Neural Networks for Flight Control

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NEURAL NETWORKS FOR FLIGHT CONTROL

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INTRODUCTION

Neural networks are being developed at NASA Ames Research Center to permit real-time adaptive control of time varying nonlinear systems, enhance the fault-tolerance of mission hardware, and permit online system reconfiguration. In general, the problem of controlling time varying nonlinear systems with unknown structures has not been solved. Adaptive neural control techniques show considerable promise and are being applied to technical challenges including automated docking of spacecraft, dynamic balancing of the space station centrifuge, online reconfiguration of damaged aircraft, and reducing cost of new air and spacecraft designs.

Our experiences have shown that neural network algorithms solved certain problems that conventional control methods have been unable to effectively address. These include damage mitigation in nonlinear reconfiguration flight control, early performance estimation of new aircraft designs, compensation for damaged planetary mission hardware by using redundant manipulator capability, and space sensor platform stabilization. This presentation explored these developments in the context of neural network control theory. The discussion began with an overview of why neural control has proven attractive for NASA application domains. The more important issues in control system development were then discussed with references to significant technical advances in the literature. Examples of how these methods have been applied were given, followed by projections of emerging application needs and directions.

OVERVIEW

Neural network applications for control have advanced rapidly in the last ten years. First, reasons why neural networks have become important for control problems were discussed. A summary of five key points was followed by a list of the most important research results in neural control with discussion of often used neural network paradigms in control system development. After examples of potential applications in the emerging New Millennium and Access to Space programs, four NASA efforts at the Ames Neuro-Engineering Laboratory were detailed. The presentation concluded with a discussion of current issues and future projections for this technology.

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Overview

- Background
  - Useful Neural Net Properties for Flight Control
- Neural Network Technology
  - The Primary Neural Control Building Blocks
- Potential Technology Application in Space Systems
  - Focus on New Millennium & Access to Space Problems
- Selected Neural Control Projects at NASA Ames 1995
  - Neuro-Engineering Laboratory
- Recognized Current Needs & Future Enabling Technology Projections

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IMPORTANT PROPERTIES OF NEURAL NETWORKS FOR CONTROL PROBLEMS

There are five main reasons why neural networks are being used for NASA Space and Aero technology challenges. Key is a neural network's ability to deal with nonlinear and adaptive online control requirements. Other advantages include parallel computation, fault tolerance, adaptivity, multi-input multi-output flexibility, and function mapping accuracy.

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Important Properties of Neural Networks for Control Problems

They Are:

- **Non linear**
  - **Ability to approximate arbitrary nonlinear mappings (Cybenko 1988)**
  - **Compactness (Potential to compress tabular rate tables and gains)**
  - **Flexible model generation (perhaps at the cost of analysis time)**
- **Parallel & Robust**
  - **Inherently parallel computation structure**
  - **Potential for high fault tolerance**
  - **Fast processing**
- **Adaptive & Trainable**
  - **Trained by observation of plant processes or measurement data sets**
  - **On line real time adaptation possible for reconfiguration learning**
  - **Generalization may increase robustness**
- **Data & Method Flexible**
  - **Can combine multiple local networks**
  - **Can accommodate hybrid solutions (Traditional, Neural, & fuzzy)**
- **Multi-Variable (MIMO)**

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A BRIEF SUMMARY OF NEURAL NETWORK CONTROL TECHNOLOGY

The next two slides summarize some of the most important issues for neural control. They include research regarding the ability of a neural network to approximate an arbitrary function, how accurately linear and nonlinear approximations can be performed, and under what circumstances forward and inverse modeling approaches are used. Next, some of the techniques which can be used for system identification are presented. Interested readers are directed to the list of references at the end of the paper for greater detail of these techniques and the complete papers alluded to in the slides. Refs. 6 and 14 provide particularly good overviews of this topical area.

