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A PROPOSAL OF ENHANSED NEURAL NETWORK CONTROLLERS FOR MULTIPLE CONTROL SYSTEMS

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Abstracts This paper presents a new construction method of candidate controllers using Multi-modal Neural Network(MNN). To improve a control performance of multiple controller, we construct candidate controllers which consist of MNN. MNN can learn more complicated function than multilayer neural network. MNN consists of preprocessing module and neural network module. The preprocessing module transforms input signals into spectra which are used as input of the following neural network module. We apply the proposed method to multiple control system which controls the cart-pole balancing system and show the effectiveness of the proposed method.

Keywords Multi-modal Neural Network, Chebyschev Polynomials, Multiple Controller

1. INTRODUCTION

In recent years, the researches of adaptive control systems have been focused on the unexplored area of logic-based switching control systems [1]–[6]. The typical logic-based switching control system consists of a plant to be controlled, a family of candidate controllers, and a supervisor [1]. A supervisor is a logical element capable of determining in real time which candidate controller should be put in feedback with a plant in order to achieve desired control performance. In the sequel we shall refer to such logic-based switching controllers informally as multiple controllers.

Approaches using multiple controller can be roughly classified into two categories by information which a supervisor monitors. In the first category, switching is carried out based on monitoring estimated plant parameter values. In the second category, switching is carried out based on monitoring observed identification errors between the plant output and multiple identification modal.

In these approaches, several drawbacks exist. One of the most serious problems is that their performance may degrade, and what is worse, systems may lose their stability in case when the enough accuracy of plant parameter estimators or multiple identification modal can't be achieved.

Then, it is reported that a construction method of logic-based switching control systems which does not require any identification schemes of environments is useful [6]. In this system, multilayer neural network [7] is used for candidate controllers so that the system using a neural controller shows hight robust performance.

Multilayer neural networks are used for various applications, e.g. learning, recognition, control and so on. Multilayer neural networks can map a given nonlinear function by it's nonlinear property. It means that multilayer neural networks is suitable to make controllers which control nonlinear systems. But it is difficult for multilayer neural networks using monotone sigmoid function to learn complicated function in enough accuracy [8]. As a function is more complicated, the more synapse and more learning time is needed. It is expected that a improvement of neural networks' nonlinear property allows controllers to learn complex relationship between input and output signals.

This paper presents a construction method of candidate controllers for multiple control system. The candidate controllers consist of Multi-modal Neural Network. We confirm that Multi-modal Neural Network can learn complicated functions efficiently in enough accuracy. An application to cart-pole balancing system [9] clarifies the effectiveness of the proposed method.

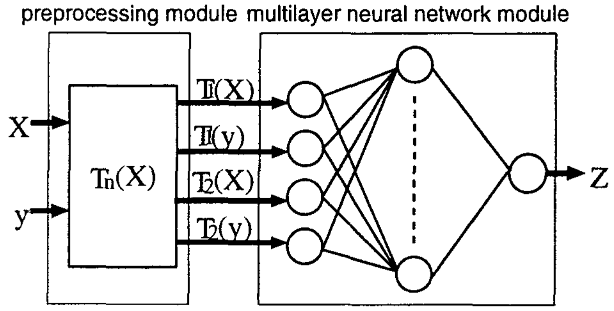


Fig.1. Structure of Multi-modal Neural Network.

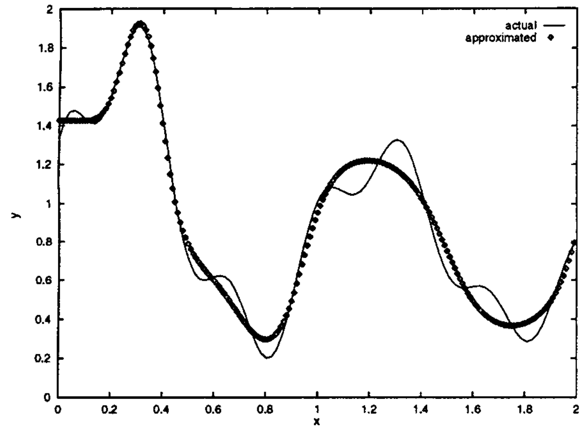


Fig.2. Approximation by NN.

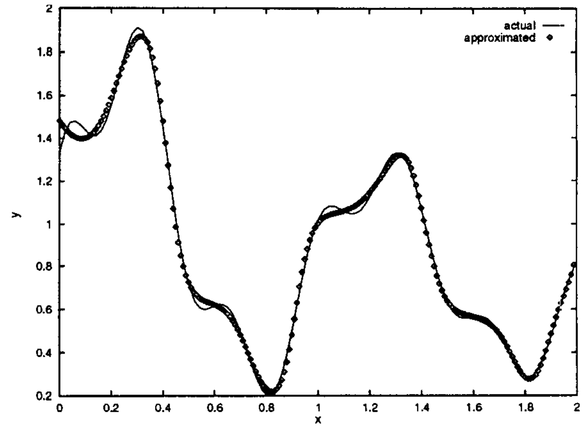


Fig.3. Approximation by MNN.

2. MULTI-MODAL NEURAL NETWORK

In this section, we propose a Multi-modal Neural Network(MNN) in order to improve multilayer Neural Networks(NN)'s ability of mapping functions. MNN consists of preprocessing module and NN module(Fig.1). The preprocessing module transforms input signals by Chebyschev polynomials. Chebyschev polynomials is defined as follows:

$$T_n(x) = cos(n \cdot cos^{-1}x)$$
$$T_0(x) = 1, T_1(x) = x, T_2(x) = 2x^2 - 1, \cdots. \quad (1)$$

The ouputs of preprocessing module are used as input of following NN module.

