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Adaptive Fuzzy Logic Control Using a Predictive Neural Network

예측 신경망을 이용한 적응 퍼지 논리 제어

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요 약

퍼지논리 제어에서 정적인 퍼지규칙은 플랜트나 환경 파라메터의 중대한 변화에 대처할수 없다. 이러한 문제를 해결하기 위하여 지금까지 스스로 조직화하는 퍼지제어 및 신경망에 기초한 뉴로퍼지 등의 기법이 도입되었다. 그러나 이러한 기존 방법들은 동적으로 변화된 퍼지 규칙이 완전하지 않거나 모순될수 있음으로 해서 퍼지 제어기를 위험한 상황에 처하게 할수도 있다. 본 논문에서는 예측 신경망을 사용하여 새로운 적응퍼지 제어기법을 제안한다. 제안된 퍼지제어기는 비록 제어 플랜트나 환경 파라메터가 변화할지라도 초기의 완전하고 모순되지 않은 퍼지 규칙과 계속해서 학습하는 예측 신경망의 예측에러를 이용하여 제어출력을 안전하게 적응적으로 변화시켜간다. 직류 서보모터의 위치제어문제를 이용하여 실험해본 결과 제안한 방법이 적응면에서 매우 유용함을 보였다.

ABSTRACT

In fuzzy logic control, static fuzzy rules cannot cope with significant changes of parameters of plants or environment. To solve this problem, self-organizing fuzzy control, neural-network-based fuzzy logic control and so on have been introduced so far. However, dynamically changed fuzzy rules of these schemes may make a fuzzy logic controller fall into dangerous situations because the changed fuzzy rules may be incomplete or inconsistent. This paper proposes a new adaptive fuzzy logic control scheme using a predictive neural network. Although some parameters of a controlled plant or environment are changed, proposed fuzzy logic controller changes its decision outputs adaptively and robustly using unchanged initial fuzzy rules and the predictive errors generated by the predictive neural network by on-line learning. Experimental results with a DC servo-motor position control problem show that proposed control scheme is very useful in the viewpoint of adaptability.

1. Introduction

Although fuzzy logic control (FLC) shows good performance especially in highly nonlinear plants, some problems still remain [1, 2, 3, 4]. One of the problems of basic fuzzy logic control scheme is that static fuzzy rules are insufficient to cope with significant changes of parameters of plants or environment [1,4]. To solve this problem, some approaches-self-organizing fuzzy control, neural-network-based fuzzy logic control and so on-have been introduced so far [4, 5, 6, 7, 8]. Most self-organizing fuzzy control methods automatically modify their fuzzy rules using adaptation machines. With a performance metric-often an expert system or simply an algorithm-, the adaptation machines change fuzzy rules for adapting parameter changes of a plant and environment. In neural-network-based fuzzy logic control, fuzzy rules are represented by the weights of connections and artificial neurons of a neural network. This makes it possible for the fuzzy logic controller to automatically acquire and modify fuzzy rules.

In this paper, we introduce a new adaptive fuzzy logic control scheme using a predictive neural network[9]. With the predictive outputs generated by the predictive neural network, proposed fuzzy logic controller can adaptively change its decision outputs. The changed plant dynamics by parameter changes of plant or environment affects the predictive neural network outputs not initial fuzzy rules. In contrast to existing methods, our scheme is more robust than existing methods in the sense that basic decision outputs are not changed dynamically. The dynamic changes of initial fuzzy rules make it possible for a fuzzy logic controller to fall in dangerous situations because changed fuzzy rules will be incomplete and inconsistent[10].

