Two-Level Optimization Strategy for Fuzzy Control Design

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Abstract – **A two-level optimization strategy is proposed for fuzzy control design in this paper. The phase-plane of dynamic system is firstly divided into two-lever nonlinear regions according to response analysis, then a neuro-fuzzy hybrid network is built to optimize the region lever by lever. By the former, control process is decomposed properly, quick dynamic response and stable steady state with high accuracy are achieved coordinately. While through the later, unreasonable factors in the design of fuzzy control are decreased/eliminated and effect of fuzzy control is improved by learning. It offers a general, simple and efficient way for fuzzy control design. The optimized fuzzy controller is adopted in an electro-hydraulic servo system, and satisfactory performance is obtained.**

I. INTRODUCTION

Generally, fuzzy control design depends on the designer's experience to a great extent[1]. It causes two effects: the design process itself is simplified, and it is also effective for these designers who have plenty of priori experience. This method is practical and highly thought by engineers. On the other hand, for these systems which are short of priori knowledge, it is difficult to design proper fuzzy controllers. Therefore, it has been urgent matter to optimize fuzzy control design and carry out knowledge acquisition automatically, self-learning and self-organizing.

In this paper, a two-level optimization strategy for fuzzy control design is addressed. After synthetically analyzed of response characteristics of the system and expected index, the phase-plane of dynamic system is divided into two-level nonlinear regions. For each level region, a neuro-fuzzy hybrid networks is adopted to acquire and modify knowledge.

In neuro-fuzzy hybrid network, neural network and fuzzy system are organically integrated and their advantages are made full use. The hybrid networks have ability of knowledge acquisition by self-learning. The experiential knowledge in hybrid network, such as membership functions and fuzzy rules etc., is stored in weights of network. The process of weights learning is namely modifying of experience. Gradually the experiential knowledge closes to the characteristics of actual plant.

So a general and efficient method for designing fuzzy control systems is given. It has an important value to achieve high control performance for complex systems.

II. NONLINEAR DIVISION OF PHASE-PLANE

Qualitative analyzing and understanding control systems: Persons mainly consider comprehensive effect of both transient state and steady state of control process. It includes response time, stabilization, accuracy of steady state and robustness etc.. But these demands are not identical. According to the characteristics of human qualitative understanding, they don't good at carefully concerning every detail (the relative aspects are hardly separately analyzed.), but care about whole effect of things. For process control, whether following control or constant adjusting, the state-varying can be described by output error e and error rate of change $\dot{e}$(even further high-order change). It is expressed as follows

$$\dot{e} = f(e, u, t) \tag{1}$$

Where u is control variable

The control object is: give control output u, sit $e=0, \dot{e}=0$ and keep stabilization. Generally, fuzzy control with two input variables is designed just based on it. The e-$\dot{e}$ phase-plane of the system can be built. It is shown in Fig.1.

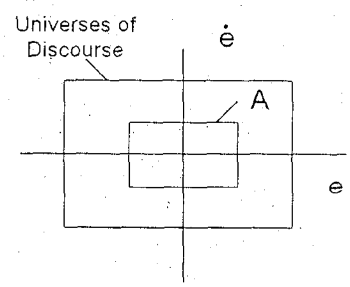

Fig.1 The e—$\dot{e}$ phase-plane

In Fig.1, by quantization of e and $\dot{e}$, a look-up table of fuzzy control is created in full phase-plane. The control output u is directly obtained by searching the look-up table. It

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guarantees real-time control. By equal division of e× ė space, the interval of quantization is neither over-coarse nor over-fine. Although smooth control pocess and high control accuracy can be obtained by over-fine quantization, compositive computation is increased largely, even can't be allowed. While by over-coarse quantization shock in control shifting and low control accracy will be not avoided. Morever, quantization will change with different controlled plant and control demands. It is noticed, under steady state, the error and error rate of change should be zero theoretically. The control process carries out transformation of states from other state to the centre of A shown in Fig.1. When large range control is demanded, fast response is mainly concerned before going into the region A. While within A, a stable control process is expected in order that the system can reach the equilibrium point or allowable error belt without over-shoot. The control action in A is the key to guarantee control accuracy. Therefore, considered the characteristics of fuzzy control and the complexity of computation, a two-level nonlinear division of the piase-plane is described as follows:

1) *Rough Division of Fuzzy Subsets Within Universe of Discourse:* Fuzzy subsets of error and error rate of change are roughly divided in full universe of discourse to form the first lever region. The phase-plane forms rough lattice with low resolution. The created look-up table will be filled by learning of a neuro-fuzzy hybrid network. At this level, there are less rules, and the structure of network isn't large. The learning process is quick.

