The Development of Neural Network Techniques for the System Identification of Aircraft Dynamics

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SUMMARY: Neural networks are investigated as an alternative to conventional mathematical models for system identification. Their use in both model generation (system identification), and derivative (parameter) estimation of aircraft dynamics is investigated for feasability, and to identify associated advantages and disadvantages. The connectionist neural network approach is demonstrated to be effective through application to simulated data, and results are presented.

1 INTRODUCTION

A great deal of time and effort is spent by aircraft manufacturers in the identification and estimation of the parameters that properly describe the aerodynamics of a particular aircraft. The derivatives of the aircraft forces, with respect to the input state have been the basis of many design and development techniques and tools, such as dynamic stability analysis, performance, simulation and control.

The system identification of the aerodynamic model using neural networks involves the selection of the necessary input and output states to the system, representation of the model, and parameter estimation of the characteristic quantities, and in this case the aerodynamic force and moment derivatives. The application of neural networks as both a model descriptor and parameter estimation technique also requires a close selection of model inputs, to most efficiently utilise the method.

System identification of the entire dynamic system as opposed to the parameter estimation of the derivatives is useful in various applications:

- It highlights deficiencies in flying handling qualities, and allows rigorous stability analysis and investigation without extensive flight testing.
- The model can be used to estimate flight performance under various configurations and missions.
- For non-adaptive flight controller design, the dynamics have to be 'known'. Thus, the modeling of aircraft dynamics is crucial to the safe and effective flight vehicle performance.
- The dynamics of an aircraft can be scrutinized under unusual flight configurations (for example high angle of attack maneuvers), and the model provides useful data in these flight regions which are hard to predict by conventional techniques.
- The model could be useful in accident investigation, since the dynamics of an aircraft can be determined from black box data, and simulations may uncover the cause of the crash.

There are several demands on the techniques of system identification, which affect the suitability of methods to different problems. These demands could be summarized as follows:

- The system must be sufficiently rapid to enable timely reduction of results, especially for real-time applications.
- The accuracy of the model must be high, so that errors will not adversely affect the model's suitability for the given application.

The research in this area has concentrated on modelling the entire dynamic system, and at the same time, the parameter estimation of specific quantities, such as the linear aerodynamic derivatives.

2 FLIGHT DYNAMIC SYSTEM MODELING

2.1 The Dynamic System

Consider a multiple input, multiple output system, where $\{x\}$ defines a set of states in a general dynamic system in response to inputs $\{u\}$. The model presented here is similar to the NARMAX nonlinear dynamic model [1]. In general, we can write the system as (for a single order system):

$$\{\dot{x}\} = f(\{x\}, \{u\}) \tag{1}$$

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This applies to higher order systems. For example, consider a second order system with first order inputs:

$$\{\ddot{x}\} = f(\{\dot{x}\}, \{x\}, \{u\}) \tag{2}$$

For simplicity, the systems described in equations 1 and 2 can be combined so that the left hand sides become $\{y\}$, and the states, derivatives and control inputs become $\{X\}$.

$$\{y\} = f(\{X\}) \tag{3}$$

The primary task of system identification is to find a function $\hat{f}$ which is sufficiently close to f to yield a low error between the estimated output $\{\hat{y}\}$ and the actual output $\{y\}$; given a training data sets of k observations $(\{X\}, \{y\})$ under the influence of noise.

From equation 3 (for a first order dynamic system[1]), the estimation problem becomes:

$$\begin{aligned} \{y\} &= f(\{X\}) \\ \{\hat{y}\} &= \hat{f}(\{X\}) \\ E &= E\big((\{y\}_1 - \{\hat{y}\}_1), \ldots, (\{y\}_k - \{\hat{y}\}_k)\big) \end{aligned} \tag{4}$$

In general, the function to be minimized, E is the square error function:

$$E = \sum_{i=1}^{k} \big((\{y\}_i - \{\hat{y}\}_i)^2\big) \tag{5}$$

This problem is further complicated by the influence of noise on the input data, {X}, and output data, {y}.

