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Using Neural Networks for Aerodynamic Parameter Modeling

Gerald E. Peterson

William E. Bond
Missouri University of Science and Technology, bondw@mst.edu

Roger Germann

Barry Streeter

et. al. For a complete list of authors, see https://scholarsmine.mst.edu/comsci_facwork/285

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Using Neural Networks for Aerodynamic Parameter Modeling

Gerald Peterson, William Bond, Roger Germann, Barry Streeter and James Urnes
McDonnell Douglas Corporation
Mailcode 106 7075
P.O. Box 516
St. Louis, MO 63166-0516
Fax: (314)232-4141
peterson@mdcgwy.mdc.com

Abstract

Neural networks are being developed at McDonnell Douglas Corporation to provide an onboard model of an aircraft's aerodynamics to support advanced flight control systems. These flight control systems, constructed using neural networks and advanced controllers, have the potential to reduce flight control development costs and to improve inflight performance. Neural networks are useful in this situation because they can compactly represent the data and operate in real-time.

1. Introduction

The aerodynamic properties of an aircraft consist of measures of the coefficients in Newton's equations of motion which represent the magnitudes of the external forces and moments which act on the aircraft. These *aerodynamic coefficients* depend on a particular state of the aircraft. The aerodynamic coefficients are normally stored in large *aerodynamic tables* so that given an aircraft state, a table lookup can be performed in order to find the forces and moments which are acting on the aircraft. Aerodynamic tables are typically created from wind tunnel tests using physical models of the aircraft, mathematical calculations based on the structure and shape of the aircraft, and the processing of recorded data from hundreds of test flights.

The aerodynamic tables are used to support development of a flight control system and to provide the coefficients for the equations of motion which are solved to provide flight simulation. However, direct use of this tabular data on the aircraft in flight control software would require a processor with significant throughput and memory capabilities.

The fundamental idea, from which all the benefits derive, is to use neural networks to replace the aerodynamic tables. Since neural networks are designed to approximate multidimensional nonlinear functions, are compact in storage, and execute rapidly, it might be possible to use them to replace tables for onboard applications. In fact, neural network models in use at McDonnell Douglas have a 50-fold size advantage (103 KBytes vs 5.3 MBytes) over the aerodynamic tables while maintaining an acceptable accuracy. These networks can be executed at 80 hz, the update frequency required by the flight control system.

In addition to the aerodynamic coefficients, the flight control system requires the network model to supply derivatives of these coefficients with respect to some of the aircraft's state variables; that is, it requires the *stability and control derivatives.*

Figure 1 shows an overview of the flight control system with emphasis on the neural network model of the aircraft. The three-dimensional graph at the right-hand side of the figure is a projection of the aerodynamic table for the coefficient of pitching moment, C_m, onto two of its input axes: velocity in units of Mach number, and angle of attack, α, in degrees. This table and others like it are used on the ground to train the neural networks. As the plane flies, the trained networks obtain their inputs from the aircraft's sensors and provide their outputs, the stability and control derivatives, to the flight control system. The flight control system uses this information along with sensor information and pilot commands to generate commands which are sent to the control surfaces on the aircraft.

2. Building Neural Networks

Figure 2 shows the input-output structure of a typical baseline neural network for the F-15 SMTD aircraft. This network is for the coefficient of pitching moment, C_m, termed the *function output,* and two of its derivatives. The coefficient of pitching moment is a measure of the moment acting on an axis which extends through the wings of the aircraft. As shown in the figure, it depends on the angle of attack, α; the sideslip angle, β; the velocity, $Mach$; the altitude, h; the deflection of the stabilator, $\delta stab$; and the deflection of the canard, $\delta canard$.