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Brief Summary of Neural Network Control Technology

- **Approximation and Model Building Theory exists**
  - Arbitrary polynomial approximation ability shown (Weierstrass theorem)
  - Feed forward network approximation power shown (Cybenko, Funahashi, Hornik, Carrol & Dickinson)
  - Theoretical proof for layer sizes exist but their utility is uncertain (The Kolmogorov Theorem vs. Girosi and Poggio's limitations)

- **System Identification can be performed**
  - *Forward Modeling* - possible but how are useful dynamics introduced
    - » Real time recurrent networks (e.g. . Williams & Zipser 1989)
      - Time delay networks
      - Series-Parallel nets (Narendra 1990)
    - » Dynamic neurons (Willis, DiMassimo, Montague, Tham & Morris 1991)
  - *Inverse Modeling*
    - » Direct inverse modeling (Psaltis 1988) is one way, but
      - its not goal directed (Jorden & Rumelhardt 1991)
      - incorrect inverses possible if not 1 to 1 mappings
    - » Specialized inverse learning

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SOME USEFUL NEURAL CONTROL ARCHITECTURES

To be used in real world systems, the learning mechanisms of neural networks must be embedded in an overall control architecture. Some of the more useful architectures are listed below along with methods for filtering input data which a neural network must use during online learning and diagnosis.

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Brief Summary of Neural Network Control Technology (Continued)

- **Control Structure Options are Available:**
  - Supervised control (Werbos)
  - Direct inverse control (Miller 1990)
  - Model reference control (Narendra and Parthasarathy 1990)
  - Internal model control (Morari and Zafiriou 1989)
  - Predictive control (Mayne and Michalska 1990 stability proofs)
  - Optimal decision control (Wilton and Schulten 1992)
  - Adaptive linear control
  - Reinforcement learning control
  - Modified Gain Scheduling
    - » Gains as stable states of attractor nets (e.g. . terminal attractors)
    - » Gains as interpolated look up tables (CMAC, Infold, SOM)
- **Filtering and Prediction Can be Added as Well**
  - Linear minimum variance filters (Ydstie 1990)
  - Linear filtering & prediction (Widrow and Winter 1988)

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POTENTIAL NEURAL CONTROL APPLICATIONS IN SPACE SYSTEMS

There are many areas suited for application of neural network technology within the scope of the current program definitions for NASA's New Millennium and Access to Space initiatives. Five that are particularly well suited for neural control are presented below along with their justification. One common element is a need for real time online reconfiguration, system identification, and platform stabilization. Whether Aero or Space, if a system changes dramatically due to accident or an unexpected event, the ability to learn a new plant online becomes very important. If the system is highly nonlinear or noisy, offline linearized models often give an inadequate approximation or are too slow. Neural control methods hold promise of providing fast online identification and adjustment.

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Potential Neural Control Applications in Space Systems

- **Navigation, Rendezvous & Docking:** Current closed-form methods do not do an accurate job of controlling spacecraft navigation for rendezvous and docking operations because spacecraft mass properties are not known exactly and are time varying. As a result, the expenditure of propellant is inefficient and spacecraft docking is not performed quickly for safety reasons. Closed-form mathematical methods do not compensate in real-time for hardware failures or severe degradation in performance such as partial thruster operation or collision damage
- **Instrument Platform Stabilization:** Stable spacecraft instrument platforms are important to ensure accurate science data measurement and to maximize science return on each mission. Current closed-form methods do not easily stabilize instrument platforms in "real-time" because the mass properties of instruments are not known and can be time varying due to mechanical articulation (instrument pointing), and expenditure of instrument resources (cryogenics). In addition, extraneous disturbances from the spacecraft itself can directly effect instrument stabilization.
- **Damage Reconfiguration:** Severe damage or unanticipated events such as unusual planetary rover configurations can dramatically effect the adequacy of the controller's plant model. Regaining control requires that the controller identify, in real time, critical stability and control properties during mission execution and hardware actuation. Algorithms for automatic synthesis of emergency or off-normal controllers are needed to maximize spacecraft performance.
- **Adaptive Parallel Hardware Architectures:** High speed parallel processing needs of on line adaptive algorithms may require new architectures to take advantage of neural network fault tolerance properties and the capability for multiple integrated adaptive . Such mixtures of hardware and software could reduce weight by omitting redundant hardware systems in favor of reconfigable adaptive control software and customized processors.
- **Real time data and signal analysis and compensation:** On line system identification requires rapid interpretation and filtering of sensor information. In some cases the sensor suite may be damaged or miscallibrated. This can lead to propagation of errors in on line identification. Improved neural tools for data analysis could benefit both control and mission science return likelihood