2.2 Neural Networks as Model-free Estimators

A neural network can be considered as a 'black box' which has a number of internal parameters that can adapt in response to the environment. The network has vectors of inputs and outputs, and processing is carried out in the *forward propagation* direction from the input to output layer (see figure 1). Neural networks are described from a dynamic systems viewpoint in [2].

A general neural network performs a mapping from the input state space to the output state space. The network can be trained using a *supervised* routine to change the mapping characteristics. In general, we can train the network to perform a particular mapping by applying a candidate input, forward propagating through the network, and finding the network output. This network output is then compared with the target (or desired) output, $\{T\}$, and the errors are propagated backwards through the network,

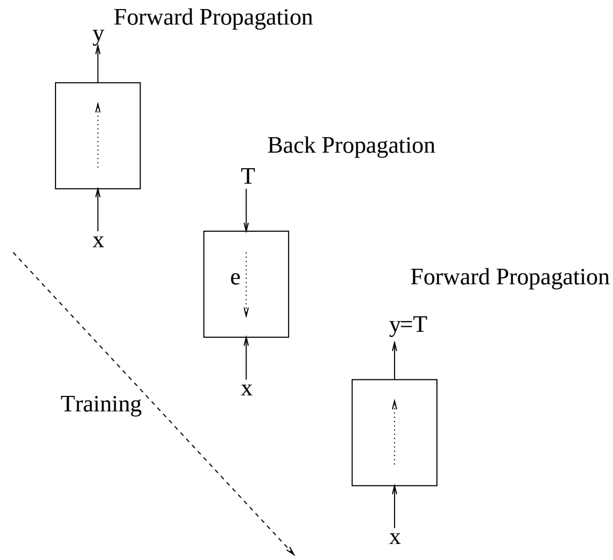

Figure 1: Supervised Training of Neural Networks

with internal corrections occurring in this direction. This is called *back propagation*, although the principles are characteristic of many supervised learning schemes.

The neural network can then be trained to perform a given functional mapping, even though its internal structure is not well defined. It is therefore a model-free estimator, since its functional properties do not specifically relate to the exact internal network structure, but to the overall network behavior. This facility is useful in modeling of dynamics, since we don't need to make as many assumptions as to the nature of the dynamics themselves[2]. Certainly, we don't have to assume linearity, since neural network processing is non-linear.

2.3 System Identification Procedure

The aircraft dynamics can, in general, be separated into two components: the aerodynamics, and the kinematic relations (see figure 2). The aerodynamics relate forces and moments on the body to the dynamic states:

$$\{P\} = F(\{X\}) \tag{6}$$

The kinematic relations give the derivatives of the states in terms of the forces and moments and the states themselves:

$$\{y\} = K(\{X\}, \{P\}) \tag{7}$$

We generally know the kinematics and hence the inverse kinematics are available, whereas the aerodynamics are unknown. In addition, it is difficult to directly measure the forces and moments from the flight test data.

The system identification procedure therefore, proceeds as follows:

[1] Since it can be shown that aircraft dynamics can be represented as a first order system.

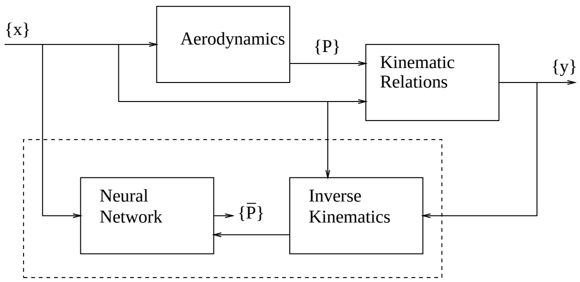

Figure 2: System Identification Procedure

1. Obtain training data $(\{X\}, \{y\})$
2. Calculate $\{P\}$ from the inverse of $K()$
3. Train the network to perform the mapping: $\{X\} \mapsto \{P\}$

The calculated forces and moments $\{P\}$ vary from $\{P\}$ due to errors in the calculations, and the effects of noise on $\{y\}$. Also, $\{X\}$ is under the influence of noise. Hence, we rely on the neural network's natural error suppression characteristics and robustness to ensure an adequate mapping. Provided that we have enough representative data, and that the errors have zero mean[2], the network will converge to the required mapping: $\{X\} \mapsto \{P\}$.

