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Robustness Enhancement of Neurocontroller and State Estimator

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ROBUSTNESS ENHANCEMENT OF NEUROCONTROLLER AND STATE ESTIMATOR.

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Abstract.

The feasibility of enhancing neurocontrol robustness, through training of the neurocontroller and state estimator in the presence of system uncertainties, is investigated on the example of a multivariable aircraft control problem. The performance and robustness of the newly trained neurocontroller are compared to those for an existing neurocontrol design scheme. The newly designed dynamic neurocontroller exhibits a better trade-off between phase and gain stability margins, and it is ***significantly more robust to degradations of the plant dynamics.***

I. Introduction. Recent advances in the fields of neural networks and control have unveiled the potential benefits of neurocontrol for complex dynamical systems [1-2]. A particularly important issue in the applicability of neural networks to serve as controllers for complex aerospace systems is that of devising neural architectures with good control robustness properties, i.e. able to maintain performance and stability in the presence of modelling uncertainties or changes in the plant dynamics [3-5]. Towards that goal, a neurocontroller with an internal structure consisting of a state feedback neuro-regulator coupled to a state neuro-estimator was trained *in the presence of feedback-delays* to achieve the control objectives of a multivariable aircraft control problem *with the nominal plant parameter values* [3]. Since the synthesized neurocontroller exhibited good robustness properties, it was decided to further exploit the potential of such dynamic architectures to enhance the robustness of flight neurocontrol systems. In this paper, a state feedback neuro-regulator and a state neuro-estimator are synergistically trained *in the presence of feedback-delays and plant parameter uncertainties* to provide independent control of pitch rate and airspeed responses to pilot command inputs, for the integrated airframe/propulsion model of a modern fighter aircraft described in Refs.[3-7].

The paper is organized as follows. The vehicle model and the desired closed-loop dynamics are briefly reviewed in Section II, and are followed in Section III by the training architecture. Nominal performance and robustness of the synthesized neurocontroller are discussed in Section IV.

II. Vehicle Model. The vehicle model consists of an integrated state-space representation for a modern fighter aircraft powered by a two-spool turbofan engine and equipped with a two-dimensional thrust-vectoring and reversing nozzle. The linearized dynamics of the vehicle model are of the form [6]

$$\dot{\bar{x}} = A\bar{x} + B\bar{u}_a, \quad \bar{z} = C\bar{x}; \tag{1}$$

where $\bar{x}$ is the 9-component state vector given in Ref.[3]. In Eq.(1), the control input vector is

$$\bar{u}_a = [WF, \delta TV]^T; \tag{2}$$

where WF is the engine main burner fuel flow rate (lbm/hr), and δTV is the nozzle thrust vectoring angle (deg). The vehicle outputs to be controlled are

$$\bar{z} = [V, Q]^T, \tag{3}$$

where V is the aircraft velocity in ft/sec, and Q is the pitch rate in deg/s.

The control design objective is to design a control system that provides decoupled command tracking of velocity and pitch rate from pilot control inputs with aircraft responses compatible with Level I handling qualities requirements [8]. In this two control inputs - two control outputs example, the task is that of

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following the trajectories generated from a linear model of the desired vehicle response dynamics to pilot command inputs [6]:

$$\bar{z}_c = f_{filter}(\bar{z}_{SEL}); \tag{4}$$

with $\bar{z}_{SEL} = [V_{SEL}, Q_{SEL}]^T$, where V_{SEL} and Q_{SEL} are the pilot velocity command and longitudinal stick deflection respectively; $\bar{z}_c = [V_c, Q_c]^T$ is the ideal response in V (ft/s) and Q (deg/s).

The fuel flow actuator was modelled as a second order function [3], with a maximum fuel flow rate $|WF|_{max} = 10,000 lbm/hr$, and a rate limit $|\dot{WF}|_{max} = 20,000 lbm/hr/s$. The thrust vectoring actuator was modelled as a first order function [3] with a maximum thrust vector angle $|\delta TV|_{max} = 10 deg$, and a rate limit $|\delta \dot{TV}|_{max} = 20 deg/s$. As a result, ***nonlinearities*** appear in the control design and evaluation in the form of actuator position and rate limits.