The main idea of our control scheme is that if a fuzzy logic controller is able to know the predictive errors of a controlled plant, then its performance can be improved and its decision outputs can be adaptively varied according to the change of parameters of plant or environment. In our control scheme, the predictive neural network generates predictive outputs of a controlled plant using the current and past outputs and current inputs of a controlled plant. With the predictive outputs, our fuzzy logic controller is able to know the values of predictive errors and to decide adaptively its decision outputs. Of course, fuzzy rules in our control scheme must be composed of three input terms-errors, change errors and predictive errors. The predictive outputs of the neural network are adaptively changed by on-line learning of the neural network. This enables the fuzzy logic controller to have adaptability for the change of parameters of plant or environment without modification of initial fuzzy rules. It is another advantage of proposed scheme that our control scheme can be easily incorporated with an existing fuzzy logic controller without large modification.

We measured the performance of proposed control scheme with a DC servo-motor system. Experimental results show that our control scheme adaptively controls the plant under the parameter changes of the plant.

2. Proposed Fuzzy Logic Control Scheme

Fig. 1 shows proposed fuzzy logic control scheme. As can be seen in Fig. 1, the proposed scheme is composed of three modules-a fuzzy logic controller, a controlled plant and a predictive neural network. Except the predictive neural network, it is a basic fuzzy logic control structure. Our scheme doesn't modify initial fuzzy rules. The changed plant dynamics by parameter changes of plant or environment only affect the predictive neural network outputs. Generally, dynamic changes of fuzzy rules of existing methods can make the fuzzy rules incomplete and inconsistent because initial fuzzy rules are dynamically changed. The dynamic changes of initial fuzzy rules make it possible for a fuzzy logic controller to fall in dangerous situations. In contrast to existing methods, our scheme is more robust than existing methods in the sense that basic decision outputs are not changed dynamically.

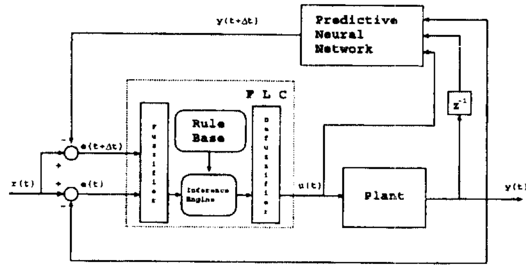


Fig. 1. Control Structure of Proposed Control System

We add a neural network to the basic FLC structure for predicting outputs of the plant with plant inputs $\mu(t)$, plant outputs $y(t)$ and delayed plant outputs $y(t\text{-}1)$. With these three inputs, the neural network estimates the predictive outputs of the plant. These predictive outputs $y(t+\Delta t)$, in other words outputs of neural network, are employed to measure the value of predictive error with reference inputs $r(t)$. The predictive error terms $e(t+\Delta t)$ are used by inference engine in addition to error and change error terms through the fuzzifier. Of course, fuzzy rules in our control scheme must be composed of three input terms-errors, change errors, and predictive errors. The predictive neural network must be sufficiently trained prior to real control and continuously trained during real control for adaptability. If the predictive neural network is sufficiently trained in operating ranges of the plant, thus, the predictive outputs are nearly equal to real outputs at next time, then the predictive error terms will contribute to enhancing the performance of the fuzzy logic controller. Moreover, these predictive error terms will considerably reduce the effect caused by the change of parameters of controller itself or environment by on-line learning without human intervention. On the other hand, if the neural network is insufficiently trained, the performance of the controller may be degraded. Thus, the neural network should be sufficiently trained prior to real control and continuously trained during real control for adaptability. In the prediction, the Δt is another important factor for improving the performance. It can be selected intuitively. If a plant has small inertia, then the Δt may be small. Otherwise, the Δt should be large. More researches about decision of Δt are necessary.

3. Controlled Plant

A DC servo-motor system is employed for experiment of our control scheme. The transfer function of the system is as follows.

$$G(s) = \frac{\theta(s)}{V_a(s)} = \frac{K_m}{s\,[(R_a + L_a s)(J_m s + B_m) + K_b K_m]} \tag{1}$$

where $v_a(t) = L^{-1}\{V_a(s)\}$ is the applied motor input voltage and $\theta(t) = L^{-1}\{\theta(s)\}$ is the angle of the motor shaft.