2.4 Flight Dynamics System Model

The determination of model input parameters is dependent on the aircraft type, particularly due to the control surface and power-plant inputs. Also, it is important that each can be practically measured or explicitly calculated from measured data.

In raw measurement form, the gravitational and aerodynamic forces are a function of: the body incidences to the free stream and rates thereof; angular rates and accelerations[2]; Euler angles; air density; viscosity; airspeed; Mach number; aircraft mass and center of gravity location—totalling twenty one inputs for a six degree of freedom model, not including control inputs (which are plant dependent).

By using an explicit reduction of flight test data[3, 4], the model input and output states can be reduced to remove the gravitational forces and all associated input states. If the remaining forces are non-dimensionalised in the standard manner, then Reynolds number alone can replace velocity, density and viscosity as the system input (if required at all).

In relatively stiff structures, angular and incidence accelerations can be neglected due to the insignificance of unsteady aerodynamic forces induced from structural vibrations. Note that although this reduces the dimension of the required input state, it also decreases the robustness of the system to turbulence. Neglecting Mach number in low subsonic flows, this reduces the required plant independent input state down to around 7 for a slow conventional aircraft, and at maximum 15 for the most agile fighter.

[2] For aircraft with complex aerodynamics, higher order derivatives may be included.

3 PARAMETER ESTIMATION TECHNIQUES

Parameter estimation of the aerodynamic derivatives has traditionally utilised various methods to establish a robust connection between one output and one input in a multi-variable system. In this way, the model is not described fully as a sub-process, but rather the required information is extracted through a set of carefully constructed flight manoeuvres [5]. This demands that the flight test data is chosen to highlight the effect of each variable in turn, which may require a time-consuming and costly set of test flights.

Parameter estimation is a subset of the aircraft dynamics system identification process. Neural network parameter estimation techniques are not bound to specific flight configurations, but requires that all inputs to the system are varied in such a manner that is representative of the flight envelope. This means that operation data may be used for analysis, eliminating the need for expensive specific flight test manoeuvers.

The least squares and maximum likelihood methods are two standard parameter estimation techniques, both geared to overcome system and measurement noise by averaging the estimates over a series of data points[6]. Through system description before parameter extraction, measurement noise is filtered before the required parameters are calculated and hence does not dominate the parameter extraction technique.

The neural network estimation method is also inherently robust against sytem noise, including turbulence, as it does not involve the averaging of data sets, but relies on the absolute value of the input state at any dicrete point in time. Provided that the correct input state can be accurately measured and modelled, then the process is totally insensitive to system noise.

These factors then extend the capability of this system to calculate the derivatives at each data sampling step. If the system is fast enough, real time derivative calculations may be performed.

3.1 Neural Networks for Parameter Estimation

Neural networks for system identification has previously been based on black box methods. Research has dwelled on problems like overfitting, learning acceleration techniques and so on. In addition, the networks have tended to be blindly generated instead of tailored to the problem at hand.

Alternately, the networks have been created too specifically for a given data set assumed to be noise and error free (as is the case for polynomial type networks)—and both the model-free properties (and hence generality) and propensity to learn new data, are lost.

In this work, the authors have attempted to keep the research at a general level, so that any supervised training scheme will be effective in this framework. We have also directed our attention away from what we consider trivial neural network problems[3], and concentrating on the problems at hand, of a connectionist system learning in a dynamic information environment.

Conventional parameter estimation methods are also subject to some of the limitations of neural network methods (multivariable optimization problems; local error minima; noise) and are in most cases additionally limited by the mathematical assumptions present, for example linearity. In some cases, the heavy reliance on matrix manipulation and computation causes numerical difficulties, especially when the dynamic system has many states or time lags [7].