2) *Fine Division of Fuzzy Subsets in Local Region A:* Choose shape and size of central region A referring to different systems to build the second lever region. Region A has high resolution.Similarly, elements in region A are modified by hybrid network. It is short-range learning. The scale of network is still small, the covergence of learning is also quick.

By such two-lever nonlinear division of phase-plane, a quick and smooth transitional process and a stable steady state with high accuracy can be obtained coordinatively. Those contradictions among demands of control performance, real-time control and compositive computation are handled effectively.

III. IMPLEMENT OF NEURO-FUZZY HYBRID NETWORK

A neuro-fuzzy hybrid network builds a fusion of neural network and fuzzy logic in both structure and function. Neural network is utilized to solve the problems of knowledge acquisition and representation by its abilities of learning and distributed storage. Fuzzy logic guarantees direct and quick reasoning and decision-making.

A. Architecture of Hybrid Network

In hybrid network, fuzzification, fuzzy reasoning and defuzzification are gradually carried out with forward running of network.

1) Fuzzification: Fuzzification gives fuzzy division of input space. A normal function described in Eq.(2) is chosen as membership functions of error and error rate of change.

$$f(x) = e^{-\frac{(x-c)^2}{\sigma^2}} \tag{2}$$

Where c and σ are centre and distributed parameter of normal function.

2) Reasoning and Defuzzification: A simplified reasoning method is chosen to realize fuzzy reasoning and decision-making[2]. The consequences are simplified as different constants.

Rule 1	A_1	and	B_1	$\rightarrow$	z_1
		………			
Rule n	A_n	and	B_n	$\rightarrow$	z_n
Fact	x_0	and	y_0		
Conclusion					z_0

Where z_i is constant.

An architecture of neuro-fuzzy hybrid network is shown in Fig.2.

Where $\mathbf{W}^{ij}$ and **1** are vectors of weights. ij means from layer I to layer j
F(x)=1/x
"+" presents plus
"x" presents multiple.

In Fig.2, layer (I) ~ (III) compose premises of rules and construct membership functions. Layer (III) ~ (VII) form consequences of rules and implement composition, reasoning and decision-making. The hybrid network expresses functional fusion of connectionism and fuzzy reasoning. It realizes true cognition to fuzzy system. Its advantages lie in the ability of learning, the way of knowledge representation, and the means of information processing. Obviously, it is convenient and easy understanding to express knowledge and information in digit.

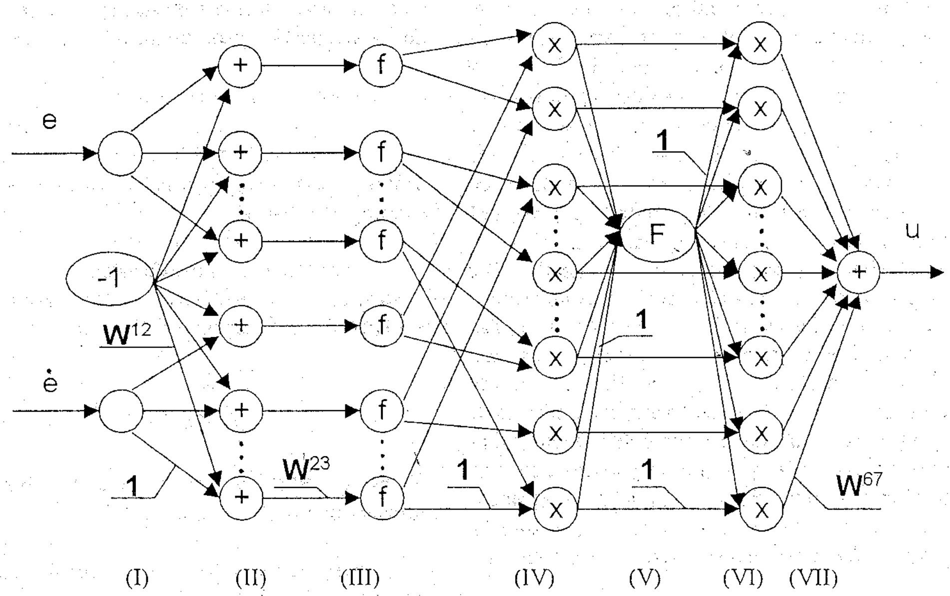

Fig. 2 An architecture of neuro-fuzzy hybrid network

B. Knowledge Acquisition of Hybrid Network

The hybrid network can acquire fuzzy rules, design membership functions and guide proper reasoning and decision-making by various ways.

