A HYBRID FUZZY LOGIC AND NEURAL NETWORK CONTROLLER FOR SPACECRAFT DOCKING SYSTEM

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ABSTRACT

A new hybrid fuzzy logic and neural network control architecture Is proposed and its application to attitude control of spacecraft docking system is described. The controller uses fuzzy logic control to construct a knowledge base of control rules and learns by updating its prediction of the physical systems behavior and fine tune a control knowledge base. It is applicable to control problems for which *the* analytical models of the process are unknown.

INTRODUCTION

With the advent of large flexible space structure, we are often faced with nonlinear control problem. for which analysis models are very difficult to develop. Hence, the conventional control methods often encounter a lot of difficulties when handle the system mentioned above.

Now, rule-based controllers which have been studied in artificial intelligence are mainly approach to solve these class of problem. Their provide powerful explanation capabilities. Approximate reasoning - based controllers which are rule-based mainly introduced by zadeh'. These controllers, which can model processes for where the control knowlege contains significant amount of uncertainties and imprecisions, have recently experienced a huge commercial success. such as the -sendai train controller, air-conditioning control system, et al. But in the meantime, the fuzzy logic controllers exist some disadvantages, such as it can not learn directly from experience.

On the other hand, artificial neural networks promise one alternative approach. Although the main application areas of neural network models have been in pattern recognition and diagnostics, the interest in neurocontrol has been 870-steadily growing. Neurocontrol models learn dynamic mapping from the input to the output of the system using parallel distributed processing models consisting of very simple neuraons. However, these models do not use the existing knowlege of a physical system's behavior and train the network from scratch. The learning process is usually long, and even after the learning is completed, the resulting network can't be easily explained.

In this paper, we proposed a hybrid fuzzy logic and neural network control architecture which uses reinforcement learning and learns from past exprience to fine-tune its knowledge base. We then discuss the application of this approach to attitude control of spacecraft docking system .

THE HYBRID ARCHITECTURE

As appeared in reference 2 , the general architecture of our controller consists of two part, the main elements are evalution network (EN) , which acts as a critic and provides advice to the main controller, and the selection network (SN), which includes a fuzzy controller. It is a extension from single - layer neural network as in Barto's work' to multilayer neural network. Here , we provide a brief overview of the architecture.

1. Evalution Network

EN is implemented by a dual parallel foward network (DPFN). The only Information received by the EN is the state of the physical system in terms of its state variable and whether or not a failure has occured, it include h hidden units and n input units from the enviroment, this structure is shown in Fig. 1. The EN produces a prediction of future reinforcement for a given state and changes in this prediction are used to guide SN in selection actions.

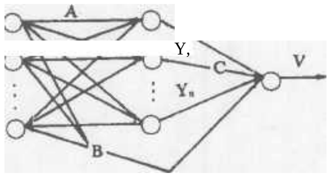


Fig. 1 The evalutlon network

The output of the units in the hidden layer is

$$Y,[t,t+1] = 9(\sum_{j-1} ai[t]xi[t+1]) \quad (1)$$

where

$$p(s) = 1/(1+e^{-}) \quad (2)$$

and t and t+l are successive time steps . The output of the EN is

$$v[t,t+1]- \sum b[t]x:[t+1] + \sum C,[t]Y,[t,1+1] \quad (3)$$

where v is the prediction of reinforcement. this network evalutes the action recommended by SN using the following equation,

$$+[t+1]=\begin{cases} 0, & \text{start .tats} \\ r[t+l]-v[t,t], & \text{fadureet.1,} \\ r[t+1]+yl[,t+l]-v[t,t], & \text{wA-Wia.} \end{cases} \quad (4)$$

where $OGytl$ is the discount rate . y is called internal reinforcement and plays the role of an error in EN's weight modifications . The weights are updated according to

$$b.[t+1] = b;[t] +,6,[t+1]x:[t] \quad (5)$$

$$C,[t+1] = _n[t] + f[t+1]Y,[t,t] \quad (6)$$

$$."Et+t] = s[s] + A:[t+l]rdt.t](1-Y,Ct.t])M,(C,Ct])x,Ct] \quad (7)$$

where p,N>0 is a constant.

2. Setection Network

The SN includes a fuzzy controller modleled by a three-layer neural network and another DPFN as shown in Fig. 2 . The input layer includes a fuzzifier whose task is to match the values of the input variables against the labels used in the fuzzy control rules . The hidden layer in this network corresponds to the rules used in the controller and includes the decision - making logic. The output layer includes the decoding (defuzzification) process.

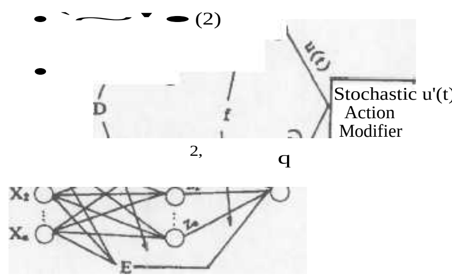


Fig. 2 The selection network

Let W (i) represent the degree to which rule i is satisfied by the input state variables in X.

$$W(i) = \quad (8)$$

where $u_c(x_{,i})$ represents the degree of membership of the input X in a fuzzy set representing the label used in the j th precondition of rule i, n is the number of the inputs. Then m(i), which represents the result of applling w(i) to the conclusion of rule i, is calculated from

$$m(i) = w:.'(w(i)) \quad (9)$$

where pe represents the monotonic membership function of the label used in the conclusion of rule i. The control action u(t) for the combined set of control rules is then calculated from

$$a(t) = \frac{\cancel{E'-If}\ X\ MW\ X\ W(i)}{E'i-,w(i)\ X\ f,} \quad (10)$$

where h is the number of units in the hidden layer. at the same time, SN also calculates a probility p that signifies a measure of confidence associated with the selection action. This measure is used later to modify u(t). The output of the units in the hidden layer is

7,[W + 1] = y(L'dyt]X;[t + 1]) (11)

where g(s) is the same sigmoidal function as in (2).