3.2 Extensions

Neural networks can be extended to concurrently process additional data, or perform other functions, using the *same internal synaptic structure*. Thus, a neural network trained to perform one functional mapping, can also be used to obtain related information.

The author has developed a technique for the instantaneous generation of derivatives by a neural network. This process relies on special neurons which have been called Hyperdimensional Processing Neurons (HPNs) [8].

This use of HPNs leads to increased capability of neural networks, to simultaneously generate derivatives, with only a limited expense in overheads.

For the parameter estimation task, HPNs are used to compute first derivatives of network outputs with respect to inputs. Hence, aerodynamic derivatives are obtained without small perturbation processing; storage requirements and processing speed are hardly affected. The training proceeds is unaltered.

4 RESULTS

The trial of the system identification method has, to date, been restricted to simulation data, as it is

[3]These trivial problems are important when considering formal proofs

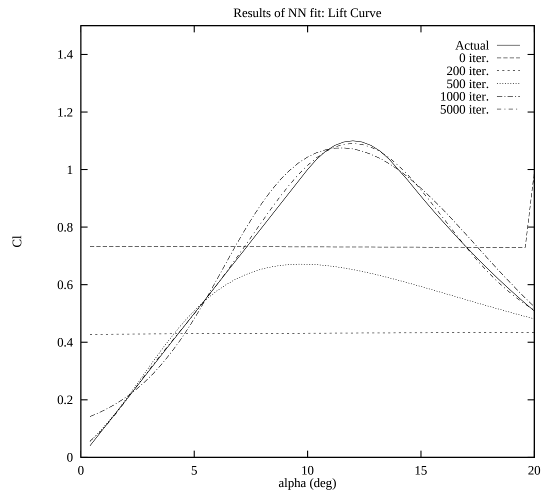

Figure 3: Results of Lift Curve Model

both a reliable and predictable platform for research. In addition, it readilly allows for the verification of results. Initial work was done using a Boeing 747 non-linear simulator model to test for noise and turbulence robustness, while later experimentation was done using a Remotely Piloted Vehicle (RPV), which allows the verification of the instantneous derivative calculation by the parameter estimation technique.

4.1 HPN Demonstration Example

To illustrate the procedure of parameter estimation using HPNs, a simple single input, single output system is generated to model the lift curve slope variation with angle of attack. The input to the network is α and the output is C_L (See figure 3). A mathematical relationship for (α, C_L) was defined as piecewise parabolic polynomials. Fifty training samples are obtained in the region: $\alpha \in [0, 20]$ degrees; note that a simple post-stall region is modeled so that the functional relationship is non-linear.

The network is trained using the system identification procedure for 0, 100, 200, 500 iterations, and the network outputs in both C_L and $\partial C_L/\partial\alpha$ are processed by HPNs. Results are shown in figures 3 and 4. As expected, the derivative fit is not quite as accurate as the function—since a small error in a functional mapping is amplified in the derivative estimation. Nevertheless, the results show that the system learns the functional mapping rapidly, and the hyperdimensional processing nature is effective in generating derivatives.

4.2 The RPV study

A remotely piloted vehicle has been developed at Sydney University as a research platform [9]. As part of the development, a sophisticated non-linear simulator with unsteady aerodynamics was created

