High-Fidelity Simulation Testing of Intelligent and Adaptive Aircraft Control Laws

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Abstract
This paper compares the robustness of seven popular adaptive and intelligent control approaches using a high fidelity aircraft simulation. The control laws were originally developed and tuned using a lower fidelity simulation of the same aircraft, which is significantly different from the high fidelity simulation used to generate all results in this paper. The control law approaches examined are fuzzy logic, linearly and nonlinearly parameterized neural network approaches, an indirect adaptive version of dynamic inversion, variable structure, and a hybrid approach that combines direct and indirect adaptive elements. In addition, a conventional scheduled dynamic inversion controller is used as a baseline. The approaches are demonstrated on a high fidelity six Degree-of-Freedom simulation with nonlinear aerodynamic and engine models, actuator models with position and rate saturations, and turbulence. Simulation results are given for single and multi-axis pitch and roll maneuvers in both nominal and failed cases.

Introduction
This paper presents results that are part of a broad study to compare different intelligent and adaptive flight control approaches. Three different but closely related design problems have been examined during the course of this study. The reason for using multiple design problems is that the relative performance of highly nonlinear controllers can be very sensitive to a variety of factors in the design problem, such as the class of inputs or operating conditions. The initial design problem focused on tracking performance during simple maneuvers, such as pitch and roll doublets over a substantial part of the flight envelope and with a wide range of failure cases. The second design problem looked at automated recovery over a more limited part of the flight envelope and with a smaller set of failure cases. The final problem, the most challenging of the three, examined an automatic carrier landing with a small set of failure cases. Each of these past studies used a medium-fidelity aircraft simulation based on an F-18. In this paper, results similar to those from the first design problem are generated using a high-fidelity simulation that has substantial differences from the simulation that was used to design the different control laws. No additional tuning of the control laws has been performed. As a result, this is comparable to a situation where an aircraft control law is designed with a simulation model that has substantial differences from the real aircraft.

The approaches examined in this paper are fuzzy logic control, linearly and nonlinearly parameterized versions of neural network control, an indirect adaptive dynamic inversion control law, a variable structure control law, and a hybrid approach that combines direct and indirect adaptive elements. A more conventional scheduled dynamic inversion controller is used as a baseline. It should be emphasized that the point of this study is not to pick winners and losers, but only to provide empirical data to show potential strengths and weaknesses of each approach on problems with some aspects of the complexity of a real aircraft design. All of the control laws examined in this paper display features that might make them a good choice for certain types of design problems. There are also numerous variations of each approach that could not be tried within the scope of this effort that might yield better results. However, for these types of approaches to be useful for real production aircraft, control designers need to be able to adopt these approaches with a reasonable amount of effort to achieve better results than they get with whatever approach they are currently using. This paper demonstrates how well some of these approaches can work when developed with limited resources by flight control engineers who have experience with the techniques, but are by no means the leading experts with that approach.

Controller Descriptions
The controllers are the approaches described in Ref. 1 with the improvements described in Ref. 2.

Dynamic Inversion (DI) – The baseline control law is a Dynamic Inversion (DI) approach shown in Fig. 1 and based on the High Alpha Research Vehicle (HARV) DI control law. The input pre-processing consisted of limiters that vary as a function of mach and altitude, and a first order lag. The outputs of the input pre-processing are combined with the sensed values of the controlled variables to create desired dynamics for the aircraft to follow. The controlled variables were

\[
\begin{align*}
q &= q + K_{\phi} \Delta \alpha - p \frac{v}{u} + g \frac{v}{V} \cos \phi \cos \theta - \cos \theta_b \\
B &= K_{b} \beta - g \frac{v}{V} \cos \theta \sin \phi
\end{align*}
\]
where \( K \) are fixed gains. This choice of variables is used to provide some axis decoupling and to minimize angle-of-attack and sideslip variations during pitch and roll maneuvers. The desired dynamics use proportional-integral feedback to provide some robustness to model errors since dynamic inversion cannot make the aircraft behave as an ideal integrator in the presence of model error and actuator limitations. Because there are seven ganged effectors, a direct allocation approach\(^5\) is used to determine the commands to the actuators. When the control allocator cannot achieve the desired moments, an integrator anti-windup approach is used. The stability and control parameters used in the inversion and the allocation were scheduled with a linear interpolation based on Mach number, angle-of-attack, and dynamic pressure with angle-of-atttack being most important. Note that these parameters are based on the values of the medium-fidelity simulation and not the simulation they will be tested on in this paper.