P[t,t + 1] - EeCiJX,Ct + 1] + !ffCt]z,[t,t + l] (12)

where p[t,t+1] is a probability associated with the action u(t) of the fuzzy controller. We use it to modify an action recommended by the fuzzy controller. In general

u',,, = *O(u(t),p[t,t + 1])* (13)

where o is a stochastic function that modifies u (t) based on the probability generated by SM. Finally, a measure s (t) for stochastic action modification is calculated based on,

S(t)=K(u(t),u'(f)) (14)

The weight changes as follows;

e,[t + 1] = e,[t] + *p"r[t + 1]S(t)X,[t]* (15)

f,[t + 1] = f,[t] +, [t + 1]S(t)7,[t] (16)

',Cr + 1] = 4D] + w:G + t7~C+let-~C+Uvs(t.CtJ)+(t>x,Ct7 *(ir)*

where p,Q,>0 is learning rate.

3. The Hybrid Architecture Algorithm

In summary, the hybrid architecture algorithm proceeds as follows,

A. Given a input, the SN

. determines an action u(t) using fuzzy rules based on equation (10).

. determines a measure of confidence in the fuzzy system's conclusion. or p based on equation (12)

B. These two decisions are used appropriately to produce the final action u' (t) based on equation (13), Which is sent to the phsical system. As a result of this action, the system moves to a new state.

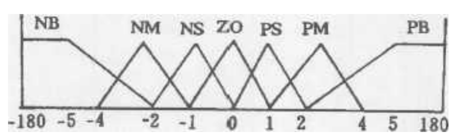
C. The EN evalute the new state, and comparision of this evalution with the score of the previous state gives a measure of internal reinforcement r.

D. Over the. time, the EN improves and becomes a good state evaluator, reinforcement estimates become more reliable. Also, the SN improves so that the recommendation of the fuzzy system becomes more correct with a higher measure of confidence.

APPLYING HYBRID ARCHITECTURE TO DOKING SYSTEM

The attitude control during spacecraft docking process is very important. A robust attitude control system enhances trajectory control because the execution of desired delta--v is much more accurate. Poor attitude control can definitely result in a mission failure. Typical controllers based on the phase plane concept have attitude errors and attitude rate errors as input values. The output controller value is a command for gererating a correcting torque.

The input variables have seven membership functions defined over the universe of discourse as shown in Fig. 3. The output variable has five membership functions as shown in Fig . 4. There are 25 rules defined for reducing the angle and angle rate error to within their zeso (ZO) range (see table 1).



degrees

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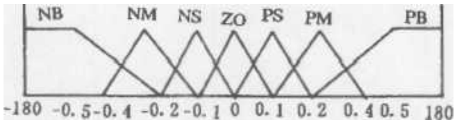

degrees per sencond

Fig. 3 Memebership functions for angle and angle rate error.

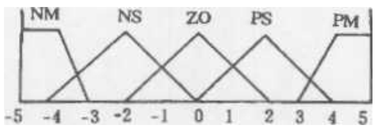

Fig. 4 Menbership functions for cammand error.

Table I. Rule Base for Attitude controller.

angle rate error	angle error						
	NB	NM	NS	ZO	PS	PM	PB
NB	PM	PM	PS				
NM	PM	PM	PS				
NS	PS	PS	PS				
ZO	PS	PS	ZO	ZO	ZO	NS	NS
PS					NS	NS	NS
PM					NS	NM	NM
PB					NS	NM	NM

Fig. 5. Presents the hybrid controller for attitude control of spacecraft. EN and SN in this figure both have three input units.

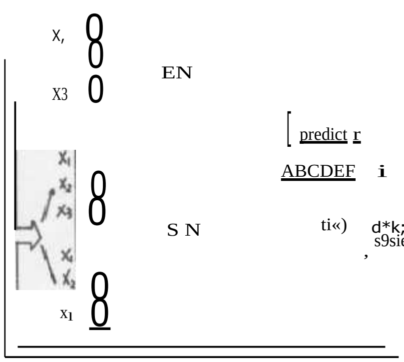

Fig. 5 Hybrid controller for docking system

Let P=1. 0, n,=0. 2, 0=. 2, .=0. 05, y=0.9. Simulation result shown that the proposed controller is feasible.

CONCLUSION

1. According to the feature of attitude control of spacecraft docking system, a new hybrid fuzzy logic and neural network controller Is proposed .
2. The controller improves upon previous models in learning control by learning to fine-tune the performance of a rule-based controller.
3. DPFN can be regarded as paralelling a single layer forword network (SLFN) with a multiple layer forword network (MLFN). SLFN has a short learning time when deal with linear problem, while MLFN can implement complicated nonlinear mapping from input to output. for this reason, DPFN has advantages which two network mentioned above have, it can decrease training time by 5-10 times.

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