

Application of Neural Network on Flight Control

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Abstract—Over the last three decades, adaptive control has evolved as a powerful methodology for designing feedback controller of nonlinear systems. Most of the studies assume that the system nonlinearities are known a priori, which is generally not applicable in the real world. To overcome this drawback, from twenty years ago, there has been a tremendous amount of activity in applying Neural Networks for adaptive control. With their powerful ability to approximate nonlinear functions, neuro-controllers can implement the expected objectives by canceling or learning the unknown nonlinearities of the system to be cancelled. Neural Networks are specially suitable for the adaptive flight control applications where system dynamics are dominated by the unknown nonlinearities.

Index Terms—Control, flight, neural network.

I. INTRODUCTION

In the past decades, major advances have been made in adaptive control of linear time-invariant plants with unknown parameters. The choice of the controller structure is based on well established results in linear systems theory and stable adaptive laws which assure the global stability of the overall system are derived based on properties of those system. In recent years, Artificial Neural Network based control strategies have attracted much attention because of their powerful ability to approximate continuous nonlinear functions.[1] In fact, a neural controller with on-line learning can adapt to the change in a system dynamics and hence is an ideal choice for controlling highly nonlinear system with uncertainty.

For adaptive control purposes neural networks are used as approximation models of unknown nonlinearities. The input / output response of neural network models is modified by adjusting the values of its adjusting the values of its parameters. Although it is true that polynomials, trigonometric series and orthogonal functions can also be used as function approximator, neural networks have been found to be particularly useful for controlling highly uncertain, nonlinear and complex systems. Neural control strategies can be broadly classified into off-line and on-line schemes based on how the parameters of the network are tuned. When the neural controller operates in an on-line mode, it has no a priori knowledge of the system to be controlled and the parameters of the network are updated while the input – output data is received. In the off-line control, the network's parameters are determined from the unknown training pairs and then those parameters are fixed for control purposes.[2]

II. FLIGHT CONTROL

The performance of aircraft systems is highly dependent on the capabilities of the guidance, navigation and control systems. This necessitates the need to have sophisticated and reliable control systems. In order to maximize the performance, the control system needs to be adaptive in nature.

Developing flight control systems for today's aerospace vehicles is time consuming. While the theory is understood, its application is lengthened as a result of three factors. First, flight control is an interdisciplinary subject that integrates mathematical models, control theory, computers, hydraulic and electrical systems, specifications, and pilots. Combining these pieces into a unified framework is a challenge. Second, imperfect knowledge of a contributing component results in costly flight-test iterations. Manufacturers have previously allotted 25% of the total flight test development time for flight control evaluation and iteration. Third, after a control system design is finalized, it can take two weeks to just evaluate the control system against the myriad of often conflicting design specifications.

The use of adaptive control system has been growing in flight control. In the past few years, there has been an increasing interest within the control community in exploring the promise of biologically motivated algorithms, like fuzzy sets, neural networks as well as genetic algorithms to solve difficult optimization and control problems [3]. Fig. 1 shows application of neural network in flight control. The nonlinear aircraft equations are linearized at several equilibrium flight conditions over the desired flight envelope. Then the control gain is designed for these different flight conditions. The optimal gains at each scheduling point should guarantee robust stability and performance, that is, they should guarantee stability and good performance at point near the designed equilibrium point. Since the feedback gains are schedule a priori, no automatic corrective action is taken to mitigate the effects of a control law that is no longer appropriate.

The Intelligent Flight Controls System (IFCS) is a piloted flight test program whose purpose is to demonstrate the ability of neural network technologies to provide compensatory augmentation to a baseline flight control system for adverse flying conditions that may be the result of damage or systems failures to an aircraft in flight. Aircraft flight control software is critical to the safety of flight. Failures of the software to meet the design requirements (e.g. for stability and handling qualities) or to perform as intended could lead to loss of mission, aircraft or human life. The purpose of the Intelligent Flight Controls System flight test program is to develop and flight-demonstrate adaptive neural network technologies capable of providing stable flight and adequate flying qualities to an

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aircraft in the presence of modeling uncertainties, failures and damage to the aircraft. The first generation intelligent flight control system was flight tested in 2003. Intelligent flight control system generation I employed an indirect adaptive scheme using neural networks to identify and augment stability and control parameters of the aircraft in flight. These parameters provided updates to a linear quadratic regulator flight controller to maintain stability and performance of the aircraft. A pre-trained neural network provided the controller with the healthy aircraft parameters

as a function of flight condition and aircraft state. Onboard real-time parameter identification algorithms provided increments to the stability and control parameters which were stored using a dynamic cell structure (DCS), self-organizing feature map routine. The incremented parameters were then passed to the flight controller to optimize performance. The dynamic cell structure algorithm allowed the flight control system to ‘remember’ identified parameter increments from previously flown flight conditions so they did not have to be re-learned. [4]