III. Training Architecture.

The neurocontroller and the neuro-estimator of the vehicle state-vector were simultaneously trained by backpropagation in the closed-loop architecture of Fig.[1]. As in Refs.[3-5, 7], the two hidden-layer feedforward neurocontroller was trained to minimize an objective function consisting of a weighted sum of tracking errors, control input commands, and control input rates. During training, the weights of the objective function were adapted to tune the neurocontroller such that the design objectives were met. To estimate the vehicle state vector, a single-layer linear feedforward net was trained to minimize the mean-square error of the vehicle state estimate, $\int(\hat{\bar{X}} - \bar{X})^2 dt$, calculated over entire commanded trajectories. The pilot commanded trajectories used to train the neurocontroller and the neuro-estimator consisted of pitch-rate doublets and velocity step functions having the same frequency-content as typical pilot command inputs. In addition, the system matrices A, B, and C, Eq.(1), were allowed to fluctuate around their nominal values, and a variable time-delay was introduced in Fig.1 between the actuator outputs and the vehicle to induce robustness in the neurocontrol design. For simplicity, robustness issues concerning the uncertainties of the actuator parameters, e.g. rate and position limits, were not addressed in this analysis. As indicated in Fig.1, the actuator outputs were estimated from the ***nominal*** dynamics of the fuel flow rate and thrust vectoring actuators.

IV. Performance and Robustness.

The neurocontroller was tested in the closed-loop architecture of Fig.2 on ***pulse*** pitch rate input commands, of a different frequency content than the ***doublets*** used in training. The input command chosen to illustrate the neurocontrol performance was defined by the pulse pitch rate command $Q_{SEL}(t) = 0.5$in for $t \leq 3$sec, $Q_{SEL}(t) = 0$ for $t > 3$sec, which was simultaneously applied with the step velocity command $V_{SEL}(t > 0) = 20$ft/sec.

Nominal Performance. Closed-loop system simulations indicated that the deviations from the ideal nominal responses are small for both pitch rate and velocity commands. The newly trained neurocontroller exhibits a very satisfactory nominal performance which is comparable to that of the existing neurocontroller of Ref.[3] trained with nominal plant parameter values in the presence of feedback-delays. As mentioned in the Introduction, actual vehicle dynamics are expected to differ from the nominal model due to modelling uncertainties, neglected high order dynamics, and changes in flight conditions. An important criterion in assessing a practical control design is its ability to maintain performance and stability in the presence of system uncertainties. A classic specification for robustness, also used in the military specifications for design of flight control systems [8], is that of stability margin, specifically phase and gain margins [9].

Phase Margin. Towards estimating the phase robustness of the dynamic neurocontroller, an additional delay τ_d was introduced between the actuator outputs and the vehicle (Fig.2) to simulate the effect of the various time-delays encountered by the signals throughout the closed-loop system. For large values of τ_d, the closed-loop system simulations showed a better and smoother tracking for the existing neurocontroller [3] than for the newly designed neurocontroller. With a 10ms sampling time of the measured vehicle outputs, the performances of both neurocontrollers were comparable and satisfactory for $\tau_d = 40$ms, which is quite representative of the time-delays to be expected in practical implementations of complex flight control designs.

Gain Margin. To analyze the robustness of the neurocontroller to uncertainties of the type that can be modelled as gain changes at the plant output, closed-loop simulations were run for various sets of the system matrices, A, B, and C distributed around the nominal values $A^{nominal}$, $B^{nominal}$, and $C^{nominal}$. For high output gains, the tracking performances in pitch rate and velocity responses of both neurocontrollers are comparable, as illustrated in the closed-loop responses of Fig.3 for V- and Q-output gains of 2, i.e. $C = 2C^{nominal}$. For low output gains, the newly designed neurocontroller ***stabilizes faster*** than the existing neurocontroller [3], as illustrated in the closed-loop responses of Fig.4 for V- and Q-output gains of 0.55, i.e. $C = 0.55C^{nominal}$.

To estimate the robustness of the neurocontroller to degradations of the plant dynamics, closed-loop system responses were simulated for 20 random settings of the A_{ij}s and B_{ij}s around their nominal values within the margins of $[\frac{1}{2}A_{ij}^{nominal}, \frac{3}{2}A_{ij}^{nominal}]$ and $[\frac{1}{2}B_{ij}^{nominal}, \frac{3}{2}B_{ij}^{nominal}]$ respectively. In each one of these 20 randomly generated system degradations, the existing neurocontroller of Ref.[3] was found to be unstable. In contrast, the neurocontroller trained in the presence of system uncertainties within the synergistic architecture of Fig.1 was found to be stable in all but one system degradation (where pitch rate and velocity responses exhibited growing oscillations leading to instability). The robustness enhancement of the newly designed neurocontroller with respect to ***plant parameter uncertainties*** is illustrated in the closed-loop responses of Figs.5 & 6.

