A Neural Approach for Fast Simulation of Flight Mechanics

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Abstract

Flight simulators have been part of aviation history since its beginning. With the development of modern aeronautics industry, flight simulators have gained an important place and the industry devoted to their manufacture has become significant.

In the case of transportation aircraft, accurate mathematical models based on extensive experimental data have been developed by their manufacturers to optimise their aerodynamic and propulsive characteristics and to design efficient flight control systems. However, in the case of small general aviation aircraft this kind of knowledge is not commonly available and the design of accurate flight simulators can result in a tedious try and modify process until the simulator presents a qualitative behaviour close to the one of the real aircraft.

This communication proposes through the use of neural networks a method to perform a direct estimation of the aerodynamic forces acting on aircraft. Artificial Neural networks appear to be an appropriate numerical technique to achieve the mapping of these continuous relationships and detailed aerodynamics and thrust models should become no more mandatory to produce accurate flight simulation software.

1. Introduction

Flight simulators are used by aircraft manufacturers to test the integration of new on board systems interfaces and to validate safely new operational procedures. However, the main use of flight simulators is related with pilot training: they contribute to lower significantly training costs and delays while improving safety. Today, the delivery of costly aircraft includes in many cases either the acquisition or the hiring of flight simulators to perform flight simulation training programs. With the increasing popularity of general aviation, a large demand for low cost flight training simulators has also emerged.

The classical way to build a flight simulation program goes through the use of an accurate model of its aerodynamical and thrust dimensionless coefficients. To obtain this data a lot of money and energy must be consumed with flight tests, raw data collection, and complex numerical analysis [1]. While some attempts have been performed using neural networks [2] to alleviate this last point, many difficulties remain. However, what is really necessary to be able to run an accurate flight simulation model is to get good estimates of the forces and moments acting along its main reference axis.

Then, this communication proposes to perform a direct estimation of the global aerodynamic forces acting on aircraft using neural networks. To validate the proposed approach, an available analytical model of a small aircraft has been used to create, through numerical simulation, reference data. From the data generated by simulation a set of neural networks devoted to the estimation of each independent entry has been built. Then these neural estimators have been integrated in a new hybrid flight simulator software.

The comparison of the qualitative behaviours of the analytical and the neural based simulators in different flight cases has been performed and the validation results appear satisfactory.

2. Nomenclature

u, w : body axis longitudinal and vertical components of inertial speed

F_x, F_z, M_y : body axis longitudinal, vertical and pitch aerodynamic effects

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θ , q : pitch angle and pitch rate, δ_e and δ_f : elevator and flaps deflection

α : angle of attack, V : airspeed, T: total engine thrust

m : aicraft mass, I_y : Pitch inertia moment, S : reference surface, $\bar{c}$: reference chord

C_x , C_y , C_m : drag, lift and pitch aerodynamic coefficients

3. Estimation of flight forces: a proposal

In this communication the proposed approach is illustrated considering the longitudinal flight dynamics of a rigid aircraft which is assumed to be free from any lateral dynamics effect. From classical analysis, the longitudinal flight dynamics equations defined in the aircraft reference frame and ready for numerical integration are given by [3]:

$$\dot{u}=F_x/m-g\cos(\theta)+T-qw \quad (1)$$

$$\dot{w}=F_z/m-g\cos(\theta)+qu \quad (2)$$

$$\dot{q}=M_y/I_y \quad (3)$$

$$\dot{\theta}=q \quad (4)$$

$$\alpha=\arctan(w/u) \quad (5)$$

The aerodynamic forces in the aircraft reference frame, can be expressed using the dimensionless drag, lift and pitch moment coefficients as given below:

$$F_x=1/2\rho SV^2(-\cos(\alpha)C_x+\sin(\alpha)C_z) \quad (6)$$

$$F_z=-1/2\rho SV^2(\sin(\alpha)C_x+\cos(\alpha)C_z) \quad (7)$$

$$M_y=1/2\rho S\bar{c}V^2C_m \quad (8)$$

There the dimensionless coefficients are related in a complex way to the main flight parameters:

