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Aerospace Science and Technology 10 (2006) 49–61
Aerospace Science and Technology
www.elsevier.com/locate/aescte

A fault-tolerant neural aided controller for aircraft auto-landing

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Received 20 October 2004; received in revised form 10 May 2005; accepted 11 May 2005

Available online 17 June 2005

Abstract

This paper presents a neural-aided controller that enhances the fault tolerant capabilities of a high performance fighter aircraft during the landing phase when subjected to severe winds and failures such as stuck control surfaces. The controller architecture uses a neural controller aiding an existing conventional controller. The neural controller uses a feedback error learning mechanism and employs a dynamic Radial Basis Function neural network called Extended Minimal Resource Allocating Network (EMRAN), which uses only on-line learning and does not need a priori training. The conventional controller is designed using a classical design approach to achieve the desired autonomous landing profile with tight touchdown dispersions called herein as the pillbox. This design is carried out for no failure conditions but with the aircraft being subjected to winds. The failure scenarios considered in this study are: (i) Single faults of either aileron or elevator stuck at certain deflections, and (ii) double fault cases where both the aileron and elevator are stuck at different deflections. Simulation studies indicate that the designed conventional controller has only a limited failure handling ability. However, neural controller augmentation considerably improves the ability to handle large faults and meet the strict touchdown dispersion requirements, thus enlarging the fault-tolerance envelope.

Keywords: RBF neural network; EMRAN; Fault tolerant; Actuator failure; Auto landing; Flight control

1. Introduction

The auto-landing control systems in modern aircraft are designed to give a satisfactory performance under nominal operating conditions and are generally unable to cope with failures such as control surfaces being stuck at certain deflections. However, if one can build some intelligence into the existing auto-landing controllers, they can react quickly to such failures and reconfigure the control system to achieve a safe landing with the desired performance requirements. Neural networks provide a fast mechanism to achieve this because of their ability to learn on-line and adapt the aircraft control systems to the sudden changes in the environment as well as sensor and actuator failures [3,11]. Napolitano et al. [11] present the investigation of on-line learning neural controllers in the context of the aircraft autopilot functions and of stability augmentation systems for both longitudinal and lateral directional dynamics. In Johnson and Calise [6] a particular architecture is proposed for the use of neural networks in flight control. It also uses Pseudo Control Hedging (PCH), which is essentially a method of modifying the command signal when the control surface is close to saturation.

An early use of neural networks in auto-landing is given in [7] where the neural network was trained off-line to generate the desired trajectories for landing under wind disturbances and worked in conjunction with a conventional PID landing controller. A feed-forward network neural network, trained off-line is used as an auto-landing controller in [5]. Here, the neural network replaced the original PID controller and similar performance has been observed.

In some of the above work [5,7], a feed-forward neural network with back propagation learning algorithm has been used. The main drawback of such a scheme is that the neural network requires a priori training on normal and faulty operating data. Also, the size of the neural network needs to be fixed beforehand. An alternate neural network is the Radial Basis Function Network (RBFN) with Gaussian functions,

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1270-9638/$ – see front matter
doi:10.1016/j.ast.2005.05.002

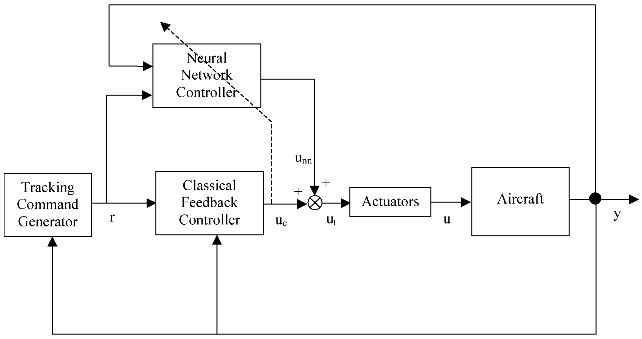

Fig. 1. Neural aided controller architecture.

which have good local interpolation and global generalization ability [8–10,14]. In this paper, we use an online learning radial basis function network (RBFN) that decides its size automatically for auto-landing control purposes under failures and we evaluate its fault tolerance capabilities.

