectly. The concern is that in such a situation, the neural network could interpret the response error as a function of plant modeling differences instead of control limitations. To prevent such a situation from occurring, the controller could turn off the adaptation process whenever a control effector is limited.

Another solution that has shown promise is known as "pseudo control hedging," whereby the neural network is prevented from seeing the effects of a saturated effector. This is accomplished by moving the reference model backward by the amount that the actual plant failed to move due to a saturated control surface. Essentially, pseudo control hedging adjusts the reference model such that it also accounts for the limited controllability. Thus, when the neural network compares the reference model output to the actual output, the resulting error encompasses only modeling errors.

4.6 Adaptive Control Conclusions

1. The Widrow-Hoff training rule, applicable to single layer neural linear networks, is fairly straightforward and was applied to a simple example.
2. The same algorithm was exercised to perform as a noise filter.
3. Direct adaptation control methodology using neural networks was revisited, and sufficient insight was gained to allow its implementation in a MATLAB simulation.
4. When the NN optimal weight computation algorithm recommended in Refs. 3, 4, 5, and 6 was used without a dead zone or a stabilizing term, it led to an instability.
5. The introduction of a dead zone was sufficient to prevent the divergence observed before.
6. Conventional adaptive control must rely on preliminary on-line parameter identification, which may be a lengthier process than direct adaptation.
7. The adaptation performance is largely dependent on the neural network design parameters such as numbers of neurons and layers and activation functions.
8. The adaptive loop introduces a nonlinear feedback element, with the associated complication of requiring analysis of a nonlinear system. Validation of a nonlinear adaptive autopilot may be an extremely time-consuming task, requiring extensive simulation.
9. A promising integrated adaptive guidance and control approach was reviewed and found suitable for reconfiguration following effector's failure.

5. RLV Adaptive Guidance and Control

Recent interest to develop technology that will enable RLVs to land autonomously and recover from failures or damage has fueled research in integrated adaptive guidance and control (Ref. 7). The new technology usually involves reconfigurable control and trajectory reshaping. Trajectory reshaping is performed in real time as follows: A database of pre-computed reference trajectories is used to select a feasible trajectory for a given failure (locked control surface or vehicle damage), while an adaptive guidance system makes corrections for errors and disturbances. The advantage of this approach is that there is no need to consider every possible control failure to generate the trajectory database. It is enough to capture the effect of control failures with a few parameters such as the total variation in lift and drag. The control system estimates these parameters online and uses them to query the trajectory database.

Traditionally, guidance and control are designed independently with an inner loop representing control and an outer loop representing guidance. The inner loop uses the control effectors to achieve a desired attitude and angular velocity. The outer loop generates inner-loop commands to steer the vehicle in order to follow a desired trajectory. The integrated adaptive guidance and control combines the inner and outer loop, which are no longer independent but rather coupled. The new approach consists of a guidance system (outer loop) that can respond effectively to force perturbations, while the inner loop responds to moment perturbations. Adaptive guidance means both online trajectory reshaping (if needed) and trajectory tracking despite potential for large force perturbations. In practice, adaptive guidance is expressed by the ability of the feedback gains to adapt to changes in the inner-loop bandwidth.

Usually, RLV guidance consists of three sequential phases. Namely, the entry phase slows down the RLV from hypersonic to supersonic speeds. The second phase, also called Terminal Area Energy Management (TAEM), transitions the RLV from supersonic to subsonic speeds. And finally, the approach and landing phase takes the RLV from 10,000 ft to the final stop on the runway.

The initial entry into the Earth atmosphere and the final landing phase are the most critical. Consequently, they are more often covered in the technical literature.

In what follows, a brief description of some of the RLV guidance schemes found in the literature is given first. Then a general block diagram common to most of the new schemes is discussed. Finally, recommendations are given about the criteria that all these schemes must meet to possibly qualify as candidates for actual use.

5.1 Review of RLV Guidance Systems

Many of the new RLV guidance schemes are variants of the proven "Shuttle Guidance," which has guided unpowered return flight to Earth quite successfully. The shuttle guidance is of the reference profile tracking type. A reference drag acceleration profile is tracked by the vehicle primarily through bank angle modulation and secondarily through angle of attack modulation. Crossrange is achieved through roll reversals to keep the heading within a narrow band.