In this paper, knowledge acquisition of hybrid network is described as: At first, to make best use of priori knowledge, the experiential rules for the controlled system are collected as initial conditions of hybrid network. Perhaps the collected experience is rough, but a rough structure of hybrid network is built. It is a process of off-line supervised learning. Then the hybrid network is connected to the actual system to collect data from worksite, and is trained on-line according to the operating perfomance index. It is a process of modificaion and fine regulation. It can be carried out by hybrid network itself automatically without person's intervention. Nodoubtedly, powerful ability for picking up featured knowledge from data of worksite is demanded. Otherwise, training may be never convergent. It is associated with structure of hybrid network and critical index. Based on training of hybrid network, look-up table for fuzzy control is modified so as to reach satisfactory control performance. In the first stage of design, the priori knowledge of system is utilized as much as possible. It causes speed up of learning and avoiding local convergence.

C. Learning Algorithm

In hybrid network, knowledge acquisition is implemented by adjusting weights of hybrid network. Adjusted weights, the actual output of controlled plant closes to the expected output, and error function is minimized.

The error function is defined as

$$E = \frac{1}{2}\sum_{i=1}^{p}(t_i - y_i)^2 \qquad (3)$$

Where p is number of samples

t_i is desired output

y_i is actual output of plant

Error-backward propagation is adopted for weights learning. The rules are

$$W(k+1) = W(k) + \Delta W \qquad (4)$$

Where $$\Delta W \propto -\frac{\partial E}{\partial W} \qquad (5)$$

Assume I_i^k and O_i^k present input and output of ith node at layer (k) respectively. According to (3)

$$\frac{\partial E}{\partial w_k^{67}} = \frac{\partial E}{\partial y_i}\cdot\frac{\partial y_i}{\partial u_k}\cdot\frac{\partial u_k}{\partial w_k^{67}} \approx -\sum_{i=1}^{p}(y_{d_i} - y_i)(\frac{\Delta y}{\Delta u})\cdot o_k^6 \qquad (6)$$

Generally, error for backward propagation at layer (m) is

$$\delta_k^m = g'(I_k^m) \cdot \sum_i \delta_i^{m+1} \cdot w_{ki}^{m(m+1)} \tag{7}$$

$$\delta_k^m = g'(I_k^m) \cdot \sum_i \delta_i^{m+1} \cdot w_{ki}^{m(m+1)} (\bigotimes_{j \neq k} w_{ji}^{m(m+1)} \cdot O_j^m) \tag{8}$$

Where g(·) presents operative function of node

(10) is for layer (I), (II), (IV), (VI) and (VII)

(11) is for layer (III), (V).

D. Control System Based on Hybrid Network

Some important problems about optimization of fuzzy control based on hybrid network have been discussed above. The scheme of control system is shown in Fig.3. Where k_u are proposional factors of control variable u

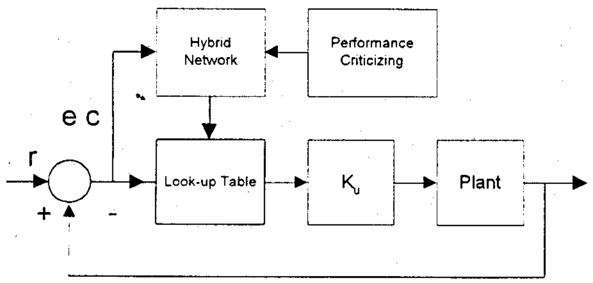

Fig.3 A fuzzy control system based on hybrid network

IV. EXPERIMENTAL RESULTS

A pump controlled motor electro-hydraulic servo system is shown in Fig.4.

