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Learning Flight Control and LoFLYTE

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ABSTRACT

Accurate Automation Corporation is leading the LoFLYTE advanced development program demonstrating the benefits of neural networks. This is a multi-phase effort to develop the technologies necessary to design, fabricate, and flight test a Mach 5 waverider aircraft. Phase I of the program consisted of a feasibility study. Phase II is the critical design phase to construct a subsonic remotely piloted aircraft that will demonstrate the low speed characteristics of a waverider. During Phase II, a number of innovative technologies will be validated. Included in this phase is the neurocontroller system test for this aircraft. Prototype actuator and sensor hardware has been developed and tested with our MIMD neural network hardware.

INTRODUCTION

Accurate Automation, working with Lockheed Martin Tactical Aircraft Systems and Mississippi State University, is currently developing a "waverider bodied" subsonic testbed aircraft termed "LoFLYTE" [Kandebo, 1995]. This program will lay the foundation for demonstrating a fully autonomous neural network controlled actuator and flight control system on a hypersonic aircraft configuration, and will serve as the initial testbed for both the inner and outer loop neurocontrollers.

The "LoFLYTE" vehicle will support two parallel control systems, a baseline digital control system and our neurocontrol system. A sensor suite sufficient to support both control systems and the remote piloting system is part of the testbed.

Construction of the 100" wind tunnel model of the LoFLYTE waverider configuration, shown in Figure 1, was completed in the fall of 1994, and subsequently tested in late 1994 and early 1995.

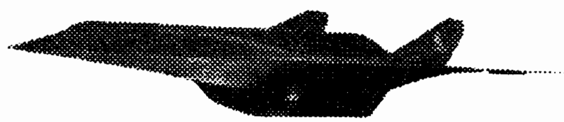

Figure 1: 100" LoFLYTE Wind Tunnel Model.

The waverider model has undergone extensive wind tunnel testing at NASA Langley Research Center in their 12 foot and 30 by 60 foot wind tunnels. A 100" neurocontrolled RC model version of the waverider is presently under construction. One area where neural networks are used on LoFLYTE is for the inner and outer loop controls.

INNER LOOP CONTROL

The *hybrid inner loop controller (designed at AAC for LoFLYTE) uses a "classical" adaptive*

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controller to train a neural network with the network eventually learning to anticipate the response of the adaptive controller. This yields a hybrid neural/adaptive controller which:

- responds much faster to new commands or changes in the flight regime and system dynamics than the underlying adaptive controller, while
- retaining the stability, robustness, and genericness of the adaptive controller.

Although we believe that the use of an adaptive controller to train a neurocontroller is new to the present program, Kwato, et al. [1988 and 1990] have used a classical (non-adaptive) controller to train a neurocontroller.

The core of our neural/adaptive joint controller is an adaptive joint controller developed by Seraji [1989]. This is a generic model reference adaptive controller which robustly tracks a prescribed set of trajectories assuming only that the actuator system can be modeled as a set of second order differential equations with positive "slow-varying" mass. Indeed, modulo this minimal set of constraints, the adaptive controller is generic, automatically adapting itself to the actuator and control surface dynamics.

Not surprisingly, given the generic and adaptive nature of this controller, the required feedback laws are both computationally intensive and cannot anticipate changes in system dynamics. In our hybrid implementation, neural networks are used to resolve both of these issues. A Functional Link network is used to implement the feedback laws thereby facilitating a parallel implementation of this computationally intensive process. Secondly, a neural network is trained to anticipate the feedback gains which would be produced by the adaptive controller and to initialize the adaptive controller with these gains at the start of each move. Indeed, we believe that this hybrid approach yields the best of both worlds.

- The neural network greatly speeds up the response of the adaptive controller, while
- the adaptive controller remains in the loop to guarantee stability and robustness, and to
- retrain the neural controller whenever the flight regime, or actuator dynamics change.

NEURAL/ADAPTIVE CONTROL ARCHITECTURE ADAPTIVE CONTROL STRATEGY

The starting point for our hybrid neural/adaptive controller is a generic decentralized adaptive controller developed by Seraji [1989]. To this end it is assumed that the plant to be controlled is modelled by a second order system of nonlinear differential equations with positive slow varying mass and a small "disturbance" term. In all other respects, the algorithm is completely generic. No *a priori* information about the dynamic pressure seen at the control surface, actuator and control surface dynamics, or the Reynolds number of the flight regime is required.