A sequential learning RBFN called Minimal Resource Allocation Network (MRAN) has been proposed by Lu Yingwei et al. [10]. In this work hidden neurons are added and removed to maintain a compact network. MRAN has been used for several applications varying from function approximation to nonlinear system identification and its application in flight control was reported in [14]. An improvement to MRAN called Extended MRAN (EMRAN), which increases the speed of the algorithm by updating parameters of only the nearest neuron, has been described in [8].

An auto-landing controller based on MRAN aided H_∞, controller was proposed in [9] for the aircraft model described in [7]. In this scheme, a simple architecture originating from Kawato's feedback-error-learning scheme (Gomi and Kawato [4]) has been utilized. This control architecture uses a conventional PID/H_∞ controller in the inner loop to stabilize the system, and the MRAN neuro-controller acts as an aid to the conventional controller. The performance of the neural controller has been evaluated under a microburst and partial loss of control effectiveness and has been found to be better than conventional control schemes.

In this paper, we use a Baseline Trajectory Following Controller (BTFC) designed using conventional methods in the inner loop and the neural controller is used to aid the BTFC during failures. This is also realistic since if one wants to improve the fault-tolerance of existing controllers without a complete redesign, then the neural network controller can be used as an add-on. The aircraft model used here is that of a high performance fighter aircraft [12]. The BTFC controller in the inner loop plays an important role in this strategy. It is not only used to stabilize the overall system, but also provides the signals to train the EMRAN network on-line.

The overall scheme for the neuro-controller is shown in Fig. 1. The landing task is autonomous, hence there is a navigation function incorporated in the block called "Tracking Command generator". The output of this block consists of reference commands (labeled as 'r' in the figure), which are input to the BTFC called "Classical Feedback Controller" in the figure. Under normal conditions, the BTFC is designed to cause the aircraft outputs 'y' to follow the reference vector 'r'. The neural controller uses the reference signals and the aircraft outputs to generate its command signal. It also uses the output of the BTFC to learn the inverse dynamics of the plant (in this case the aircraft) as in the feedback error learning scheme [4].

Table 1
Touchdown specifications (pillbox conditions)

X-distance	$-100\text{ m} \leqslant x \leqslant 300\text{ m}$
Y-distance	$\lvert y\rvert \leqslant 5\text{ m}$
Total velocity	$V_T \geqslant 60\text{ m/s}$
Sink rate	$\dot{h} \leqslant 1.0\text{ m/s}$
Bank angle	$\lvert\varphi\rvert \leqslant 10\text{ deg}$

The auto-landing problem studied in this paper consists of a high performance fighter aircraft executing four phases of flight segments consisting of a wing-level flight, a coordinated turn, glide slope descent and finally the flare maneuver. The trajectory segments corresponding to these four phases have to be flown with severe winds and specified trajectory deviations have to be met. The touchdown conditions are given with tight specifications, named for convenience as the *touchdown pillbox* (Table 1). The BTFC controller is first designed to meet all these specifications under no failure conditions of the actuators. We wish to point out that the above trajectory for landing may be more appropriate for an Unmanned Air Vehicle (UAV) and may be severe for an aircraft, nonetheless, we have used it here for the evaluation of the neural controller.

The fault scenario studied consists of control surfaces stuck at different deflections. In this case, they correspond to elevator and aileron surfaces stuck at different deflections either alone or in combination. The occurrence of these faults has been studied for all the segments; however, the results are given in this paper for the failures that occur at the most critical phase. The critical phase is before the turn and descent maneuvers.

When the above failures are introduced in the landing phase, it was found that the BTFC controller is unable to meet the strict touchdown dispersions (pill box conditions) except for actuator stuck faults for small aileron deflections. When the neural controller was introduced in the control scheme, it was found that these stuck deflections could be made large thereby enhancing the fault tolerance envelope for meeting the strict touch down pillbox conditions for all the failure cases.

The paper is organized as follows. Section 2 deals with the aircraft, actuator model and the landing task (including winds) used in this study. Section 3 describes the Baseline trajectory Following Controller (BTFC) design and its performance with and without severe winds and with no failures. Its performance is then evaluated under single and multiple control surface failures. Section 4 briefly describes the EMRAN algorithm. Section 5 presents the main results of this paper showing the impact of the neural controllers