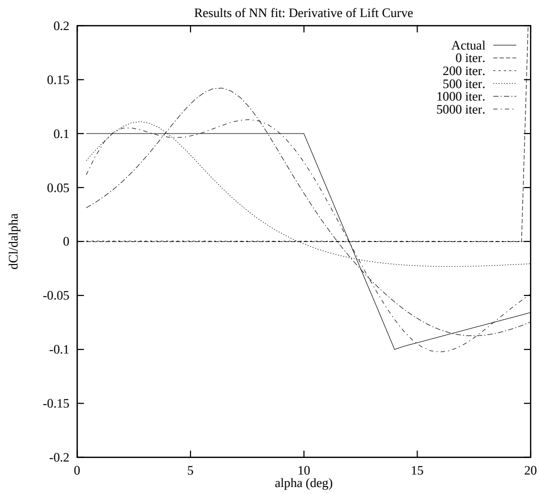

Figure 4: Results of Lift Curve Derivative Model

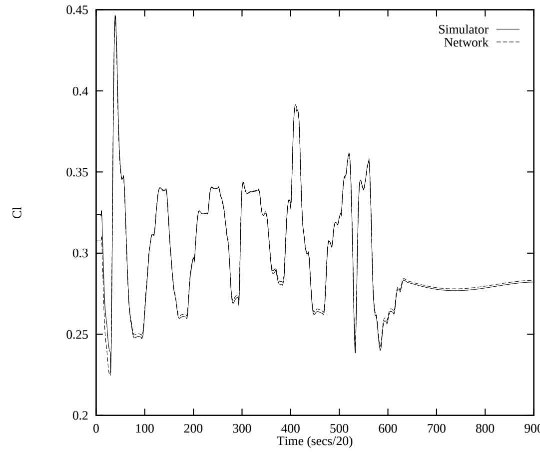

Figure 5: RPV time history comparison of lift force

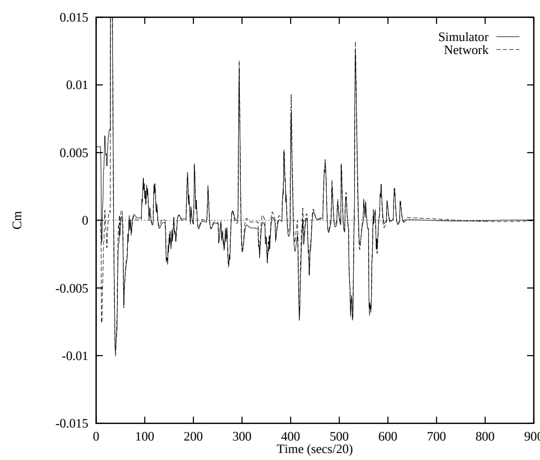

Figure 6: RPV time history comparison of pitching moment

using a wind tunnel database. Due to the database curve fit construction of the simulator, time histories of the actual derivatives can be calculated as well as flight test measurement data. Higher order derivatives are also available via the same method.

4.2.1 Model Selection

The study on the RPV uses only the longitudinal equations of motion to reduce the processing time and data storage problem. This assumes no cross coupling between the lateral and longitudinal dynamics, but nevertheless extension to the full six degree of freedom model requires no modification to the technique. With only one longitudinal control surface and one engine input, the total input state dimension amounts to seven, with three non-dimensional force/moment outputs: (C_L, C_D, C_M).

4.2.2 Model Depiction

The baseline simulator run generated data spanning around 50 seconds, with an update frequency of 20 Hz, and is restrained to motion in the longitudinal plane. A variety of maneuvers were made to excite all of the relevant input quantities at different levels. After training each of these model data sets, they were validated on the same final data set, where actual force outputs from the simulator were compared to those produced by the network.

Figure 5 shows the time history variation of lift for the particular baseline comparison maneuver for both the simulator and the network. A very close match is obtained, with the exception of the initial few seconds where the trim condition produced by the simulator is in effect; a phenomenon not encountered in actual flight data. Likewise, figure 6 shows the time history variation of pitching moment for the same maneuver.

This particular network was trained on a large perturbation model for approximately five minutes on an 80486 computer using a serial implementation of the back propagation neural network algorithm. With the incorporation of parallel hardware currently available for PC's or workstations[10], this training process can be accelerated many orders of magnitude, rendering such a process much faster than real time. This is particularly important for such applications as adaptive flight control and fault diagnosis. This leads to an efficient technique for the parameter estimation of aerodynamic derivatives.

5 CONCLUSIONS

This new approach to system identification of aircraft dynamics and the parameter estimation of the associated derivatives, has been proven to be a highly feasible concept. The results, to date, have demonstrated the capability to withstand measurement noise. The system has been accurately emulated and the aerodynamic derivatives simultaneously calculated. Real time processing has also been shown to be possible. The performance of this process exceeds the capabilities of the more traditional methods currently used.

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