**Indirect Adaptive (IA)** - An indirect adaptive version of the above DI controller was created by replacing the parameter scheduling block of Fig. 1 with on-line parameter estimation. Parameter Identification was used for 11 stability terms, 3 bias terms, and for 13 control effectiveness terms. This included a few cross-coupling parameters that are only significant following damage cases and are not used in the model for the baseline DI controller. The parameter identification approach used was Modified Sequential Least Squares (MSLS).\(^6\) MSLS attempts to optimize a cost function that includes both the more conventional predicted squared error of the estimate over a weighted window of data, and a term that penalizes the estimate for deviations from constraints. The constraints penalize the estimate for large deviations from a weighted blending of previous and a priori estimates of the parameters.

**Neural Network, Linearly Parameterized (NL)** - This is another modification of a dynamic inversion controller based on the approach of ref. 7. The neural network outputs are added to the outputs of the desired dynamics block to compensate for model error. The neural network had 172 basis functions and its inputs were aircraft states and the past output of the desired dynamics block passed through a squashing function. The adaptation law uses is chosen using a Lyapunov approach. Adaptation is halted when actuator saturation occurred.

**Neural Network, Nonlinearly Parameterized (NN)** - This controller is similar to the above neural network one except that it uses a nonlinearly parameterized neural network with a smaller set of inputs as described in ref. 8.

**Variable Structure (VS)** - This is another modification of a DI controller that adds a nonlinear adaptive element to the desired dynamics block of Fig. 1. The nonlinearity is a continuous approximation of a discontinuous nonlinearity that has been proven to have considerable robustness properties in theory. In addition, an adaptive gain is used.

**Fuzzy Logic (FL)** - The FL used in this paper was based on the Automatic Carrier Landing System of refs. 9-10. There were 3 rule bases that control roll, pitch, and yaw. Separate rule bases were necessary because fuzzy logic controllers can become very unmanageable if there are more than a few important inputs. The main inputs were error and integrated error of the controlled variable. The rules that use these inputs make up the majority of the rules, and are used essentially to create a nonlinear response with lower damping for large errors and higher damping for small errors. In addition, a small number of rules used some aircraft states and past commands. These rules were designed to deal with extreme damage or failure cases, and are of the form “if the aircraft is doing something substantially different from what was commanded, then perform this compensation”. Each rule base had between 40-55 rules and outputted commands of desired moments. As with the earlier designs, direct allocation was used to determine the actuator commands. Some additional scheduling was done by scaling the inputs to the rule bases based on angle-of-attack.

**Hybrid (HY)** - This control law combines the nonlinearly parameterized neural network approach and MSLS parameter identification. The major change from the above designs lies in the necessity to modify some of the parameters to minimize adverse interactions between the parameter identification and the neural network adaptations.

**Results**

All results were computed in Matlab/Simulink 6.1 at a sampling rate of 80 Hz. For each of five failure scenarios, a maneuver set of 19 pitch and roll doublets was used at flight conditions of .7 M and 30,000 ft. altitude and .8 M and 20,000 ft. altitude. The maneuvers lasted 8 sec. and the total simulation runs were 15 sec to allow some settling time. All failures were simulated starting at 1.5 sec. Table 1 shows the magnitude of the maneuvers.

Fig. 2 shows the average absolute error for the maneuver sets at the two flight conditions with no failures. It is notable that only the Hybrid (HY) approach does as well as the baseline Dynamic Inversion (DI) controller for this case. This is very much in contrast to results using the lower fidelity
Simulation models for which the intelligent and adaptive approaches did comparably or better than the baseline controller in the no failure case. However, for this case in the current study, none of the controllers had significant errors during the last 5 seconds of the maneuvers so there do not appear to be any problems with stability robustness, just performance robustness.

Table 1 - Magnitude of Maneuver Sets (deg.)

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<tr>
<th>Single Axis (deg.)</th>
<th>Multi-Axis (deg.)</th>
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<td>Pitch</td>
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Fig. 3 shows average absolute errors for the maneuver set with an aileron hardover condition. In this case, the nonlinearly parameterized neural network (NN) and hybrid approaches do best. The Indirect Adaptive Control law, however, is the only one that does significantly better than the baseline DI control law. The Variable Structure (VS) and Fuzzy Logic (FL) ones do worst. Fig. 4 shows the number of cases for which there were significant large or small errors in the last 5 sec. of the maneuver. Errors after completion of the maneuver typically indicate that the controller is having some significant difficulties. Large errors were considered to be greater than 15 deg. and small errors were considered to be greater than 5. deg but less than 15 deg. As can be seen, only the NL, NN, and HY approaches do not have a single large error case.

