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A direct adaptive neural command controller design for an unstable helicopter

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ABSTRACT

This paper presents an off-line (finite time interval) and on-line learning direct adaptive neural controller for an unstable helicopter. The neural controller is designed to track pitch rate command signal generated using the reference model. A helicopter having a soft inplane four-bladed hingeless main rotor and a four-bladed tail rotor with conventional mechanical controls is used for the simulation studies. For the simulation study, a linearized helicopter model at different straight and level flight conditions is considered. A neural network with a linear filter architecture trained using back-propagation through time is used to approximate the control law. The controller network parameters are adapted using updated rules Lyapunov synthesis. The off-line trained (for finite time interval) network provides the necessary stability and tracking performance. The on-line learning is used to adapt the network under varying flight conditions. The on-line learning ability is demonstrated through parameter uncertainties. The performance of the proposed direct adaptive neural controller (DANC) is compared with feedback error learning neural controller (FENC).

1. Introduction

Traditional flight control design for helicopters involves linearizing the vehicle dynamics about several operating conditions throughout the flight envelope, tuning the gains of the linear controllers for each condition, and scheduling these gains with an interpolation scheme. Although gain scheduling has historically proven successful in a variety of applications (Apkarian et al., 1995; Leith and Leithead, 2000), the present helicopter control requires flight control schemes which explicitly account for the intrinsic nonlinearities of the system. The limitation of the classical gain scheduling techniques is that they exploit the behavior only in the vicinity of the equilibrium operating points and it generally imposes as inherent slow variation requirement on the system to ensue that the state remains close to equilibrium. A neural network approach attempt to relax restrictions to operate near equilibrium point (Leith and Leithead, 2000). In addition, tactical military flight requirements for agile helicopters and stringent day-visual civil flight regulations demand more accurate track control through out the flight envelope (Aeronautical Design Standard, 1994; Tischler, 1996). The complex gain scheduling which requires time consuming flight tests and stringent requirements can be circumvented using nonlinear adaptive control system design. In addition, variation in the helicopter model may occur due to battle damage or component failure, requiring rapid on-line reconfiguration of the control system to maintain stable flight and reasonable levels of handling qualities (Calise and Rysdyk, 1998). Therefore, there is presently a strong interest in the development of on-line adaptive control methods that are applicable to flight control problems.

The emergence of the neural network paradigm as a powerful tool for learning complex mappings from a set of examples has generated a great deal of interest in using neural network models in various applications in aeronautics (Faller and Schreck, 2000; Melin and Castillo, 2003). Neural networks have been used in the identification and control of dynamical systems (Uraikul et al., 2007; Peng et al., 2007; Wang et al., 2006; Pepijn et al., 2005; Castillo and Melin, 2003; Kiong et al., 2003). Due to their approximation capabilities as well as their inherent adaptive features, artificial neural networks present a potentially appealing alternative to modeling of nonlinear systems (Roy and Ganguli, 2006). Furthermore, from a practical perspective, the massive parallelism and fast adaptability of neural network implementations provide more incentive for investigating the connectionist approach in problems involving dynamical systems with unknown nonlinearities. Among various adaptive control schemes, model reference adaptive control, dynamic inversion, adaptive critic and feedback error learning controls are widely used

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(Narendra, 1996; Anon, 1990; Narendra and Parthasarathy, 1990; Polycarpou, 1996; Li et al., 2001; Werbos, 1995; Leitner et al., 1997). Investigations have been done to study the on-line learning ability of these control schemes in the presence aerodynamic uncertainty, damage to the helicopter components and loss of control surface. Neural network based control schemes for helicopters have been investigated in Leitner et al. (1997), Saade et al. (1996), Narendra and Mukhopadhyay (1992). A complete survey of adaptive neural control systems for various applications is presented in Ng (1997).

Most of the applications using neural network as control architecture, use a conventional controller in the inner loop to stabilize the system dynamics, while the neural controller acts as an aid to the conventional controller by compensating for the nonlinearity. This control scheme is commonly known as feedback error learning control (FENC) (Li et al., 2001). The necessary bounded signal requirement for neural network training is satisfied using an inner conventional state feedback controller (SFC). Assuming the inner conventional controller provides necessary bounded signals in fault and non-nominal conditions, the neural network is further adapted to provide the required tracking performance.