By substituting each parameter values with those in Table 1 and letting $Y(s)=\theta(s)$, $U(s)=V_a(s)$, it can be rewritten as follows.

$$G(s) = \frac{Y(s)}{U(s)} = \frac{2.2}{s\,(8.959\times 10^{-6} s^2 + 7.268\times 10^{-3} s + 0.9449)} \tag{2}$$

This plant is simulated by 4'th order Runge-Kutta method with 1 ms time step. We used a back-propagation neural network with 3-30-1 network structure. The learning rate η is 0.02. For the inputs of neural network, we used singletons without complicated fuzzification. However, the predictive error had better use fuzzification because the value of predictive error is not exact. By using total sum square error (TSSE) as a measure of fuzziness of predictive error, the predictive errors can be fuzzified. For simplicity, however, we did not use the fuzzification process for the predictive errors in experiments. For training, 1000 training patterns are gathered with uniform distribution in operating ranges and trained before starting real control.

Table 1. DC servo-motor spec.

R_a	3.9 Ω
L_a	5.27 mH
K_b	0.215 $V \cdot sec$
t_m	14 $msec$
K_m	2.2 $kgf \cdot cm/A$
J_m	0.0017 $kgf \cdot cm \cdot sec^2$
B_m	0.121 $kgf \cdot cm \cdot sec$

4. Experimental Results

Fuzzy rules of a basic fuzzy logic controller are

Table 2. Rule Table of Basic Fuzzy Logic Controller

e\ce	pb	ps	pz	zo	nz	ns	nb
pb	pb			pb			ps
ps		pb	ps	ps	ps	pz	
pz			pz	pz	zo		
zo		ps	pz	zo	nz	ns	
nz			zo	nz	nz		
ns		ns	nz	ns	ns	nb	
nb	ns			nb			nb

Table 3. Part of Rule Table of the Proposed Fuzzy Logic Controller

When $e=pz$

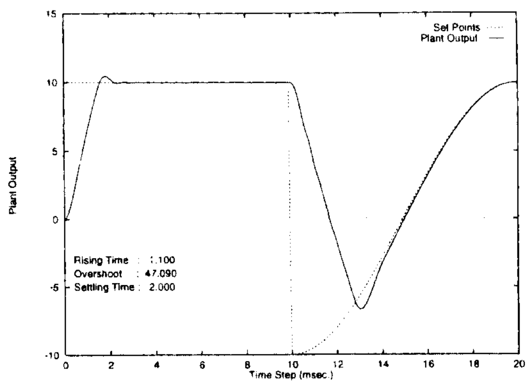
pe\ce	pb	ps	pz	zo	nz	ns	nb
pb							
ps							
pz			pb	pb	pb		
zo			pb	ps	ps		
nz			ps	ps	pz		
ns							
nb							

When $e=zo$

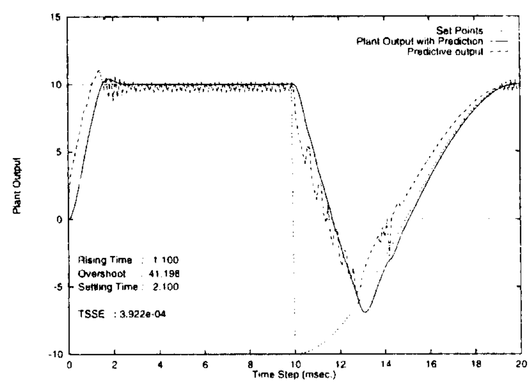
pe\ce	pb	ps	pz	zo	nz	ns	nb
pb							
ps					pb		
pz		pb	ps	pz	ps	zo	
zo		ps	pz	zo	nz	ns	
nz		pz	zo	nz	ns	nb	
ns					nb		
nb							

shown in Table 2. Fuzzy rules of the proposed fuzzy logic control scheme are more complex than those of the basic fuzzy logic one because the predictive error term makes another dimension. The number of fuzzy rules for the basic fuzzy logic controller is 27, while the number of fuzzy rules for proposed fuzzy logic controller is 90. We show only one part of fuzzy rules of the proposed fuzzy logic controller for simplicity in Table 3.