Fig. 5 shows the average absolute errors for a stabilator hardover case. In this case, the HY and IA controller do the best due to their ability to optimize the remaining control power most effectively. The other controllers do somewhat comparably except for the VS and FL ones that do rather poorly. Fig. 6 shows the average absolute errors for a rudder hardover case, which is perhaps the most difficult. In this case, the HY, NN, and surprisingly, the FL ones do the best. The FL one does particularly good in this case due to its robust stability that prevents any departures in contrast to the other methods as can be seen in Fig. 7.

Fig. 8 shows the average absolute errors for a combined stabilator, aileron, and rudder failure to a neutral position. Such a failure might occur with a hole-in-the-wall fail-safe. In this case, the IA does the best with the NN, FL, and HY all doing comparably. This is also one of the few cases where the VS does better than the baseline. As can be seen in Fig. 9, the VS one does have some problems with converging on a final value. However, it avoids any extreme departures and maintains a reasonable value on the error metrics.

Conclusions

The baseline DI controller had fairly good robust stability, which allowed it to perform better than some of the intelligent and adaptive cases for a number of failure scenarios. It also had some of the best robust performance for the no failure case. However, it did have some ugly departures following severe actuator failures like hardovers, and damage conditions that significantly altered the stability properties of the aircraft. Its robust performance following failures was not as good, as evidenced by its much poorer tracking performance in some failure cases compared to the other approaches. These results show that for a relatively stable aircraft with conventional effectors and a fairly accurate design model, a well-designed traditional robust control law may be capable of dealing with all but the most severe failure situations. Thus, there is a clear design trade-off between achieving that extra capability to react to failures, and paying the additional design costs involved with applying the current state-of-the-art in adaptive and intelligent control laws. The Dynamic Inversion (DI) controller was by far the easiest approach to design and to redesign for each successive problem since one can use many traditional analysis tools despite the fact that it is technically a nonlinear controller.

The Indirect Adaptive Controller (IAC) generally did quite well and was particularly good on problems where it had some time to adapt and where there was very limited control power to maneuver the aircraft. An example of this is the stabilator hardover case, which affects all axes of the aircraft significantly. It also had particularly good robust performance following the transient identification period, though its transient performance was sometimes a problem. From a design point of view, the experience was mixed. On the positive side, indirect adaptive control allows a great deal of flexibility to design the underlying control law as desired using traditional techniques. On the negative side, there are many parameters that need to be set and not a lot of guidance in the literature about how best to do this. It is not even clear whether it was better to adjust these parameters to get the most accurate open-loop identification or the best closed-loop response or...
some combination thereof. There may also be a need to schedule some of these parameters.

The nonlinearly parameterized neural network approach was by far the most capable of the Lyapunov-based approaches that were examined under this study. It did much better than either the variable structure or linearly parameterized neural network controllers in terms of ease of design, robust performance, and just not having occasional unpredictable highly erratic behavior. Compared with all the controllers, the neural network approaches had particularly fast adaptation (less than one sec.) and were quite good at dealing with situations where time was a factor. However, it ran into some limitations due to its inability to change the control allocation in some situations. Both neural network approaches generally were quite effective at dealing with changes in control effectiveness, but the nonlinear neural network seemed to do significantly better at dealing with changes to the aircraft's stability properties, particularly in the lateral-directional axes. From a design point of view, this type of control law was reasonably easy to design. The NN has limited effect on the system when errors are small. When failures occurred, robust performance was generally satisfactory relative to a desired response model when the parameters were chosen correctly. However, there was some sensitivity to parameters that led to oscillatory behavior, particularly for the linear approach. It may be of value to have some type of variable adaptation rate to minimize this problem.

The hybrid approach did extremely well on this test and was the only of the intelligent and adaptive approaches to not do poorer on performance than the baseline controller for the no failure case. However, this controller had all of the design complexities of both indirect and direct approaches combined with additional new problems caused by adverse interactions between the 2 adaptive elements.