Error Loop Failures. In the classical approach of flight control design, an inner loop compensation ($\bar{z} \rightarrow \bar{u}$) is first designed to provide stability augmentation, and to place the augmented plant dynamics within the handling qualities specifications. An outer loop compensation ($\bar{e} \rightarrow \bar{u}$) is subsequently designed to provide decoupled command tracking in order to reduce pilot workload. The inner loop compensation of this dynamic neurocontroller was evaluated by considering failures in the outer compensation loops. Like the neurocontroller of Ref.[3], the newly designed neurocontroller tracks very satisfactorily the ideal pitch-rate and velocity responses in the presence of e_V and e_Q error loop failures respectively, indicating that it uses pitch rate and velocity measurements in a manner consistent with the classical idea of providing inner loop plant augmentation.

V. Conclusion. A training scheme has been proposed to enhance the robustness of neurocontrollers consisting of a state-feedback neuro-regulator operating in conjunction with a state neuro-estimator. A neurocontroller with such an internal structure has been synthesized for an aircraft control design example by simultaneously training the neuro-regulator and state estimator in closed-loop, in the presence of feedback-delays and plant parameter uncertainties. This neurocontrol design technique was found to enhance the trade-off between phase and gain stability margins, and in particular the robustness of the neurocontroller with respect to degradations of the plant dynamics.

As noted in Ref.[10], the fast processing resulting from the massive parallelism of neural networks, wether analog or digital, is likely to reduce the time-delays that are typically encountered in conventional control implementations. Requiring smaller phase stability margins would further enhance the robustness of practical implementations by allowing neurocontrol designs leading to larger gain stability margins. This potential benefit of neural computation to robust control design warrants additional analysis and simulations.

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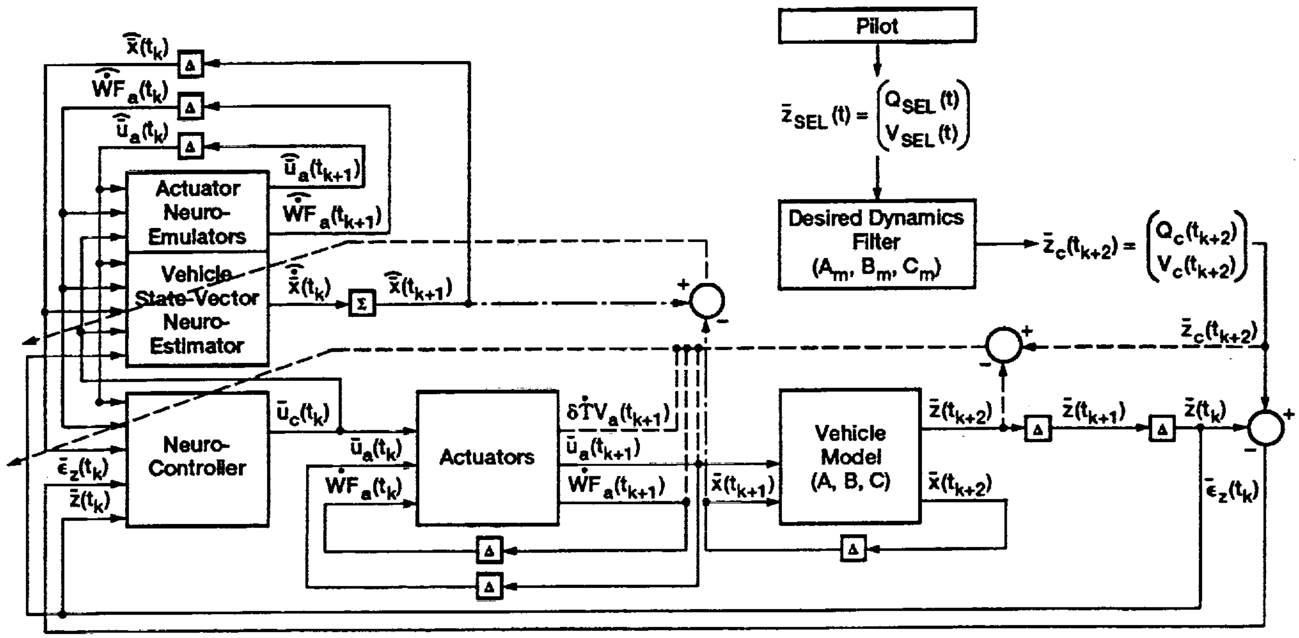

Figure 1.—Training Architecture.

