Title of the MsC Thesis

Name of author
author.name@ist.utl.pt

Instituto Superior Técnico, Lisboa, Portugal

December 2011

Abstract

Following the current ATM industry paradigm shift to allow for commercial aircraft to follow 4D trajectory, in order to increase both safety and air capacity, a controller was design and implemented in this work to reach such a goal in cruise conditions. The control law used is based on feedback linearisation, and a neural network is also implemented in order to restrain errors caused by modelling uncertainties caused by poor estimation of the aircraft parameters, external disturbances or fault systems. The neural network is trained online using the back-propagation algorithm to optimise the nonlinear inversion, resulting in an overall adaptive model-based controller. Simulation results show this controller is able to maintain stability and controllability in conditions that would otherwise render the aircraft unstable.

Keywords: non-linear control, feedback linearisation, neural network, flight control, back-propagation

1. Introduction

As the aeronautic industry grows, so is bound to also grow the air traffic dramatically. To answer this problematic ATM researchers have proposed over the last few years Trajectory-Based Operations (TBO), a concept allowing the use of 4D trajectories to manage both safety and air capacity. In both the US and Europe, initiatives to put such systems in place are currently being developed and implemented, namely the NextGen by the FAA and and SESAR EUROCONTROL. Therefore, in order to adopt this air traffic management paradigm, automation will play a crucial role in 4D guidance control, allowing an aircraft to follow flight plans more accurately.

In order to fully automatize a commercial aircraft to follow a 4D trajectory in cruise conditions, this work will focus on designing and implementing an autopilot capable of controlling the aircraft attitude, improving flight quality and stability in hazardous piloting situations, to be integrated in a Fly-by-Wire system. The ultimate aim of this project will be to focus on auto pilot to provide 4D trajectory guidance to a commercial aircraft. To do so a model based controller is used, unlike in the currently implemented framework of robust control composed of several PID layers. This model based controller distinguishes fast and slow dynamics, using a nonlinear inversion of the fast dynamics to determine the necessary deflections of the control surfaces.

This method, however, also has some limitations, the main one being that the feedback linearisation requires an exact knowledge of the system model, to obtain an exact inversion of the system. This is not usually feasible, and errors in the model of the airplane will inevitably lead to inversion errors, especially in cases of heavy external disturbances. A solution for this limitation will be proposed, studied and implemented in this work.

Over the recent years, research in intelligent and adaptive flight control systems has seen a consistent increase, in an attempt to solve these limitations, in order to develop flight systems able to adapt to external disturbances [2]. Of the existing intelligent control techniques used to solve the dependency of model-based control systems on an accurate mathematical model and the uncertainties caused by external disturbances or component failures, neural networks have been the most successful in doing so. Applied to UAV control, research works such as [4], [5], [1] and [3] have showed neural networks can be used to increase flight control stability and and rendering flight systems adaptable to disturbances. For this work an online neural network was used to improve a model based flight controller of a commercial aircraft.

This paper is organized as follows, Section 2 focuses on the model-based approach used to control the aircraft, as well as a description on the neural network used to improve said control law. Section 3 provides the mathematical model used as well as actuator dynamics. This section will also cover the implementation of the NN described previously and the guidance law used to ensure 4D trajectory following. Lastly Section 4 shows simulation results of the control approach, and conclusions are given in Section 5.

2. Background

Place text here...

2.1. Sub-section...

A generic CFD design problem can be formally described as

$$\begin{aligned} \text{Minimize} \quad & Y(\alpha, \mathbf{q}(\alpha)) \\ \text{w.r.t.} \quad & \alpha\,, \\ \text{subject to} \quad & \mathcal{R}(\alpha, \mathbf{q}(\alpha)) = 0 \\ & C(\alpha, \mathbf{q}(\alpha)) = 0\,, \end{aligned} \tag{1}$$

where Y is the cost function, α is the vector of design variables and $\mathbf{q}$ is the flow solution, which is typically of function of the design variables, and $C = 0$ represents additional constraints that may or may not involve the flow solution. The flow governing equations expressed in the form $\mathcal{R} = 0$ also appear as a constraint, as the solution $\mathbf{q}$ must always obey the flow physics.