$$C_x=f(V,z,\alpha,\dot{\alpha},\delta_e,\delta_f) \quad (9)$$

$$C_z=f(V,z,\alpha,\dot{\alpha},\delta_e,\delta_f) \quad (10)$$

$$C_m=f(V,z,\alpha,\dot{\alpha},q,\delta_e,\delta_f) \quad (11)$$

In a classical flight simulator program, it is necessary to obtain at each iteration of the simulation a new estimate of the aerodynamic forces and moments which would be acting on the real aircraft in the current flight conditions. With respect to longitudinal dynamics, dimensionless drag, load and pitch moment coefficients are computed online. This is one of the most computational-costly tasks for those flight simulators. The coefficients calculation is made either searching the coefficients values corresponding to the flight conditions in aerodynamic databases composed of many data tables or using some analytical models. The first case leads to repeated searches in tables followed by interpolations (in general this data has an experimental origin and it is not free from approximations). The latter one speeds up the computation of the dimensionless coefficients but in general at the expense of a lower accuracy. Figure 1 displays the general structure of a flight simulation program.

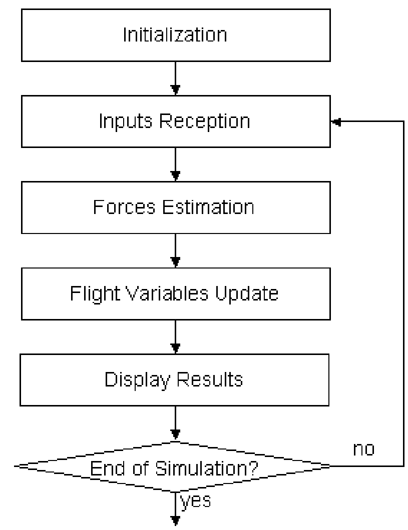

Figure 1. Simulation scheme

The tests to build a relevant database and the computations necessary to obtain accurate analytical models are costly and the results are not directly available to flight simulator manufacturers when they are different from the aircraft manufacturer. Sometimes the aerodynamics data necessary to build a simulator for a specific general aviation aircraft is not available at all. Observe also that the values of the aerodynamic dimensionless coefficients remain completely transparent to the flight simulator user. Even, to run the flight simulator program, what is really necessary is an on-line accurate estimation of forces and moments corresponding to the current flight conditions and control inputs and not the values of the associated aerodynamic dimensionless coefficients.

Then, what is proposed here is to obtain direct estimates of the current aerodynamic forces and moments using neural network estimators. Once, the neural networks estimators at each iteration, provide the values for F_x , F_z and M_y : F_{xNN} , F_{zNN} and, M_{yNN} , these values can be used to integrate numerically the longitudinal flight dynamics equations corresponding to equations (1-3).

The structure of the resulting neural based flight simulator program will be the same than the one of a classical flight simulator, the classical aerodynamics forces computation being replaced by a neural based one.

4. Neural estimation of flight forces

A feed-forward artificial neural network is a computational tool composed of interconnected elements called neurons [4]. Each neuron is an elementary processor which uses a continuous function called activation function to evaluate its output according to the inputs which are submitted to it by other neurons. When the neurons are arranged in layers, the connections are made between consecutive layers, and to each connection it is attached a weight which is defined through a beforehand training process. For a given network structure, the training is based on real input-output data from the system and is performed by adjustment of the connection weights so as to reduce a mean squared difference between the network outputs and the reference outputs. So, neural networks are particularly useful when a convenient mathematical model of a system is not at hand while a rich input-output field database is available for it. It has been shown that the combination of non-linear activation functions with weighted connections between neurons provide to these networks the capacity of approximating any non-linear mapping relating the inputs and the outputs of a given causal system [5]. They present also a generalization capability, that is, the property of interpolating and extrapolating accurately the data used for training. When neural networks are implemented in hardware, they display a parallel computing structure, which leads to a reduction of computing delays. However when neural networks are implemented in software in a serial computer, computation delays are not a problem since in general their size is quite reduced.