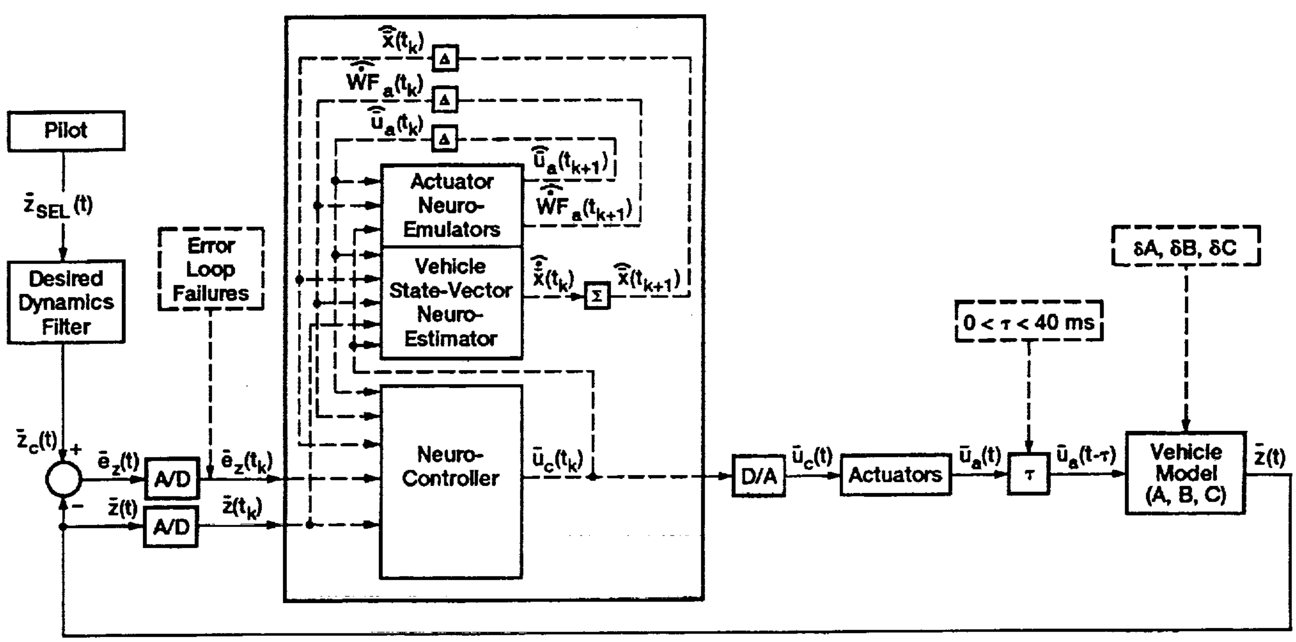

Figure 2.—Evaluation Architecture.

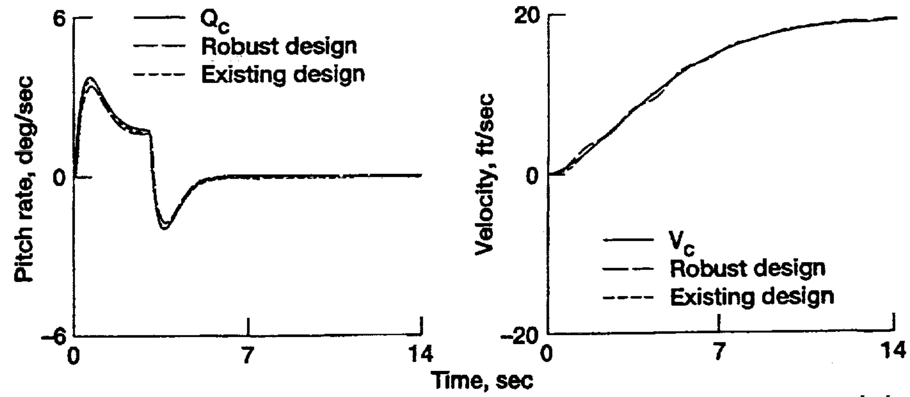

Figure 3.—Closed-loop responses with a gain of 2 in V- and Q- outputs ($C = 2\ C^{nominal}$).