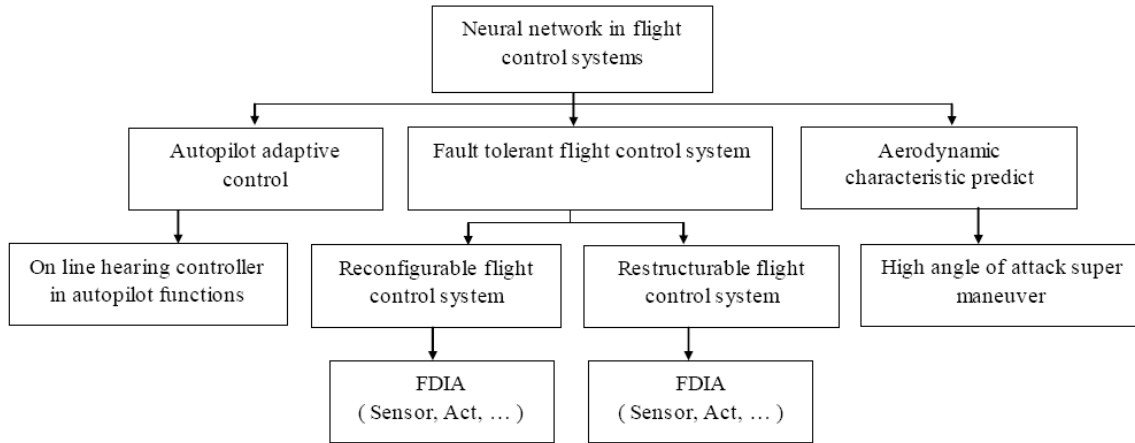


Fig. 1. Application of neural network in flight control

The second generation IFCS employed a direct adaptive approach to the flight control of the aircraft in USA. That is, adaptive compensation to the controller was based on aircraft tracking performance and sensor measurements without an explicit, on-line estimated aircraft model. The baseline intelligent flight control system generation II controller architecture used a model inverting scheme to provide commands to the aircraft control surfaces that produce the accelerations commanded by the pilot. The neural network architecture is of the Sigma-Pi type. The Sigma-Pi neural networks are described in next section.

The neural networks interface with the baseline controller by providing augmentation signals to the commanded accelerations when the error regulation portion of the baseline controller fails to provide adequate handling qualities, as determined via measurement of the aircraft state feedback tracking errors signals. One of the features of the intelligent flight control system generation II concept is that the neural network architecture software can be integrated with any conventional flight controller configuration. This offers significant cost savings, especially for retrofit additions to existing controller configurations.

The intelligent flight control system generation II flight controller was designed to meet the standard requirements for stability and handling qualities of a piloted aircraft. The baseline controller with no neural network augmentation was demonstrated to meet these requirements using standard flight controls development techniques.

The addition of the neural networks introduces nonlinearities to the system that complicate the application of traditional stability and performance assessment techniques.

III. CONTROLLER PROPERTIES AND ARCHITECTURE

The intelligent flight control system generation II controller architecture consists of the baseline research flight controller and Sigma-Pi neural networks. A separate neural network was implemented in each of the three axes (Longitudinal, Lateral and Directional) in the generation II controller. As mentioned above, the baseline research flight controller can operate with the neural networks active or inactive. First, we detail the baseline intelligent flight control system generation II controller architecture and then we describe the neural network architecture and its interaction with the baseline. Fig. 2 provides an overview of the intelligent flight control system generation II system architecture.

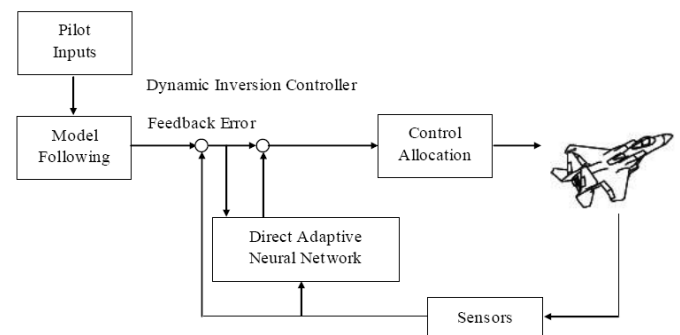


Fig. 2. Intelligent flight control system generation II system

The intelligent flight control system generation II flight controller uses a dynamic model inverting control scheme with Proportional, Integral, Derivative (PID) regulation of

the errors between the pilot commands and the sensed aircraft response. The pilot's stick and pedal commands are converted into desired aircraft angular rates. The PID error regulator computes tracking error compensation signals that are summed with the desired angular accelerations. These signals are the total desired aircraft angular accelerations.