In case of no parameter changes, control results of basic fuzzy logic controller and the proposed adaptive fuzzy logic controller are nearly same each other as shown in Fig. 2. As shown in Fig. 3, however, proposed fuzzy logic controller outperforms the basic fuzzy logic controller in case of parameter change. For the parameter change, we added a value, 0.59, to the value of simulated plant output. Of

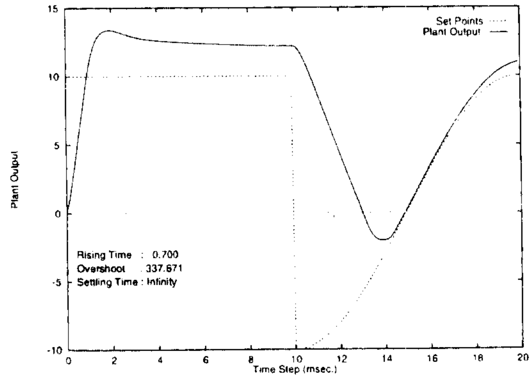


(a)

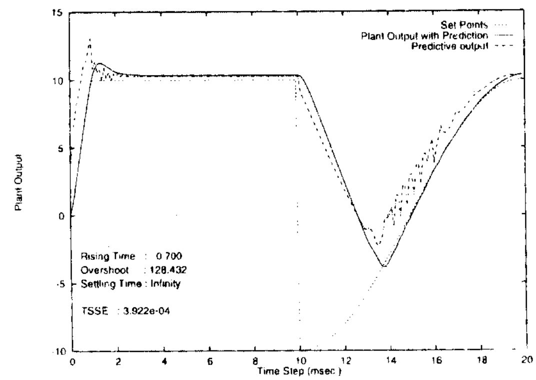


(b)

Fig. 2. Control Results without Parameter Change (a) Bsic Fuzzy Logic Controller (b) Proposed Fuzzy Logic Controller



(a)



(b)

Fig. 3. Control Results with Parameter Change (a) Basic Fuzzy Logic Controller (b) Proposed Fuzzy Logic Controller

course, control results of our fuzzy logic controller show nearly the same as those of basic controller directly after the parameter is changed. However, as the predictive neural network continuously learns changed plant dynamics, control results show better performance. Generally, the parameters of a plant or environment do not change abruptly. Thus, the predictive neural network will be able to track continuously the dynamics of the plants. In this experiment, however, we assumed that the abruptly changes of parameters occurs for a worst scenario.

Fig. 3(b) shows the result after the abruptly changes occur and learning with 10,000 iterations. Assuming that no abrupt changes of parameters occur, then only few iterations are needed. As shown in Fig. 3, our fuzzy logic control scheme produces a good result while the basic fuzzy logic control scheme produces a bad result. Neural network generates a predictive output $y(t+4\times t_s)$ where t_s is a time step. If this increase, then the rising time will be reduced. The increasing of Δt, however, may affect in the direction of disadvantage. Thus it should be selected carefully.

5. Conclusions

This paper introduces a new fusing method of a neural network and a fuzzy logic controller. In contrast to previous works, proposed control scheme is more robust because initial fuzzy rules in this scheme are not changed. Also, this can be shown as a loosely coupled method. Thus, proposed control scheme can be more easily incorporated into existing basic fuzzy logic controllers than previous schemes. Experimental results with a DC-servo motor system show that proposed control scheme is very useful in the viewpoint of adaptability. More extensive experiments and more researches for systematic decision of Δt are needed.

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