Style for IFAC Conferences & Symposia: Use Title Case for Paper Title ⋆

First A. Author * **Second B. Author, Jr.** ** **Third C. Author** ***

* *National Institute of Standards and Technology, Boulder, CO 80305 USA (e-mail: author@ boulder.nist.gov).*
** *Colorado State University, Fort Collins, CO 80523 USA (e-mail: author@lamar. colostate.edu)*
*** *Electrical Engineering Department, Seoul National University, Seoul, Korea, (e-mail: author@snu.ac.kr)*

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.

⋆ Sponsor and financial support acknowledgment goes here. Paper titles should be written in uppercase and lowercase letters, not all uppercase.

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 SANTOSO et al. (2017). 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 Tang and Patton (2013), Xiang et al. (2016), Lin et al. (2013) and Shastry et al. (2016) 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 provides the mathematical model used as well as actuator dynamics. Section 3 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. 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. FLIGHT DYNAMICS

2.1 Frames of Reference

The first step before describing the dynamics of a commercial aircraft will be to define the frames of reference used to do so. The first frame of reference, on which 4D trajectories are described, corresponds to the WGS84 frame of reference. A second frame of reference corresponding to the aircraft body frame will be used to provide its fast rotational dynamics. Lastly all aerodynamic forces will be applied in the axial directions of the wind frame. This frame is aligned to the wind speed vector relative to the airplane, given by both the angle of attack α and the sideslip angle β. For these last two frames of reference, a rotation matrix can be defined from the wind frame to the body frame by

$$R_{BW} = \begin{bmatrix} c_\alpha c_\beta & -c_\alpha s_\beta & -s_\alpha \\ s_\beta & c_\beta & 0 \\ s_\alpha c_\beta & -s_\alpha s_\beta & c_\alpha \end{bmatrix} \tag{1}$$

To describe the attitude of the plane Euler, roll, pitch and yaw angles, will also be used, namely $\phi\{-\pi,\pi\}$, $\theta\{-\frac{\pi}{2},\frac{\pi}{2}\}$,v$\psi\{-\pi,\pi\}$. From these angles the rotation matrix from the body to the earth frame is given by

$$R_{EB} = \begin{bmatrix} c_\theta c_\psi & s_\phi s_\theta c_\psi - c_\phi s_\psi & c_\phi s_\theta c_\psi + s_\phi s_\psi \\ c_\theta c_\psi & s_\phi s_\theta s_\psi + c_\phi c_\psi & c_\phi s_\theta s_\psi - s_\phi c_\psi \\ -s_\theta & s_\phi c_\theta & c_\phi c_\theta \end{bmatrix} \tag{2}$$

2.2 Fast Dynamics

2.3 Translation Dynamics

2.4 Actuator Dynamics

3. IMPLEMENTATION

Place text here...

3.1 Feedback Linearisation

More text...

3.2 Online Neural Network

More text...

3.3 Guidance Law

4. RESULTS

Place text here...

4.1 Inversion Errors

More text...

4.2 System Failures

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

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. doi: 10.1109/IMCCC.2013.326.

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

Abhishek Kumar Shastry, Anay Pattanaik, and Mangal Kothari. Neuro-adaptive augmented dynamic inversion controller for quadrotors. *IFAC-PapersOnLine*, 2016.

Yimeng Tang and Ron J. Patton. Reconfigurable flight control using feedback linearization with online neural network adaption. *Conference on Control and Fault-Tolerant Systems*, 2013.

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. doi: 10.1109/MFI.2016.7849485.

Appendix A. A SUMMARY OF LATIN GRAMMAR

Appendix B. SOME LATIN VOCABULARY