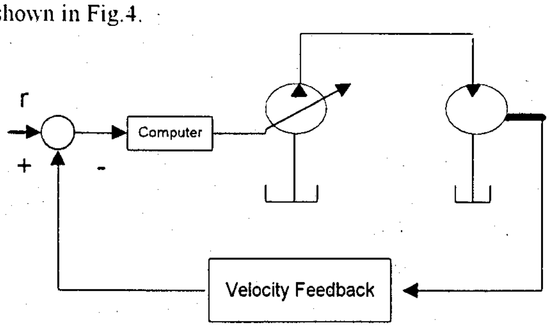

Fig.4 A pump controlled motor electro-hydraulic servo system

Generally, hydraulic systems have typical nonlinear and time-varying features. Parameters of system change with operating state. Therefore, it becomes difficult to reach effective control, especially under the demand of large range control.

Considered large range control, the universe of discoursc of error and error rate of change are chosen as [-1000, 1000] and [-200, 200] respectively. A rectangle is chosen for central universe of discourse A, [-200, 200] (error) and [-40, 40] (error rate of change). Fuzzy subsets of input variables are directly defined within actual universe of discourse.

Fig.5 shows responsive curves of optimum fuzzy control (OFC) and simple fuzzy control (SFC) under 200 r/mn and 400 r/min step input. Fig.6 shows regulating results of control system suffered from step load disturbance by OFC. The amplitude of step load is 6 MPa and 8 MPa.

Compared curves of OFC with curves of SFC both in Fig.5, the dynamic over-shooting of SFC is larger. Performance of OFC is better than that of SFC. They show effectiveness of optimization.

It is well known that a lot of experiments are necessary for priori knowledge acquisition in simple fuzzy control design. Much time, for example, has been spent for the results of SFC in Fig.5. Morever, successful or failing design heavily depends on the designer's experience and understanding to the actual system. For unknown or more complex plants, the ordinary fuzzy control design is even helpless. While by optimization, no priori conditions and constraints are needed. Much time for control design can be saved.

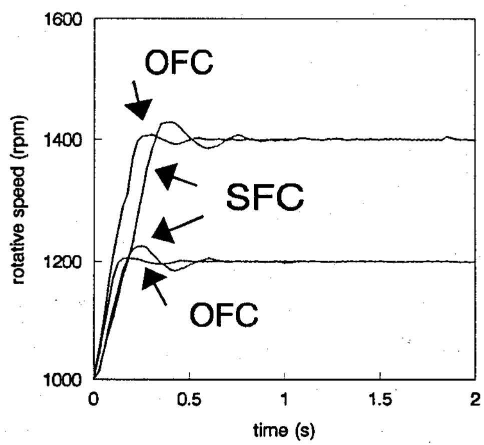

Fig.5 Response of OFC and SFC under step input

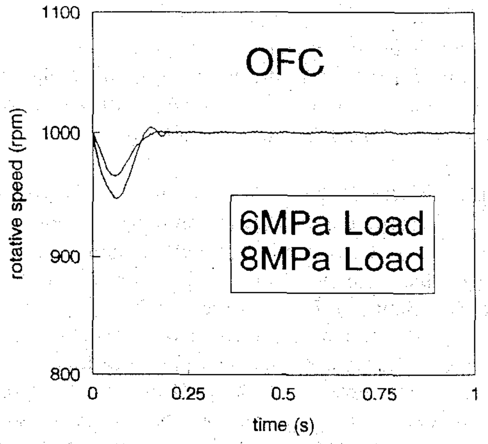

Fig.6 Response of OFC under load disturbance

V. CONCLUSIONS

The two-level optimization strategy for fuzzy control design is a synthesis of nonlinear division of e—$\dot{e}$ phase-plane by designer and learning by hybrid network. The former shows human qualititative understanding to responsive characteristics of system as a whole. Control process is properly decomposed, contradictions among demands of performance, real-time control and compositive computation are effectively solved, and quick dynamic response and stable steady state with high accuracy are achieved coordinately. The later expresses quantitative processing to knowledge of system. By learning of hybrid network, unreasonable factors in the design of fuzzy control are greatly decreased and effect of fuzzy control is improved. This is a general and efficient method. The control experiments for an electro-hydraulic servo system reach satisfactory results.

VI. REFERENCES

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[2] M. Mizumoto, "Simple Fuzzy Theories", Computer, Vol. 28, 1989, pp. 32-45