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NEURAL CONTROL PROGRAMS AT NASA AMES

Four NASA programs were discussed in detail at this workshop. Each illustrated a different aspect of neural network control application problems. First, the intelligent flight control program which dealt with online reconfiguration of a modern jet aircraft after a scenario of system failure or damage that significantly deviated from the original controller design model. The second described work which permits flight control of a commercial airliner after a total hydraulic actuator failure permitting only differential thrust from remaining engines. The third considered vibration damping in the Space Station Freedom centrifuge and problems associated with dynamic load balancing. The fourth concerned the use of neural nets in the earliest stages of flight system controller designs.

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Neural Control Programs at NASA Ames

- Intelligent Flight Control
  - ARC, Dryden, & McDonnell Douglas developing real time on line neural flight controllers
  - Reconfiguration flight tests on F-15 ACTIVE aircraft
- Propulsion Control Augmentation
  - Control of B757 assuming total hydraulic failures using only differential thrust
- Space Station Freedom Centrifuge Stabilization
  - Centrifuge balancing under conditions of moving animals and "biomass" deposits that dynamically change stabilization parameters
- Kuiper / SOFIA Airborne Observatory Telescope Balancing
  - Rapid change out of new experiment payloads with non linear actuator drags caused by cabling and mass displacements
- Wind Tunnel Design Parameter Estimation
  - Early Aircraft Design enhancement by learning aircraft coefficients directly from wind tunnel testing and linking to on line learning and virtual reality flight simulation

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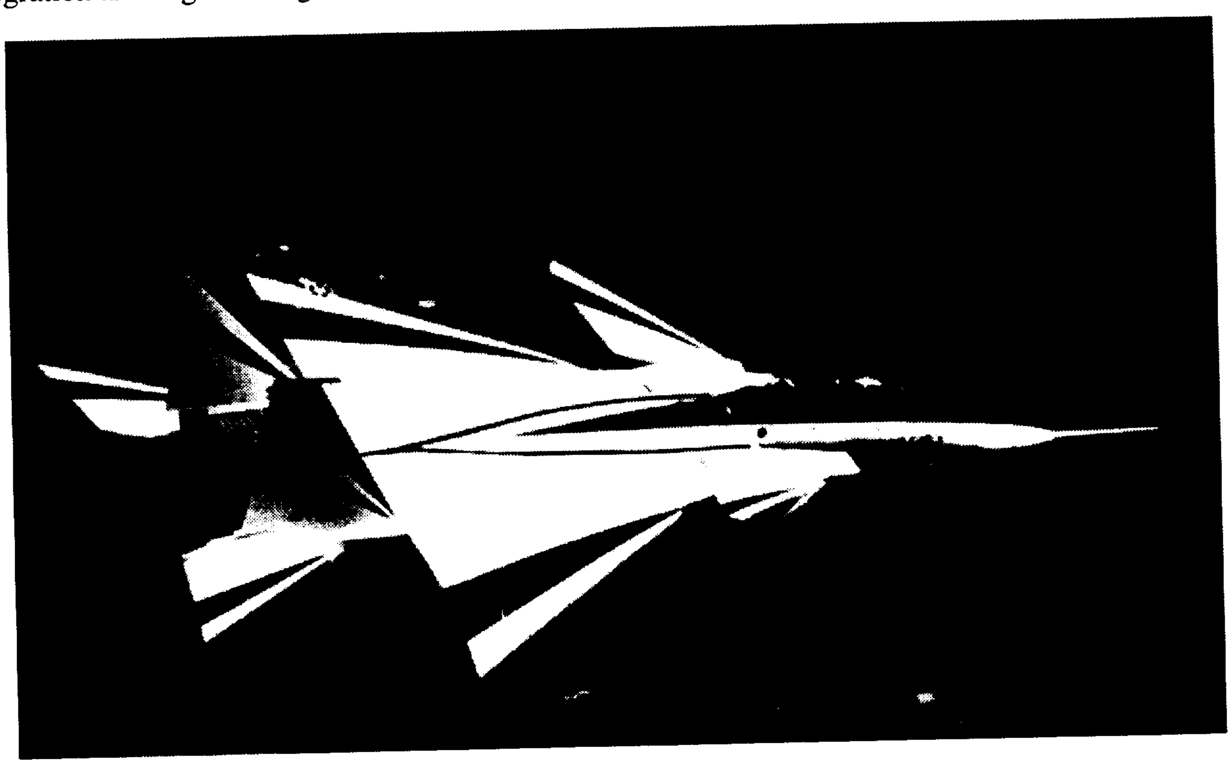
INTELLIGENT FLIGHT CONTROL