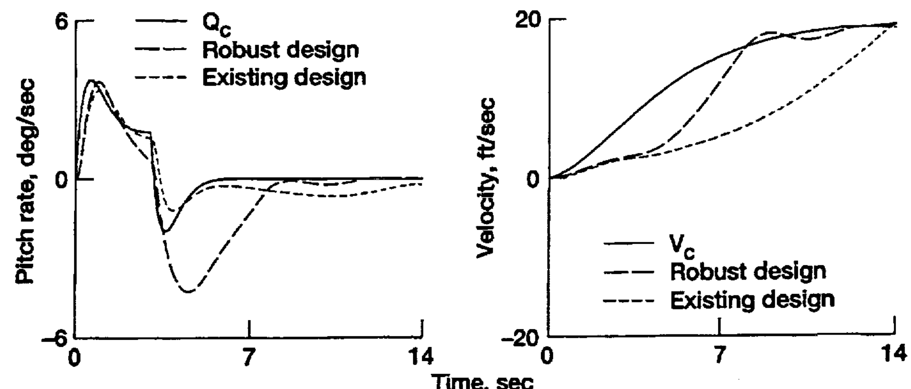

Figure 4.—Closed-loop responses with a gain of 0.55 in V- and Q- outputs ($C = 0.55\ C^{nominal}$).

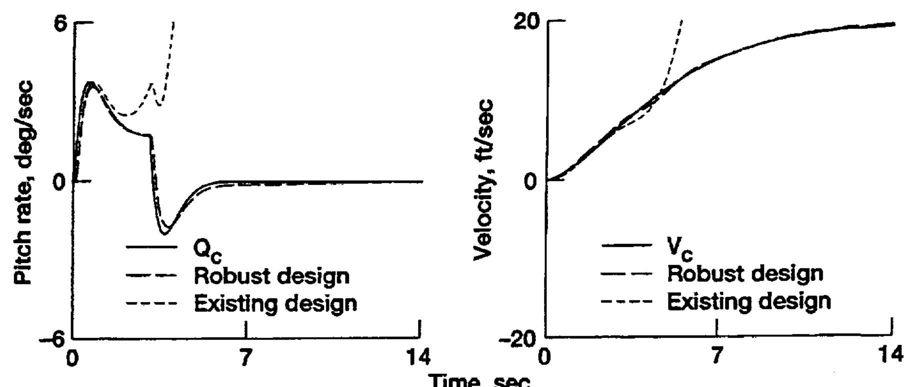

Figure 5.—Closed-loop responses for random variations of A_{ij}'s and B_{ij}'s within $\pm 50\%\ A_{ij}^{nominal}$ and $\pm 50\%\ B_{ij}^{nominal}$.

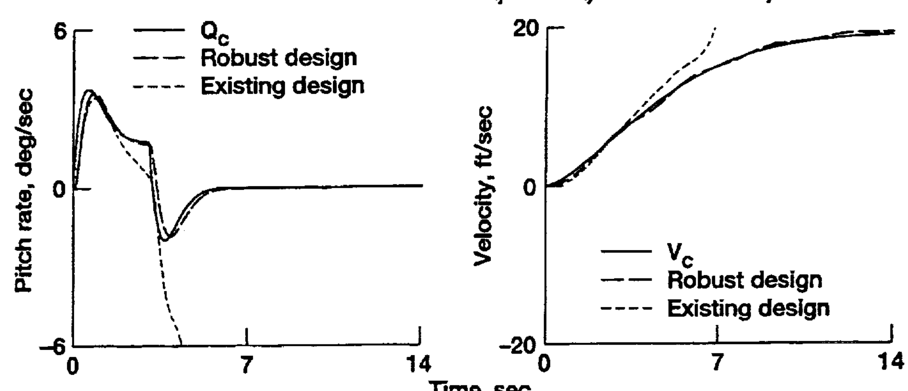

Figure 6.—Closed-loop responses for random variations of A_{ij}'s and B_{ij}'s within $\pm 50\%\ A_{ij}^{nominal}$ and $\pm 50\%\ B_{ij}^{nominal}$.

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