In many applications of Feed-Forward Artificial Neural Networks it has been shown that the training of a neural based input-output system is much easier and more effective when the system is composed of multi input single output neural networks [6]. In this study three neural networks have been attached to the estimation of each component (F_x, F_y and M_y) of the aerodynamical forces acting on the longitudinal flight dynamics. This results in the structure displayed in Figure 2. The structure retained for each neural networks is a three layer feed-forward neural network with as many neurons in the first layer as there are variables affecting the forces calculations (V , z , α , q , δ_e , T – for instance), with a larger number of neurons in the hidden layer and a single
neuron for the output layer. The number of neurons in the hidden layers has been determined by trial-and-error tests during the training phase of the neural network.

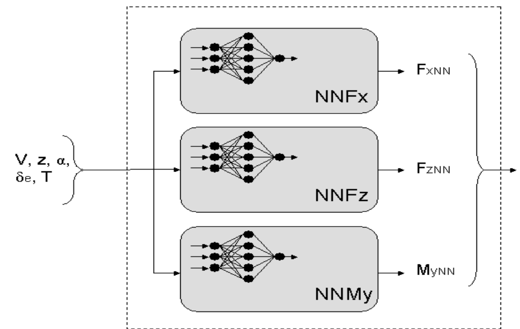

Figure 2. The modified forces estimation module

The algorithm which has been used for the networks training is backpropagation associated with the Levenberg-Marquadt non-linear least squares implemented to compute the weights update at each iteration [7]. In fact backpropagation is the specialization of a gradient descent algorithm. Backpropagation Levenberg-Marquadt is known to conduct to a faster training, though memory requirements are greater than the conventional backpropagation scheme. A comparative analysis between different modified backpropagation algorithms is given in [8].

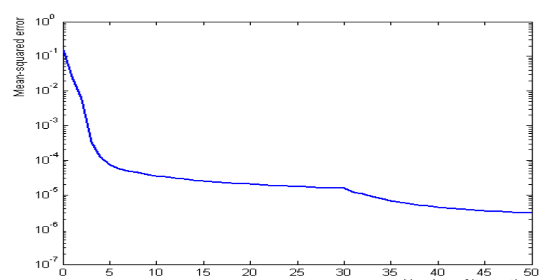

Figure 3. Error evolution during training

5. Methodology

Since no real flight data was available, the training of the neural networks has been performed using data obtained from a flight simulator program where the dimensionless forces and moment coefficients are computed from analytical expressions of the variables used as inputs to the different neural networks. This program available at ENAC implements the dynamics of a small general aviation aircraft, the TB20 from SOCATA, a subsidiary of Airbus.

Figure 4. TB20 Aircraft

A set of standard manoeuvres have been recorded for different flight conditions covering the whole flight envelope of the aircraft. The reference points in the flight domain have been chosen taking into account the known non-linear effect of the air speed on the aerodynamic forces. Note however that since this aircraft operates exclusively in the incompressible domain, no Mach number effect has been considered in this study, and this has been a rather simplifying factor for this study.

Since sigmoid functions (tangent hyperbolic) were used in the network's input and output neurons, it was necessary to perform a scaling over the raw training data. Then the networks were trained starting from different initial weightings to avoid local minima effects. The mean squared error (MSE) obtained for a training case is shown in table 1. An initial validation was performed considering flight conditions different from the ones used for training. This validation data was built from simulated data relative to the flight variables and the input signals, covering a time interval of 120 seconds sampled at 1Hz. From the samples of simulated flight variables, the networks provided estimations of the corresponding forces and moments. These estimations were compared to the forces and moment computed by the analytical simulator. The mean difference (MD) between forces computed by the analytical simulator and forces estimated by the neural networks is displayed in table 1.

Table 1. Training results

Network	NNFx	NNFz	NNMy
MSE	$3{,}5901.10^{-6}$	$1{,}9276.10^{-6}$	$6{,}7084.10^{-6}$
ME	0,3531N	0,5244N	0,02621Kg m^2/s

6. Results

Figure 5Figure 6Figure 7 show a comparison between F_x, F_z and M_y computed analytically and estimated by a neural network.