One of the most important aspects of a control systems design is the process of validation that the design meets the overall system requirements. Three of the major requirements concern quantification of system stability, aero servoelastic margin and aircraft performance (or handling qualities). Each of these requirements is critical for control systems design and the approach to meeting each of these requirements for the intelligent flight control system generation II control system had to be amended to accommodate the neural network algorithms.

System stability is the tendency of a system to return to an equilibrium state when perturbed from that equilibrium. For an aircraft, this means that if the aircraft is in steady flight (i.e., with zero rotational rates) and it is perturbed via a temporary pilot command or disturbance, then it will return to steady flight after some settling period. Stability robustness margins provide quantitative measures of the strength of this tendency to return to equilibrium. These measures are gain margin and phase margin. The gain and phase margins, respectively, quantify the amount of gain or phase uncertainty can be withstood by the system without the system becoming unstable.

If the controller were allowed to output commands in the frequency range of the aircraft's structural mode frequencies, it could cause the natural flexure of the aircraft to be interpreted by the sensors as uncommanded disturbances that the controller would try to regulate by commanding more deflection in the frequency range of the flexible structural modes. This creates a positive feedback loop that could literally shake the aircraft apart. To avoid this phenomenon, bending mode compensation filters are applied to the feedback signals to attenuate them in the frequency range of the aircraft structural modes.

Handling qualities for an aircraft are assessed using both linear and nonlinear analysis techniques. These three requirements (stability, ASE and handling qualities) are somewhat contradictory and require tradeoffs in the design of the controller to simultaneously meet them.

The neural network architecture chosen for the intelligent flight control system generation II system is of the Sigma-Pi type. This architecture was chosen based on the results of a trade study conducted to compare the accuracy and adaptation speed of multiple neural network architectures. The Sigma-Pi neural networks provide adaptation to the intelligent flight control system generation II controller by adding augmenting signals to the total desired aircraft accelerations described above. Fig. 3 shows the neural network architecture.

The Sigma-Pi network is so-called because it calculates the weighted sum of basis functions. For intelligent flight control system generation II these basis functions, u_i , are sensor measurements and functions of the tracking errors in the three aircraft axes. The signal U_{ad} is the augmenting signal that is provided to the baseline controller to compensate for tracking errors induced by the simulated

surface failures.

The neural network weights, w_i , are adaptive. The adaptive laws that govern the evolution of the neural network weights are derived from Lyapunov nonlinear systems stability theory and ensure bounded command tracking while guaranteeing that the system remains stable. [5]. Where σ is the hidden-layer activation function, v_{jk} are the first-to-second layer interconnection weights and w_{ij} are the second-to-third layer interconnection weights.

The bias terms q_{wi} and q_{vj} represent thresholds. This architecture has N_1 inputs, N_2 hidden-layer neurons, and N_3 outputs.

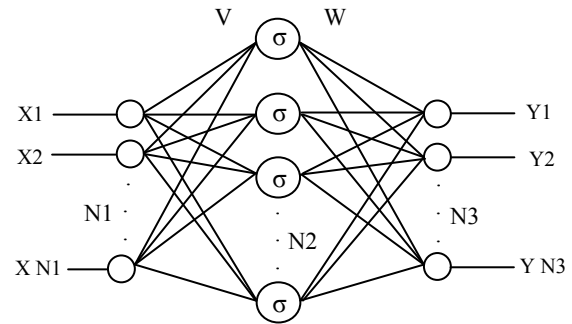


Fig. 3. Neural network with one hidden layer

The bias terms q_{wi} and q_{vj} represent thresholds. This architecture has N_1 inputs, N_2 hidden-layer neurons, and N_3 outputs.

The functional form of the hidden-layer activation is a design parameter, but we will consider the case of sigmoidal activation functions.

The main benefit of networks with this architecture is that they are universal approximators. Another important issue concerns robustness of adaptive systems to unmodeled dynamics.

IV. CONCLUSION

The performance of aircraft systems is highly dependent on the capabilities of the navigation and control systems. In order to maximize the performance, the control system needs to be intelligent. There are numerous opportunities envisioned for transitioning neural network technology to applications within the aerospace industry, besides the tiltrotor application described in a previous section. The potential payoffs in aircraft applications include:

- Reduced flight control system design/development costs.

- Reduced costs associated with the need to develop a large aerodynamic data base.

- Reduction of control related accidents, and maintenance of handling qualities immediately following failures and damage.

- Payoffs in missile and guided munition applications include several of the above mentioned factors, and in addition:

- Accommodation of variants within a class of munitions with a single control design.

- Improve and more predictable weapon performance and the potential for eliminating the need for wind-tunnel testing.

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