This effort is a four year advanced concepts research program funded under the NASA Office of Aeronautics Critical Technologies Division and involves NASA Ames, NASA Dryden, and McDonnell Douglas Aerospace Corporation, St. Louis. The objective of the program is to develop and flight demonstrate a revolutionary control concept that can efficiently identify aircraft stability and control characteristics using neural networks, and utilize this information to optimize aircraft performance. The program addresses the needs of the U.S. aerospace industry for control systems that can be developed and tested at lower cost, and for flight systems that can accommodate major changes to aircraft stability and control characteristics which might result from failures to flight control actuation or damage to aircraft control surfaces.

Three technology elements are combined in this program. First, neural networks will be used to continuously identify critical stability and control properties during flight. Second, algorithms for automatic synthesis of optimal controllers will maximize flight performance, and finally, high capacity digital flight computers will process optimum flight controller data and integrate and use the neural network identification information. In 1993 the ability of neural network technology to rapidly prototype a new aircraft flight control system was demonstrated on a full-scale F-15 flight simulator. In 1994, work began on line neural control methods at Ames Research Center and on the configuration of the F-15 aircraft to accept neural control codes. The next major step will be taken when a modified F-15 aircraft (the ACTIV program) at Dryden will be flight tested using the neural controllers. Mr. C. Jorgensen at Ames is the principle investigator for the neural algorithms, and Mr. James Urness at McDonnell Douglas serves as the corporate principle investigator leading systems development, integration and flight testing.



PROPULSION CONTROLLED AIRCRAFT (PCA)

Partial failures of aircraft flight control systems and structural damage to aircraft during flight have led to catastrophic accidents with subsequent loss of lives (e.g., past crashes of a DC-10, B-747, C-5 , B-52, and others). These types of accidents can be prevented if sufficient alternate control authority remains which can be used by the pilot to execute an emergency safe landing. Following a United Airlines (Flt 232) DC-10 accident at Sioux City, Iowa in 1990, the National Transportation Safety Board recommended "research and development of backup flight control systems for newly certified wide-body airplanes that utilize an alternate source of motive power separate from that source used for the conventional control system." The problem in the general case was that currently there is no satisfactory means onboard the aircraft for effectively controlling the aircraft with a disabled primary flight control system. In addition, using only manual throttle control of engines is extremely difficult because of pilot unfamiliarity with dynamic response of the aircraft in this mode.

NASA Dryden Flight Research Center (DFRC) successfully demonstrated in 1993 that throttle control of engines alone can be used to augment or replace the aircraft primary flight control system to safely land an aircraft. The NASA DFRC concept used specifically developed control laws in the aircraft flight control computer system to drive the engines in response to pilot input commands for bank angle and flight path angle. PCA control laws provided aircraft longitudinal flight control by equally increasing or decreasing thrust of both engines in response to pilot commands for increased or decreased flight path angle. PCA control laws provided aircraft lateral-directional flight control by asymmetrically increasing or decreasing thrust of both engines in response to pilot bank, heading, or track commands.