Then the networks were used in the simulator, substituting the analytical models for the forces. They were tested individually, in pair and the three networks at the same time. A comparison between the performances of the simulator using the analytical model and the performance provided by the neural estimators was made by comparing the evolution of the main flight variables with both kinds of simulations.

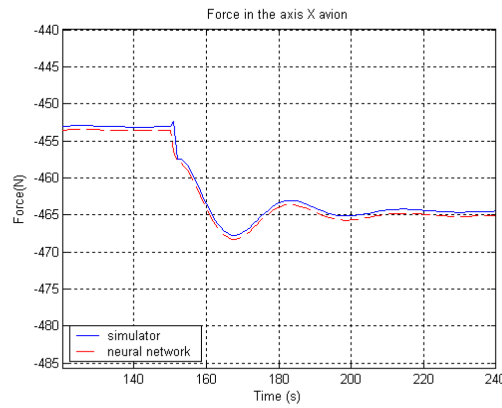

Figure 5. Estimated and computed longitudinal force F_x

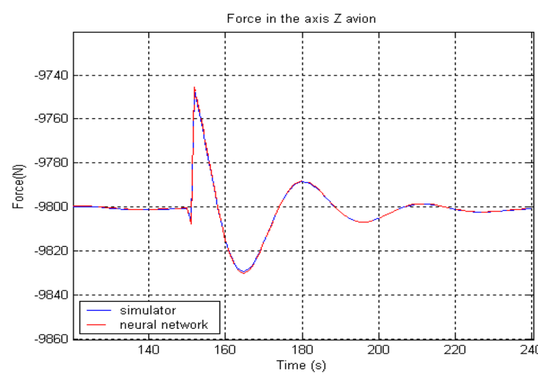

Figure 6. Estimated and computed longitudinal force F_z

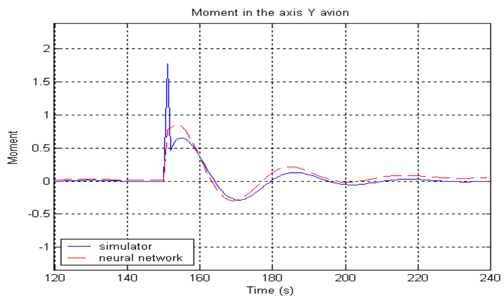

Figure 7. Estimated and computed longitudinal moments

Figure 8 shows that with respect to flight qualities of the simulated aircraft (damping coefficients and natural frequencies) , the two kinds of responses are quite similar.

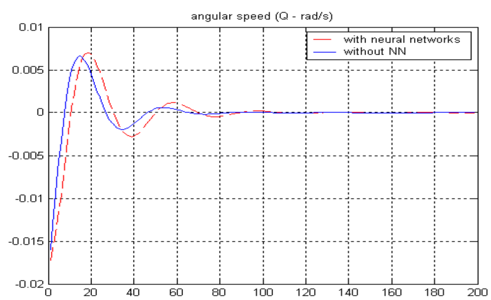

Figure 8. Neural and Analytic Estimations of pitch rate

With respect to guidance variables (speed, altitude and angle of attack), the time trajectories obtained through the neural simulator can present some drift with respect to those obtained from the analytical simulator, however the consequences of these discrepancies can be somehow minored since in a training device the pilot is in the loop and the corrections which should be added to a nominal action by the pilot to join and maintain guidance references will remain transparent since they are very small.

7. Conclusions

In this communication a proposal has been made to simplify the construction of flight simulator programs. This approach, based on the power of neural networks to relate complex causal signals, has been tentatively validated. The validation results displayed here, while encouraging, are not fully conclusive and this work should be pursued to obtain a practical methodology of direct use in the flight simulator industry. One particular area of further research considers the refinement of the training process to obtain accurate neural estimators of forces and moments from minimal flight data.

10. References

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