Fifth IFSA World Congress (1993), 1346-1349

Optimization of A Fuzzy Adaptive Network For Control Applications

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Abstract \ In this paper, we describe the use of certain optimization techniques, principally dynamic programming and high level computational methods, to enhance the capabilities of a fuzzy adaptive neural network controller which we had developed for on-line control and adaption of complex nonlinear processes. Potential applications to an array of processes from diverse fields are discussed.

I. INTRODUCTION

The appeal of fuzzy control as a tool for practical and cost-effective implementation of control strategies for complex, nonlinear, imprecisely-defined processes for which standard models and controls are impractical or cannot be derived has begun to attract the attention of various researchers and practitioners including those outside the fuzzy field and profession. However, deriving fuzzy control rules is often difficult and time-consuming. Furthermore, problems of high-dimensionality are incurred in the implementation of controls for systems with multiple inputs and outputs. More efficient and systematic methods for knowledge acquisition and fuzzy controller synthesis are needed, such as adaptive fuzzy controllers capable of learning from process data to automatically generate a set of fuzzy control rules and improve on them over time. For a recent review of the issues, problems and the future of fuzzy adaptive control, see Esogbue and Murrell [11].

It is quite apparent that a considerable amount of work has been done and is still being done in this area . Each of these efforts is targeted at the eradication, the minimization, or the mitigation of the problems attendant on fuzzy logic control methods and algorithms. Some of these include: i) the fuzzification process-how to partition the universe of discourse and assign membership functions, ii) the rule combination process- how to combine rules and/or ensure their completeness, mutual exhaustiveness, consistencies, etc. as well as interpolated control decisions especially when the method of means is inapplicable, iii) analysis- how to derive a meaningful analysis of any resulting control or the performance of the control system; for example, do the usual performance criteria of classical control theory apply? How can we make some sense of our fuzzy control system when applied to novel situations or when small perturbations of the original conditions are applied? When the situation becomes considerably complex and thus necessitating complex sets of rules, how can we ensure efficiencies both in modeling and computational aspects of our controller? One way to wrestle with these issues is to consider optimization a priori in our controller designs.

II. RESUME OF A FUZZY ADAPTIVE CONTROLLER

As a leitmotif for our discussion, we consider a fuzzy adaptive neural controller network which we have proposed as an approach to mitigating some of the problems of fuzzy logic controllers. The details are given in Esogbue and Murrell[12] Briefly,the proposed controller has a unique combination of features and capabilities. It is adaptive and has the capability of learning from process data on-line. It performs a fuzzy discretization of the process state and control variable spaces and implements fuzzy logic control rules as a fuzzy relation. The membership functions of the fuzzy discretization are adjusted on-line and the fuzzy relation is learned using a performance measure as feedback reinforcement, requiring little prior knowledge about the process; no training data sets nor any error signal derived from knowledge of the desired plant trajectory are needed. The fuzzy discretization procedure employs a statistical data compression technique permitting multivariable state vector inputs. Additional plant variables can be added without a geometric increase in the complexity of the controller structure. This procedure extracts the essential information from each variable needed to form fuzzy subsets of the process state space. While it adapts both the membership functions and the control rule state-control association, the controller primarily learns the control rule associations, unlike many other methods which fix the rule relationships and adjust the membership functions. The controller is implemented with neural networks, featuring a self-organizing neural network, a reinforcement learning neural network, and an associative memory network.

III. THE CONTROLLER OPERATION

The operation of the controller is summarized here. At each interval of a discrete time sequence, the current process state vector is input to the controller. Its membership in each of several reference fuzzy subsets of the input space is calculated in terms of its similarity to the ideal, prototype member of each fuzzy set. Initially the locations of the prototype vectors in the state space are uniformly distributed. Throughout the time sequence, an adaptive algorithm adjusts these locations to reflect the actual clustering of the state vectors into fuzzy sets. The dispersion of the corresponding membership functions are also adapted to the state vector inputs by a similar algorithm. Once an input state has been given its fuzzy characterization in terms of the reference fuzzy sets, the appropriate control fuzzy set is selected. Initially, the selection is arbitrary, but a learning algorithm based on the reinforcement of a performance measure is used to increase the frequency with which good controls are selected. In the process, the controller learns a fuzzy relation between the input state vector and output control vector which embodies the fuzzy control rules. After the learning phase, the fuzzy relation is used to calculate fuzzy control in terms of the reference fuzzy sets of the control space. From this, a crisp control vector is computed.