Piloted simulations were conducted in the Advanced Concepts Flight Simulator (ACFS) at NASA Ames Research Center. The ACFS is a moving base simulator representative of a mid-size two-engine jet transport with engines located under the wings. The ACFS aerodynamic and engine models are similar to those of a Boeing 757 aircraft . The cab layout of pilot controls and displays is very similar to those of a typical Boeing jet transport with CRTs for pilot and copilot primary flight displays and map displays, and with a typical Boeing mode control panel (MCP) located above the instrument panel for selection of various auto pilot modes. The visual out-the-window display is a night visual scene for landing at San Francisco Runway 28R.

We are currently using neural net concepts for expanding the emergency envelope available to the pilot over and above that of current PCA concepts using classical control laws. Neural nets are being used to identify in real-time unexpected changes in aircraft dynamics and control. Control laws will be updated and modified in real-time in response to neural net identification of the new aircraft stability and control characteristics. Mr. John Bull at NASA Ames is the principal investigator for this effort in conjunction with Mr. Bill Burcham at Dryden Flight Research Center.

SPACE STATION CENTRIFUGE BALANCING

Space Station Freedom is intended as an orbiting microgravity research facility for conducting life sciences and material processing experiments. The key hardware in the life sciences research program is an onboard artificial gravity research centrifuge. Satisfactory operation of this hardware is extremely important because vibrations can interfere with delicate onboard experiments such as remote sensing and crystal growth. Imbalances can be caused by 1) dynamic redistribution of internal mass (specimen movements), 2) time varying experiment-related effects (specimen weight change, food and water consumption, and biological waste buildup), 3) resource resupply and delivery (water, food), and 4) dynamic reconfiguration (cage removal/insertion). An automatic robotic extractor/installer is used to remove and insert cages without stopping the centrifuge. The accompanying change in the centrifuge moment of inertia can cause the angular velocity to increase, decrease or oscillate. The corrective torques issued by the centrifuge angular velocity controller are in themselves torque disturbances which can affect the microgravity environment of Space Station Freedom. If the moment of inertia variations are unmodeled or inaccurately modeled, these torques can be large.

An automated mass balance system is currently under development to cancel centrifuge imbalances. There are shortcomings, however, in the methods currently available. First, current methods cannot cancel centrifuge imbalances in real time. They require that unknown imbalances be measured and averaged over many rotational cycles before an estimate of magnitudes and locations can be determined. As a result, extraneous disturbances are left unabated during the estimation cycle. In some situations, the mass balance system can actually become a source of significant disturbances.

Adaptive neural control techniques are well-suited to this problem because they operate in real-time and can be trained online to learn quasi-static changes in a centrifuge. Adaptive neural techniques can also be used to capture the underlying function using only a small subset of the total data for the training set. Thus, if the neural algorithm is appropriately trained with an adequate data set of "mass imbalance vs. correct mass balance parameters," or "responses to a change in moment of inertia vs. controller parameters," it may be possible to capture the required underlying functions. Real-time determination of the balance parameters to cancel centrifuge imbalances and the controller parameters to compensate for moment of inertia changes is possible because neural networks operate efficiently in a table lookup mode. The objective of this research is to examine the applicability of adaptive neural algorithms for real-time control of disturbances due to mass imbalances and inertia property changes. Dr. Bob Mah at NASA Ames Research Center is the principal investigator for this effort.

NEURAL NETWORKS FOR AIRCRAFT MODEL ESTIMATION IN WIND TUNNELS

Neural networks were demonstrated in 1994 to increase productivity and reduce costs in wind tunnel operations by learning to predict the performance of aircraft models undergoing tunnel testing. A significant amount of test time is normally spent measuring aerodynamic effects from geometric variations. Such variations include flap and slat positions, deflection angles, elevator and rudder deflections, and power settings. If a neural network can be trained to accurately predict the effects of these various parameters on the aerodynamic coefficients while using a smaller subset of the test matrix than would normally be required to generate an adequate database, significant savings in test time and associated costs can be realized.