The architecture of our hybrid neural/adaptive controller is shown in Figure 2. The Functional

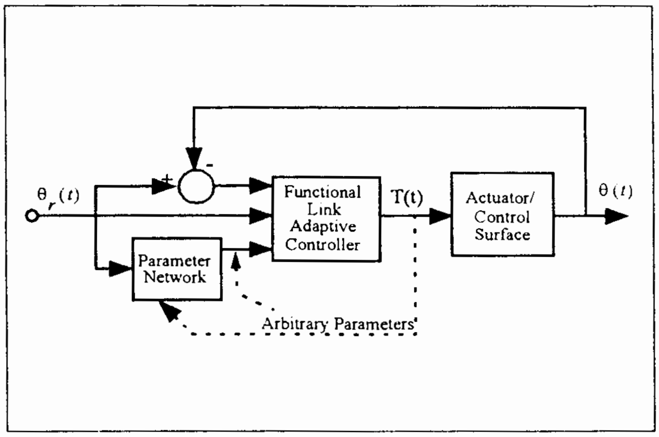

Figure 2: Hybrid Neural/Adaptive Control Architecture.

Link adaptive controller is just the adaptive controller described above but implemented via a Functional Link neural network rather than numerical integration. The key to the architecture is the parameter network of Figure 2, which adjusts the arbitrary parameters ($f(0)$, $k_j(0)$, $q_j(0)$, w's, δ's, α's, γ's, ρ's, β's, and λ's) in the adaptive controller algorithm for each reference input based on the prior performance of the adaptive controller under the same circumstances.

However, the adaptive controller remains in the loop guaranteeing asymptotic stability and robust asymptotic tracking independently of the choice of the arbitrary parameters. As such, if the pressure distribution varies on the control surface or its dynamics change, the adaptive controller guarantees that the prescribed performance criteria will be achieved, while simultaneously producing a response that can be used to update the neural controller's training.

PARAMETER NETWORK

The key to the performance of the architecture is the parameter network which is *trained by the adaptive controller to tune its initial coefficients for each command reference*. The parameter network is designed to find accurate solutions for the initial coefficients required by the adaptive controller for each actuator. This represents a significant improvement over the previous solution to the problem [Seraji, 1989] where a coarse approximation to an auxiliary term was made based on *a priori* knowledge of the system dynamics. Since the parameter network learns as the controller goes about its tasks, it needs no *a priori* knowledge and it continually improves its estimate of the initial coefficients. It can account for unexpected nonlinearities after it encounters them and it has a capacity to generalize. This approach has resulted in a significant reduction in both the maximum and average absolute tracking errors achieved by the controller.

STABILIZING AERODYNAMICS CONTROL

An Adaptive Critic (i.e., approximate dynamic programming) learning algorithm [Werbos, 1993] is used in implementing a learning controller. This algorithm represents a particular implementation of a reinforcement learning control algorithm in which the system is operated in a series of "training runs", then uses reinforcement learning [Barto, Sutton, and Anderson, 1983; Barto, 1993] to improve the performance of the system with each run. In its most general form, reinforcement learning control can be applied to linear or nonlinear systems and used to implement either quantitative or qualitative performance criteria. The primary constraint is that the control used in each training run must be "well behaved" (usually interpreted as stable) while the learning process should be designed to improve the performance of the system as the training process proceeds.

This outer loop control strategy differs fundamentally from the above described actuator controller in two respects. Since we assume a linear plant model, some type of gain scheduling program is required for the actuator controller as LoFLYTE passes through its various flight regimes, whereas the inner loop controller adapts automatically to changing flight regimes. Secondly, the actuator controller learns interactively in a mission simulator or in flight, while the inner loop controller learns in a fully autonomous mode. The aerodynamics controller, however, can deal with systems of arbitrary complexity while the actuator controller is restricted to second order systems.

NEURAL NETWORK HARDWARE

The design of the control system demonstrates that the neurocontrol method will control the actuators in flight. One of the primary problems is to demonstrate how the implementation can be accomplished to run in real time. Our design is implemented around the Accurate Automation Neural Network Processor which is based upon a Multiple Instruction/Multiple Data architecture described in Saeks, et al [1994]. This equipment allows the actuator and aerodynamics controllers to be realized in hardware and tested. Presently, the neurocontrol hardware is attached to a simulated cockpit that is controlling hardware in the loop with sensors as well as an actuator and a wing operating in our lab.

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