2.2. Sub-section...

More text...

3. Implementation

Place text here...

3.1. Sub-section...

More text...

3.2. Sub-section...

More text...

4. Results

Place text here...

4.1. Sub-section...

More text...

Figure 1 shows the contour of pressure on the hub and blade surface planes corresponding to the baseline blade geometry.

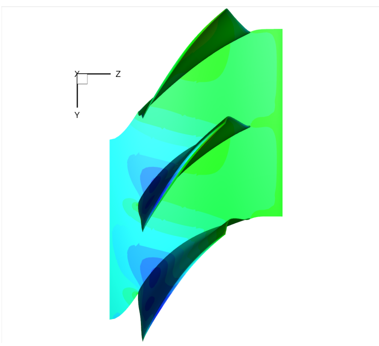

Figure 1: Pressure distribution.

As seen in Fig.1...

4.2. Sub-section...

More text...

Table 1 summarizes...

Model	C_L	C_D	C_{My}
Euler	0.083	0.021	-0.110
Navier–Stokes	0.078	0.023	-0.101

Table 1: Table caption

As seen in Tab.1...

5. Conclusions

The nonlinear control law for fast dynamics was submitted to different types of perturbations and inversion errors. The controller showed to be robust to not only to errors in inertia estimation as well as small system failures. For more serious control perturbations however, the aircraft could not, as would be expected, follow the desired inputs. Using a 99.5% smaller inertia relative to its true value in the NLI algorithm, increasing by 200% the drag coefficient or by heavily reducing the ability of the control surfaces to influence the plane's dynamics, the aircraft's behaviour showed much higher reference tracking errors, sometimes even becoming uncontrollable. Concluding this first section the designed controller, using a model based approach, proved to be robust to most external perturbations and internal errors.

Taking firstly the errors caused by errors in parameter estimations and gain tuning (for the linear law controlling the aircraft's model linearised by the FBL), the network showed improvements in robustness and reduced errors in airspeed and heading following, when compared to the same controller without the network. Similar tests were made with reduced control from actuators and in icing conditions. For the actuator failure case although the network slightly improve heading convergence times, reducing $C_{\delta_{ail}}, C_{\delta_{ele}}, C_{\delta_{rud}}$ by 80% is still a too big perturbation for a commercial aircraft to recover from. For icing condition were simulated reduced lift coefficient, increased drag and reduced roll control ($C_{\delta_{ail}}$ was reduced by 30%). For this case however, while the non corrected was unable to follow a heading and flight path angle references, this was not the case once the online neural network was added to the system. Indeed the network allowed the aircraft to follow a sinusoidal heading reference and to reduce the difference between γ and its desired value.

The same network architecture was used for all cases described above. Taking this into account it can be concluded that the goal of designing a neural network that would make the original NLI law more robust and able to adapt to different perturbations was indeed achieved.

Acknowledgements
The author would like to thank ...

References

[1] Q. Lin, Z. Cai, Y. Wang, J. Yang, and L. Chen. Adaptive flight control design for quadrotor uav based on dynamic inversion and neural networks. In *2013 Third International Conference on Instrumentation, Measurement, Computer, Communication and Control*, pages 1461–1466, Sept 2013.

[2] SANTOSO et al. State-of-the-art intelligent flight control systems in unmanned aerial vehicles. *IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING*, 2017.

[3] A. K. Shastry, A. Pattanaik, and M. Kothari. Neuro-adaptive augmented dynamic inversion controller for quadrotors. *IFAC-PapersOnLine*, 2016.

[4] Y. Tang and R. J. Patton. Reconfigurable flight control using feedback linearization with online neural network adaption. *Conference on Control and Fault-Tolerant Systems*, 2013.

[5] T. Xiang, F. Jiang, Q. Hao, and W. Cong. Adaptive flight control for quadrotor uavs with dynamic inversion and neural networks. In *2016 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, pages 174–179, Sept 2016.