The controller has five subsystems: the Statistical Fuzzy Discretization Network (SFDN), Fuzzy Correlation Network (FCN), Stochastic Learning Correlation Network (SLCN), Control Activation Network (CAN), and the Performance Evaluation System (PES). A block diagram of these and the plant is shown in Fig. 1.

IV OPTIMIZATION OF NETWORKS

To illustrate how fuzzy logic networks can be optimized at the design phase, we outline the injection of optimization seeking methods in two sub-systems of our network namely the SFDN and the FCN; the other sub-systems will be considered later. An example of its injection at the operation phase may be gleaned from the work of Smith and Takagi[20].

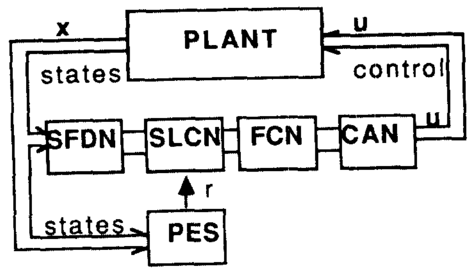

Fig. 1. Controller subsystems and plant

One of the ways to optimize the performance of the controller is to employ other methods of performing fuzzy partitioning of the state space in the SFDN. For example, one could use some techniques from the field of qualitative simulation as employed by Co and Narasimha [6]. Specifically, depending on the required model tolerance, the method based on the concept of **landmark** region will give a minimal partitioning of the universe of discourse.

The SFDN provides a means of aggregating similar plant states, thus permitting implementation of the control as a discrete relation. The adaptation update equations are of the simple delta-rule type. This is particularly advantageous when considering parallel distributed computation of neural networks. Even here, it is instructive to apply the techniques of distributed dynamic programming as well as optimal routing and flow control methods used in complex network processing as discussed, for example ,by Bertsekas [3].

Another potentially useful approach is to invoke optimal clustering algorithms such as those based on fuzzy dynamic programming as proposed by Esogbue [9]. This is both computationally efficient and less arduous to implement ,even on line, as the spirit of the adaptive network dictates.

The second area of improvement involves the FCN. The FCN implements the fuzzy control rules as a fuzzy relation G (learned by the SLCN) which associates the collection of fuzzy sets $X_1, ..., X_r$ for input vectors $x \in X$ with the fuzzy sets $U_1, ..., U_s$ for the controls $u \in U$. This is accomplished with a fuzzy associative memory (FAM) or correlation network Again, see Esogbue and Murrell for the details. Of particular interest is optimal mapping when multi input-multi output systems are involved. Here, we propose the use of parallel architecturing schemes to implement the multi-fuzzy state variables. One form of this technique involves multiple level fuzzy bank arrays operating in multiple stage pipeline. The other uses fully parallel multiple level fuzzy bank arrays to enhance the performance of mapping processing. Details of the use of these techniques are given by Hwang and Tai [12].

V. SOME APPLICATIONS .

The enhancements provided by the injection of optimization driven considerations to the type of control that this controller can provide is potentially applicable in many settings. It can be used in control situations in which there are multiple sensor measurements which may be noisy or imprecise or which require sensor fusion to generate a coherent picture of the process state. It can be used for high-level decision-making or control of data processing, intelligent system reconfiguration in response to changing conditions, or to direct flow in networks. Control of highly nonlinear dynamical systems (e.g., robot arms, etc.) for which it has been difficult to apply standard control theory methods is another application area where adaptive fuzzy controllers have proven effective. It can be used for failure detection and diagnosis or in a statistical process monitoring and control mode. Wherever intelligent decision-making in real-time is required for coping with an uncertain, noisy and/or changing environment, this type of automatic controller may be useful.