Even though the tracking error is less, the control effort required to follow the command is very high. To overcome these problems, we present in this paper, a direct adaptive neural controller (DANC) scheme to track the pitch rate command signal. The lateral and directional axes are stabilized using state feedback design and the longitudinal axis is controlled using a neural network. This control approach can as well be used to control other axes such as lateral and directional, however, this investigation is not subject of this paper. Since the helicopter model considered is unstable, off-line (finite time interval) and an on-line learning strategy presented in Suresh et al. (2004) is used to adapt the neural controller. The proposed learning scheme is based on the assumption that the states and outputs of the system do not escape to infinity in a finite time interval. Using the above assumption, a neural network with linear filter is trained off-line using the backpropagation through time learning algorithm to approximate the unknown control law. The off-line trained neural network is used as the starting point for on-line adaptation under variations in aerodynamic coefficients or control effectiveness deficiencies caused by control surface damage.

Performance of the proposed control scheme is evaluated for a flight controller design based on a linear model of a helicopter. To investigate the on-line learning ability of the proposed neural controller, different fault scenarios representing large model error and control surface loss are considered. The performances of the proposed DANC scheme are compared with the FENC scheme.

2. Mathematical model

Before presenting a mathematical statement of the proposed neuro-control strategy, we shall describe first quantitatively the class of problem which is encountered in practical situations. A plant to be controlled (Σ) is unstable for a given class of bounded input signal ($\mathbf{u}$), and the question is raised whether a neuro-controller can be designed to stabilize the plant and follow the reference model or command signal. A finite data set from the reference model is provided for the purpose of designing a neuro-controller. The objective is therefore to estimate the controller parameters such that the given plant tracks the reference model or command signal accurately.

Neural controller used in this paper is direct adaptive neural controller as shown in Fig. 1. In this control strategy, a reference model that meets the requirements of ADS-33 is implemented in the scheme. The feedback error is the difference between helicopter model output and the reference block and is feed back to the neural controller obtained from a reference model.

The input to the system is the sum of pilot input $r(t)$ and neural controller output $\mathbf{u}^*(t)$

$$\mathbf{u}_{\text{danc}}(t) = \mathbf{u}^*(t) + \mathbf{r}(t) \quad (1)$$

The neural controller provides stabilization and compensates for nonlinearities and parameter uncertainty. The on-line learning neural controller augments the performance of the baseline controller in order to achieve better performance. The basic building block in the neuro-controller is a Nonlinear Auto-Regressive eXogenous (NARX) input model. The controller parameters are updated using a Lyapunov based synthesis.

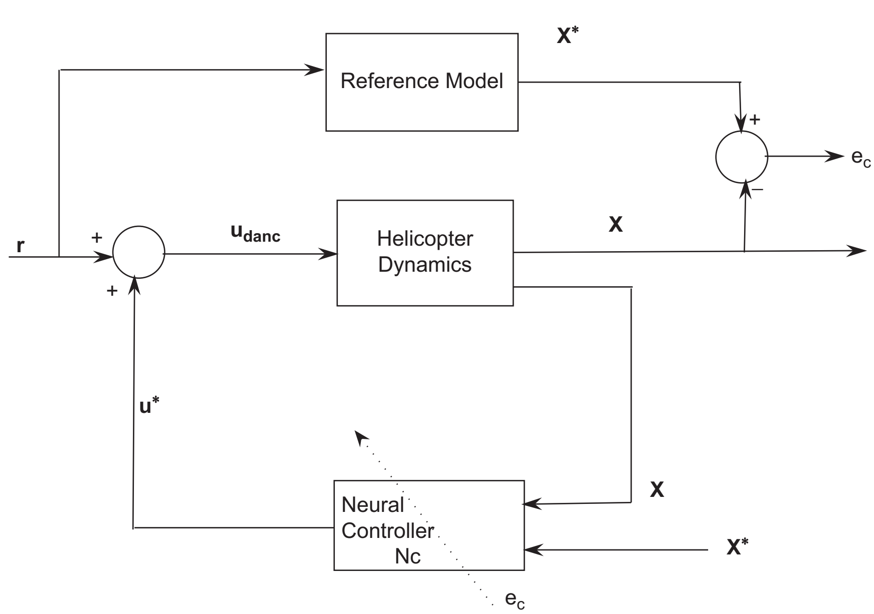

Fig. 1. Schematic diagram of DANC scheme.