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Neurocontrol of an Aircraft: Application to Windshear

S. M. AMIN, E. Y. RODIN AND Y. WU
Center for Optimization and Semantic Control
Department of Systems Science and Mathematics
Campus Box 1040, Washington University in St. Louis
St. Louis, MO 63130-4899, U.S.A.
massoud@rodin.wustl.edu

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Abstract—In this report, we consider the part of our work which concerns the design of neuroidentifiers and neurocontrollers which attenuate the effects of disturbances. Examples for linear-systems identification and disturbance rejection, as well as nonlinear control of an aircraft encountering wind shear on take-off are briefly discussed, and the following three problems are addressed.

1. System identification via dynamic neural networks.
2. Disturbance attenuation via memory neurons.
3. Aircraft control in the presence of wind shear after takeoff.

Keywords—Dynamic neural networks, Robust control of nonlinear systems, Aircraft control, Systems identification and control.

1. INTRODUCTION

The lack of rigorous mathematical representation of control systems in current paradigms of feed-forward and recurrent neural networks is a drawback to the development of research on neural networks for control. The feed-forward networks are known to work as a mapping between two information domains. Most of the current research in neurocontrol and related publications discusses this type of architecture for learning a model or a controller, which is usually either nonlinear or difficult to implement. The published results show that while these approaches yield satisfactory results in many cases, there is little development in relating the theories of classical and modern control systems to neural networks. Neural networks are usually treated as "Black Boxes" and thus, there is no direct contact with the "internal" information of the "Box." A linear control system, which may also be called a "Black Box," can be represented by transfer functions, matrix fraction representations, and/or other input-output, as well as frequency response parametrizations. Therefore, the input-output relationship, as well as performance, can be studied thoroughly. In our previous work [1–5], the "internal information" of the network is parametrized as a control system; the goal has been to represent the identifier and the controller in terms of this information, and thus integrate two types of dynamic neural network architectures into controllers. Suitability of feedforward architectures with dynamic neurons for identification

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and control of dynamic systems has been shown; several important issues concerning controllability, observability, and feedback linearizability of such neural models are also investigated. The network itself is not only a control system, but is also capable of learning and improvement. In this report, we provide a brief literature survey as well as discuss a relevant aerospace-related example.

A noticeable advance and development in parallel computation and parallel algorithms has occurred in the past decade. A highly parallel structured computer is capable of performing multiple tasks simultaneously, and operates much faster. Parallel computations and architectures have become important issues in the control community. Some achievements have been made in utilizing a parallel computational mechanism to compute inverse dynamics of a robot arm. In particular, *Flavor™'s* Parallel Inference Machine exemplifies the utilization of parallelism in control systems. One important requirement for applying parallelism in control systems is to establish a solid mathematical foundation for it. Clearly, the interaction between computer developments and control systems mutually reinforces both disciplines. It is generally recognized that the rapid development in sequential computers in the 1950's–70's motivated a remarkable advancement in control system synthesis and design. During this period, optimal control and estimation, multivariable control, and adaptive control were making great advances, with many important results such as the Maximum Principle, Kalman-Bucy filter, State-Space analysis and techniques, etc. It is also interesting to notice that the developments of discrete-time systems and discrete-time state-space representation were mainly motivated by the availability of sequential computers of the time. In view of today's rapid development in parallel computers and parallel algorithms, it is natural to consider the problem of how to model control systems, by appropriate mathematical tools, using the mechanism of parallel computing. This has been the main motivation for our work during the past five years. In this period, we have developed theories and implemented simulators for the incorporation of dynamic and memory neurons for real-time system identification and control [1–5]. By going beyond the universal approximation property of neural networks, we have considered the internal state information of the recurrent neural networks so that a control system can be modeled using the highly parallel structure of this computational mechanism. Based on a new paradigm of neural networks consisting of Neurons with Local Memory (NLMs), the representation of a control system was discussed [2,5]. Modeled by NNLM, the resulting system is a nonlinear one that, through mathematical analysis [5], was shown to be locally linearizable via a static feedback and a nonlinear coordinate transformation. We have applied a similar methodology to the design of a neurocontroller for aircraft (using data for a Boeing 727), where a differential game-based neurocontroller formulation was used to reduce the effects of external disturbances on the aircraft.

2. LITERATURE SURVEY

A brief survey of previous work dealing with dynamic neural nets follows.

Farotimi *et al.* [6] provided a weight synthesis technique based on optimal control theory for dynamic neural networks. Gori *et al.* [7] presented a back propagation algorithm for a particular class of dynamic neural networks where some processing elements have a local feedback, and applied this class of neural networks to the problem of speech recognition. Gherrity [8] derived a learning algorithm for a recurrent neural network which is described by a system of coupled differential equations. Willis *et al.* [9] discussed advantages of a neural network estimator for feedback process control.

Perfetti [10] considered the effect of positive self feedback on neural networks, and showed that binary output can be guaranteed with finite sigmoid slope such that nonbinary solutions become unstable. Sudharsanan and Sundareshan [11] proposed a descent procedure as a learning rule to minimize the error between the stable equilibrium points of the network and the desired memory vectors. Sato *et al.* [12] discuss their work on an adaptive nonlinear pair oscillator with local