In 1994, data was collected as new aircraft design tests occurred and were simultaneously used to train a multilayer neural network. As more and more data was acquired, the network learned to produce highly accurate estimates of test results for new, unseen conditions after being given only aircraft test configuration parameters. The network eventually learned a complete static model of the aircraft and this model along with a set of developed software analysis tools, was used to predict the results of the next session's tests and identify key design points such as maximum lift.

The procedure that was developed proved to be extremely robust to different test conditions and has been applied to previously collected data from the T-39 and High Speed Civil Transport scale models. In December 1994 it was used in tests of the Super High Alpha Research Concept aircraft (SHARC). The method proved to be very fast relative to approaches using mathematical simulation of flows. Learning a model of the entire aircraft occurred in under thirty seconds to an accuracy level well under 1% root mean square error. The need for much less test data than is required using current methods was also demonstrated. In tunnel tests of the SHARC the learning of an adequate predictive model was done with approximately 40% less data. This reduction translated into marked savings in facility operations costs resulting from less electricity, faster test turn around, earlier identification of critical performance test areas, and improved analysis tools. Increased wind tunnel throughput resulted from freed up tunnel resources. Cost savings occurred through a reduction in the number of tunnel test hours required for a new aircraft test. Long term implications of the method include faster development of new aircraft prototypes through more rapid simulation of aircraft flight performance and possibly the need for less intermediate scale models to estimate aircraft design characteristics. Currently, the method has been installed in the Ames wind tunnels as part of a neural software package and a patent application has been filed. Dr. Charles Jorgensen is the principal investigator for this effort.

ENABLING TECHNOLOGY DEVELOPMENT REQUIREMENTS

If neural networks are to be fully used in future NASA programs, a number of issues must be resolved. Some of these issues have been recognized and are under research in university and government laboratories. Others are more global and require joint agreement by coordinated government regulatory and research groups. Among the more immediate problems are a need for new certification procedures which will be accepted by hardware development and FAA review panels so as to permit the application of nonlinear computational intelligence technologies in areas in which there is potential risk to human life or property. Without methods which go beyond the current linearization, stability and robustness tools, the full use of CI techniques is likely to be inhibited.

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Enabling Technology Development Requirements

- **Stability Proofs for Dynamic Adaptive Neural Controllers**
  - **Lyapunov & Hyperstability methods have been developed for adaptive time invariant linear systems but can be overly restrictive**
  - *** New proofs & methods are needed for dynamic non linear plants**
- **Excitation and Convergence Requirements**
  - **How to improve generalization through persistent excitation of plant until convergence is reached**
  - **The correct number of system parameters for good estimation**
  - *** More work needs to be done to determine bounds on what can be learned with limited on line parameter sampling (e.g. . after aircraft accidents before stabilization)**
- **Robustness**
  - *** When are control properties such as stability and convergence retained given the presence of system dynamics not modeled by the controller**

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ENABLING TECHNOLOGY DEVELOPMENTS (Cont.)

This presentation has surveyed the state-of-the-art in neural network control. It has done so in the context of a series of key issues which must be considered when a control system for a highly non-linear, time varying system must be developed. Examples were provided of how neural control is being used to increase the safety of commercial airlines, how damage survivability is being increased in military aircraft, and how these same techniques are being positioned for application in the evolving NASA programs called New Millennium and Access to Space.

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Enabling Technology Development Requirements

- **Applicability Guidelines**
  - **Where do networks fail to improve over existing control methods**
  - *** For which classes of non linear systems are networks best applied**
  - **What optimization metrics are best for which engineering objectives**
- **Real Time Performance Demonstration**
  - *** More work is needed to evaluate real time on line learning control system architectures e.g.. adaptive critics or hybrid linearization schemes**
  - **New, accepted certification procedures need to be developed to facilitate migration of non linear control methods into safety certified commercial industries**

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