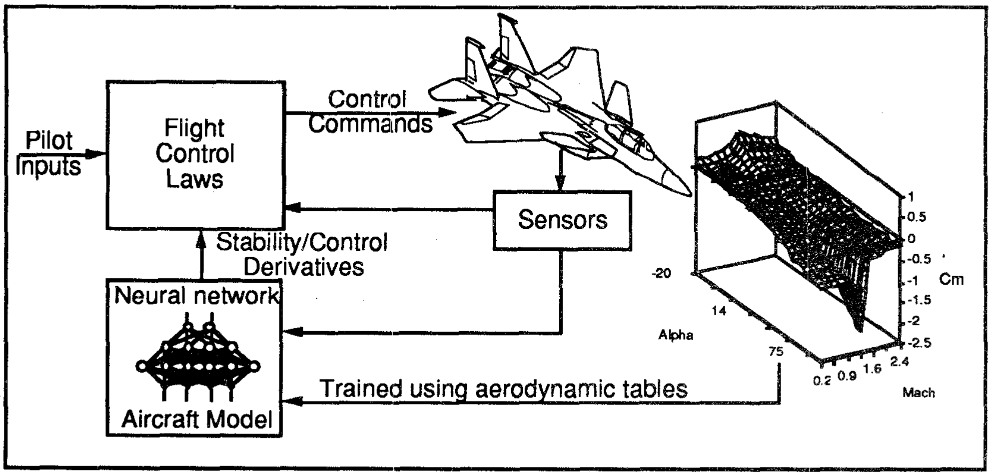

Figure 1. Overview of the flight controller, emphasizing the neural network model

In addition to C_m, the outputs are $\partial C_m/\partial\alpha = C_{m_\alpha}$, and $\partial C_m/\partial\delta stab = C_{m_{\delta stab}}$. The network receives inputs that continually change, typically at a rate of 20 to 80 hz. The outputs must be calculated during each input cycle such that the values computed by the network remain within accuracy bounds needed by the flight control system.

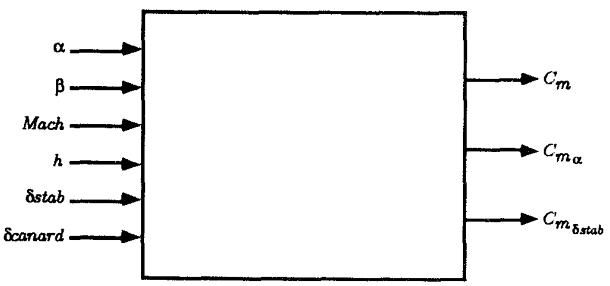

Figure 2. Input-output structure of a typical network in the model

Training data for the baseline networks can be obtained from existing tables. Given a range of values for each of the inputs α, β, $Mach$, h, $\delta stab$, and $\delta canard$; it is possible to determine C_m, C_{m_α}, and $C_{m_{\delta stab}}$ at every point which is simultaneously in each of the input ranges. Doing so creates the training data for the network. If the input ranges cover the entire flight envelope, the training data will also. Since there are six inputs, if each input range consists of d points, there will be d^6 patterns in the training set. For example, if $d = 10$, there will be one million training vectors.

The baseline neural networks must provide highly accurate aerodynamic coefficient and derivative values over the entire flight envelope. Large errors cannot be tolerated because excellent control must be maintained wherever the plane might fly. This necessitates focusing on maximum errors for each sample cycle, as opposed to any kind of averaged error such as RMS error. One of the most difficult requirements to meet is that of maintaining high accuracy for all the derivative outputs. It was concluded that the training data must contain expected derivative outputs, and the networks must be trained on the derivative outputs as well as the function outputs.

3. Network Validation

Network validation will be performed both in a stand-alone mode and with the network embedded in the flight control system. The validation goals are to assure that the network meets the requirements which were stated in the previous section, and to assure that all other systems continue to work properly when the neural network is integrated into the flight software.

The network should first be evaluated off-line by constructing a test set which has the same coverage of the flight envelope as the training set, and is at least as dense, but has completely different input points. The errors observed on this test set should be representative of those which will occur in flight.

The primary validation of the aerodynamic networks will come from flight testing. The network will be integrated into the flight software in such a way that it receives incoming sensor data as its inputs, and its outputs are recorded on the data stream. Later, on the ground, the network's outputs for the aerodynamic coefficients will be compared with predicted results.

4. Conclusion

Neural networks can be used in flight control system designs to provide a model of the host vehicle. The use of neural networks can significantly reduce onboard processor requirements.