The fuzzy logic controller sometimes had good robust stability for a fixed non-adaptive controller, although it had some significant problems with the aileron and stabilator hardover cases. FL can be tailored to have excellent performance in narrow circumstances. It is quite challenging, however, to create a fuzzy logic controller that has good performance and robustness against a wide range of flight conditions and requirements. This is particularly true due to the lack of analysis tools that are as effective as those that exist for the feedback linearization based approaches. There are many uncertain design issues dealt with through questionable rules of thumb such as membership function type and number, type of operators, implication and defuzzification, stability and transient analysis, etc. As a result, fuzzy logic may be best if used only for specific tasks that require the use of heuristics or nonlinear responses, particularly for narrowly defined outer loop and guidance tasks.

References

![Fig. 1 — Dynamic Inversion Controller](image-url)
Intelligent Landing Control Using Linearized Inverse Aircraft Model*

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Abstract

Neural network applications to aircraft automatic landing control based on linearized inverse aircraft model are presented. Conventional automatic landing systems can provide a smooth landing which is essential to the comfort of passengers. However, these systems work only within a specified operational safety envelope. When the conditions are beyond the envelope, such as turbulence or wind shear, they often cannot be used. The objective of this study is to investigate the use of neural networks with linearized inverse aircraft model in automatic landing systems and to make these systems more intelligent. Current flight control law is adopted in the intelligent controller design. Tracking performance and robustness are demonstrated through software simulations. This paper presents five different neural network controllers to improve the performance of conventional automatic landing systems based on the linearized inverse aircraft model. Simulation results show that the neural network controller can successfully expand the safety envelope to include more hostile environments such as severe turbulence.

1. Introduction

On August 22, 1999, China Airlines Flight 642 had a hard landing at Hong Kong International Airport. The lifting wing of the airplane was broken at the landing. The accident killed 3 passengers and injured 211 people. After 15 months investigation, a crash report was released on November 30, 2000. It showed that the accident was mainly due to the improper crosswind correction by Software 907 on the Boeing MD-11. Boeing also confirmed this software problem later and replaced nearly 190 MD-11 crosswind-correction software with the 908 software. Although this accident was attributed to software problem, the automatic landing system (ALS) has been the focus of the safety issue. The first ALS was made in England in 1965. Since then, most aircraft have been installed with this system. The ALS relies on the Instrument Landing System (ILS) to guide the aircraft into the proper altitude, position, and approach angle during the landing phase.

Most conventional control laws generated by the ALS are based on the gain scheduling method [1]. Control parameters are preset for different flight conditions within a specified safety envelope which is relatively defined by Federal Aviation Administration (FAA) regulations. According to FAA regulations, environmental conditions considered in the determination of dispersion limits are: headwinds up to 25 knots; tailwinds up to 10 knots; crosswinds up to 15 knots; moderate turbulence, wind shear of 8 knots per 100 feet from 200 feet to touchdown [2]. If the flight conditions are beyond the preset envelope, the ALS is disabled and the pilot takes over. An inexperienced pilot may not be able to guide the aircraft to a safe landing. According to Boeing's report [3], 64.5% of the flight safety events are due to human factors and 3.2% are attributed to weather factors. It is therefore desirable to develop an intelligent ALS that expands the operational envelope to include more safe responses under a wider range of conditions. This study has demonstrated that the proposed neural network controllers can automatically guide the aircraft to a safe landing in different wind disturbance environments.

Recently, many researchers have applied intelligent concepts such as neural networks, fuzzy systems, and genetic algorithms [3-8] to flight control to increase the flight controller's adaptation to different environments. Among these intelligent concepts, neural network techniques are used most because of its better adaptivity and robustness for unmodeled systems and the hardware implementation capability [9-10]. Most of the improvements in the ALS have been on the guidance instruments, such as the GNSS Integrity Beacons, Global Positioning System, Microwave Landing System and Autoland Position Sensor [11-14]. By using improvement calculation methods and high accuracy instruments, these systems provide more accurate flight data to the ALS to make the landing more smooth. However, these researches did not include weather factors such as wind disturbances. There have also not been many researches on the problem of intelligent landing control [15-17]. This study focuses on neural network applications to aircraft landing control. Different neural network structures using a modified learning-though-time process of previous studies [18-20] is utilized in the controller design. The weight calculations of the basic backpropagation are not capable of solving the time delay problem which involves past calculations. Thus, a modified method is needed in this case. Different strengths of turbulence are also implemented into the flight simulations. The proposed learning technique can overcome the problem encountered in [16], which is a trained controller can not be used under various wind disturbance situations, and make the neural network controller more robust and adaptive to the ever-changing environment.

2. Aircraft Landing Control

Prior to landing, the pilot descends from the cruise