These shuttle types of guidance are robust with respect to winds and navigation errors; however, they were not designed to adjust to altered vehicle dynamics caused for example by locked control surfaces or vehicle damage. At the time of the shuttle guidance development, reconfiguration technologies were not yet available because of limitations of on-board real time computation.

A number of new RLV guidance schemes capable of adapting to failures are currently being developed. They can be classified into three broad categories. The first one is the so-called predictor-corrector approach. The predictor algorithm propagates the equations of motion forward in time up to a target position. The control profile is initially assumed and the in-flight measurements are used to increase the accuracy of the predicted trajectory. The error signal is the predicted miss at final time relative to the target. The target miss vector is defined as the down-range and cross-range component errors. If the target errors are larger than the acceptable tolerance, then additional predictions are conducted to estimate the sensitivity of the final target miss vector to control perturbations. The sensitivities are consequently used to calculate the controls that yield the desired target. The process just described is iterative and may require several iterations for convergence.

The second category refers to the linear quadratic regulator (LQR) based guidance schemes. This is a relatively simple approach to the RLV guidance problem. Reference profiles for the range-to-go, altitude, flight path angle, bank angle, and angle of attack versus energy are prescribed. A linear control law using state feedback is then used with energy-scheduled gains. The gains are computed using the LQR method. Lateral control is performed by the familiar roll reversals used by the Space Shuttle. This simple approach produced good results and was shown to be robust with respect to initial re-entry conditions. In addition, this scheme can be easily coupled with on-board trajectory optimization algorithms to enhance its operational capabilities.

The third category refers to Shuttle-like guidance with the added capability to optimize on-board the trajectory, should a failure occur. To effectively respond to a failure, guidance and control must work together to compensate for control degradation or vehicle altered characteristics. As a result, research in integrated adaptive guidance and control has been started for the next generation of RLVs. A block diagram depicting the system architecture of the new guidance and control unit was shown in Figure 2-1. This unit consists of four functional boxes; namely, the on-board trajectory generation which reshapes the trajectory to be flown in real-time, the integrated guidance and control which provides vehicle tracking and stability, the control allocation which distributes control effort to the available actuators, and finally a system identification box which feeds information back to the other boxes.

The integrated guidance/control box shown in the diagram consists of a coupled inner loop representing control and an outer-loop representing guidance. In a traditional design, the inner and outer loops are designed independently. The inner loop uses the control effectors to achieve a desired attitude and angular velocity. The outer loop generates inner-loop commands to steer the vehicle in order to follow a desired trajectory. The new approach consists of a guidance system (outer loop) that can respond effectively to force perturbations while the inner loop responds to moment perturbations. Adaptive guidance means both online trajectory reshaping (if needed) and trajectory tracking despite potential for large force perturbations. In practice, adaptive guidance is expressed by the ability of the feedback gains to adapt to changes in the inner-loop bandwidth.

5.2 Certification Tests and Guidelines

The interest here is not so much the technical merit of the various guidance schemes but rather the formulation of general guidelines that the different approaches must meet to qualify as potential candidates for actual use. The first requirement is naturally the demonstrated ability of the proposed guidance scheme to operate free of failures in nominal and perturbed conditions. Perturbed conditions consist of the usual 3-sigma vehicle and environmental dispersions including winds. This first requirement is a prerequisite to the second one, which is the ability of the vehicle to fly safely with certain failures. It is not possible to predict all possible failures; nonetheless, the RLV is expected with the help of the new reconfiguration technologies to adapt to certain type of failures especially to partial failures of the control system effectors. Consequently, a number of standard failures of the control effectors should be used as a measure of performance recovery. Also a failure can occur at any time during the three major guidance phases. Again, it seems natural to test the system for a failure occurring during each of the phases. An early failure is likely to impact the remaining part of the trajectory.

In conclusion, extensive simulations are in order to validate the new adaptive guidance and control schemes. Actual flight tests are to be followed for final certification.