In particular, we feel that this optimized network and others with optimization in place will provide considerable enhancements to the following interesting scenarios whose model configurations are depicted in the sequel: i) in the field of anesthesia, the fuzzy controller, with feedback, used by Meier et al. [17] to control the depth of anesthesia during surgery with isoflurane; the adaptive closed circuit controller of Vishnoi [21]; and our fuzzy dynamic programming model for Intra-operative anesthesia administration [8] ii) the model of fuzzy medical diagnosis and patient treatment proposed by Esogbue and Elder [6] and in the area of flexible manufacturing, the robust adaptive scheduler for an intelligent workstation controller applied to a shop floor control system consisting of three hierarchical control levels-shop, workstation, and equipment proposed by Cho and Wysk [2]. The problem of freeway traffic control studied by Ngo and Li [18] may also benefit from this model.

ACKNOWLEDGMENT

This research was sponsored in part by the National Science Foundation under Grant ECS-9216004.

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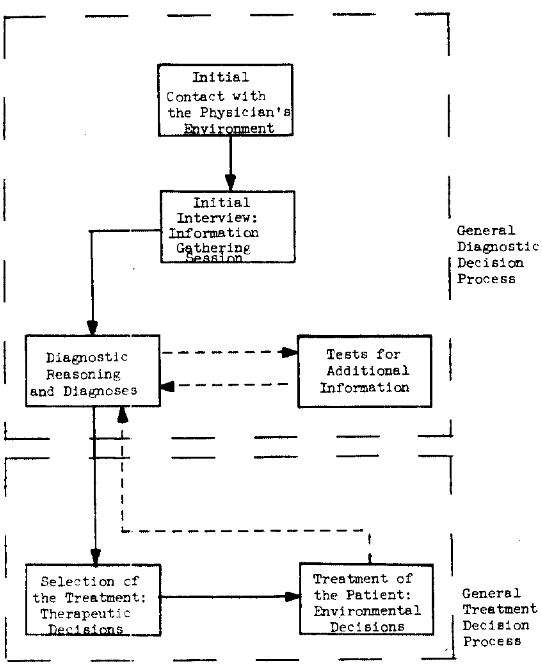

Fig 2 Systems Diagram of the General Diagnostic and Treatment Proce-sses Studied in [7]

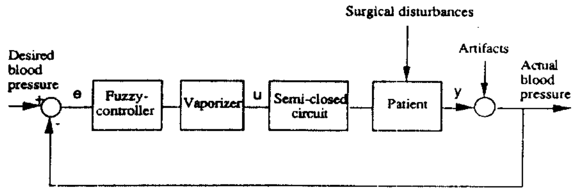

Fig. 3. Block Diagram of the Control Loop For The Control of Depth of Anesthesia Studied in [17]

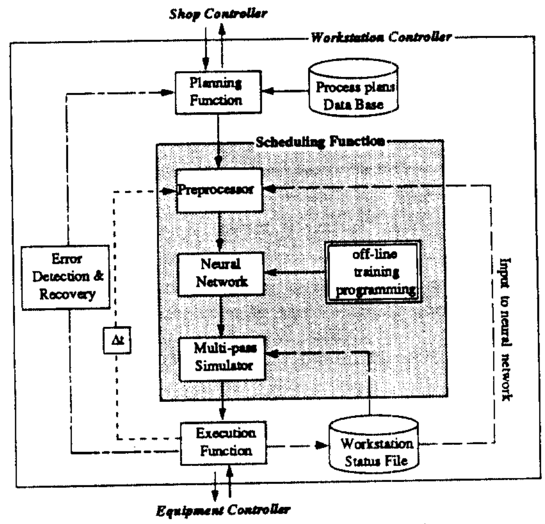

Fig. 4. Detailed Scheme of Scheduling Function For an Intelligent Workstation Controller Study[5]