The test matrix in Table 5-1 lists possible test scenarios for the classical 3-sigma tests as well as failures of the control system. These failure tests are designed to demonstrate whether or not the new integrated adaptive guidance and control schemes can cope effectively with a standardized test of a locked body flap for example. The overall performance is to be assessed for each proposed scheme. Early failures will obviously have a more dramatic effect on the trajectory as compared to failures occurring during the approach and landing phase. One may choose to consider first the failures of the third phase and then the second and first phases.

Table 5-1. Entry Guidance Test Matrix

Entry Guidance Test Matrix					
	3-sigma Dispersions	Monte Carlos Runs	Loss of RCS Thruster	Locked Flap	Locked Rudder
Entry Phase	Vehicle wind/atmosphere initial conditions	Vehicle wind/atmosphere initial conditions	1 2 3	0 deg 10 deg 20 deg	0 deg 5 deg 10 deg
TAEM Phase	Vehicle wind/atmosphere initial conditions	Vehicle wind/atmosphere initial conditions		0 deg 10 deg 20 deg	0 deg 5 deg 10 deg
Approach/Landing Phase	Vehicle wind/atmosphere final conditions	Vehicle wind/atmosphere final conditions		0 deg 10 deg 20 deg	0 deg 5 deg 10 deg

5.3 Guidance Conclusions

A review of RLV adaptive guidance schemes for re-entry has been conducted. This review is not exhaustive; it however gives an account of many of the research efforts in the area. General guidelines have been formulated for the validation of the emerging reconfiguration technologies, which have the potential to greatly increase the safety of future RLVs.

6. Conclusions and Recommendations

6.1 General Guidelines for Application of Reconfiguration Technologies

The literature survey and independent evaluation conducted by Aerospace of reconfiguration technologies has resulted in a series of conclusions in the areas of control allocations, adaptive control, and guidance (Sections 3.3, 4.6, and 5.3, respectively) that can be used as guidelines for the GN&C practitioner.

6.2 Recommendations for Further Work

Aerospace has developed standalone tools to evaluate control allocation algorithms. In addition to the linear programming method, Aerospace would evaluate the other competing algorithms discussed in this report.

An adaptive control methodology using an approach developed at Georgia Institute of Technology was evaluated. Our initial study assumed a fixed control allocation configuration. Additional evaluations would consider simultaneously implementing adaptive control and control hedging.

Finally, our standalone simulations could be incorporated into an existing RLV 6-DOF simulation tool to evaluate these technologies throughout an entire mission profile.

7. Abbreviations, Acronyms, and Symbols

Note: Vector symbols in **bold** font.

a	output
A	inequality constraint matrix
ADAPT	a MATLAB adaptive algorithm
Aeq	equality constraint matrix
AMS	admissible moment set
AoA	angle of attack
AST	Office of Commercial Space Transportation
b	bias
b	inequality constraint
Beq	equality constraint
c_1, c_2	cost coefficients
C	effectiveness matrix
COTR	Contracting Officer's Technical Representative=
DOF	degrees of freedom
e	error
e(k)	error signal
f	transfer function
FAA	Federal Aviation Administration
FDI	fault detection and isolation
GN&C	guidance, navigation & control
Hz	hertz
J	cost function
k	current sampling time
k	sampling interval
K_{EQ}	attitude rate gain
λ	learning rate
lb	lower effector limit
LMS	least mean squares
LP	linear programming
LQR	linear quadratic regulator
NASA	National Aeronautics & Space Administration
NN	neural network
p	input
$\mathbf{p_1}$ and $\mathbf{p_2}$	input vectors
P+I	proportional plus integral
Π	multiplier
psf	pounds per square foot
$\dot{q}_c$	attitude rate command
$\dot{q}_{elevon}$	elevon deflection rate
$\dot{q}_{RCS}$	equivalent RCS deflection rate
QP	quadratic programming
R	number of elements in input vector
RCS	reaction control system

RLV	reusable launch vehicle
S	number of neurons in layer
TAEM	terminal area energy management
$\mathbf{u}$	control deflections
ub	upper effector limit
$\mathbf{u_p}$	trim value of $\mathbf{u}$
v	input to adaptive filter
$\mathbf{v}$	commanded control
w, w_1, w_2	weighting factors
$\mathbf{W_u}$	weighting matrix
$\mathbf{x}$	state vector
ξ, φ	states of compensator
z	cost function

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