Preprocessing module causes NNs' nonlinear performance improve and it is expected that MNN can learn a given complicated function.

To confirm the effectiveness of MNN, we compare MNN with NN by the function approximate problem. We use the following function:

$$y = \{1 + log(1 + x) + sin(2\pi x) + \frac{1}{3}cos(6\pi x)\}/(x + 1). \quad (2)$$

The range of x is $[0, 2]$. As preprocessing module, we use Chebyschev polynomials of degree three. The learning time and the number of synapse are same. Fig.2 represents a result of approximation by NN. Average of square errors is 5.997×10^{-4}. Fig.3 represents a result of approximation by MNN. Average of square errors is 8.288×10^{-5}. These results show that MNN can approximate the non-linear function accurately compared with NN.

In the following section, we apply MNN to the candidate controllers which control the cart-pole balancing system.

3. CONTROLLERS USING MULTI-MODAL NEURAL NETWORK

3.1 Multiple Control System

Multiple control system is a kind of adaptive control systems for nonlinear systems whose dynamic characteristic and environmental conditions change widely. A multiple controller consists of a supervisor and candidate controllers. The supervisor switches candidate controllers one by one according to environmental conditions. A schematic diagram of the structure of the multiple control system is shown in Fig.4.

We focus on a multiple control system which does not have any model to identify environmental conditions. In this system, candidate controllers are composed of multilayer neural networks.

In this paper, we improve the nonlinear characteristics of each candidate controllers using MNN and examine the efficacy.

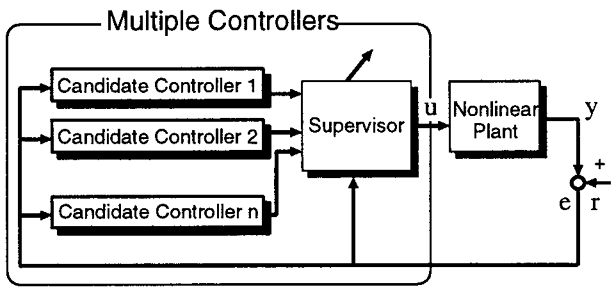
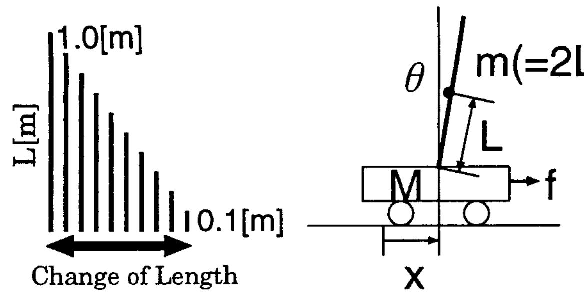


Fig.4. Multiple Control System.

3.2 Candidate Controllers

We mention a construction method of candidate controllers for multiple control systems. As an application of multiple control systems, we focus on a cart-pole balancing problem.



L	:	Half Length of Pole
m	:	Mass of Pole($= 2L$)
M	:	Mass of Cart
θ	:	Angle of Pole from Vertical
x	:	Position of Cart on Track
f	:	Force Applied to Cart

Fig.5. Cart-Pole Balancing System.

3.2.1 Cart-Pole Balancing Problem

A cart is free to move along a one-dimensional track while a pole is only free to rotate in the vertical plane of the cart and track. A schema of the physical system is shown in Fig.5. The cart-pole system is simulated by following equation:

$$\begin{bmatrix} 4/3mL^2 & mLcos\theta \\ mLcos\theta & m+M \end{bmatrix} \begin{bmatrix} \ddot{\theta} \\ \ddot{x} \end{bmatrix}$$

$$+\begin{bmatrix} D_1 & 0 \\ 0 & D_2 \end{bmatrix} \begin{bmatrix} \dot{\theta} \\ \dot{x} \end{bmatrix} - \begin{bmatrix} mLgsin\theta \\ mL\dot{\theta}^2 sin\theta \end{bmatrix} = \begin{bmatrix} 0 \\ f \end{bmatrix}. \quad (3)$$

The fourth-order Ruge-Kutta method with a step size of 0.01s is used to calculate θ,$\dot{\theta}$,x and $\dot{x}$.

The objective of the control is to balance the system such that the pole is balanced in a vertical position,simultaneously not falling beyond predefined vertical angles $\pm$ 15(deg) and the cart remains within the bounds of the horizontal track ($\pm$ 1 meter from the center). We define "settling" as the condition which satisfied $|\theta| < 1.0 \times 10^{-3} and |\dot{\theta}| < 1.0 \times 10^{-3}$. We pose the pole length changes from 0.1(m) to 1.0(m) by 0.1(m). It is assumed that dynamics of the system and length of the pole are unknown for controllers. Initial states are $\theta = 0, \pm 1, \pm 2, \pm 3(deg), \dot{\theta} = 0, \pm 3, \pm 6, \pm 9(deg/s), x = 0(m)$ and $\dot{x} = 0(m/s)$.

3.2.2 Generating Candidate Controllers

We construct two kind of candidate controllers.
(a)Candidate controllers using NN
(b)Candidate controllers using MNN
The parameters of neural network is shown in Tab.1.

Tab.1. The parameters of neural networks.

	Net structure	No. of synapse
NN	4-10-1	66
MNN	8-6-1	61

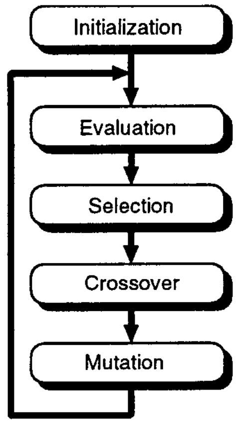


Fig.6. Generating procedure of controllers based on Genetic Algorithm.

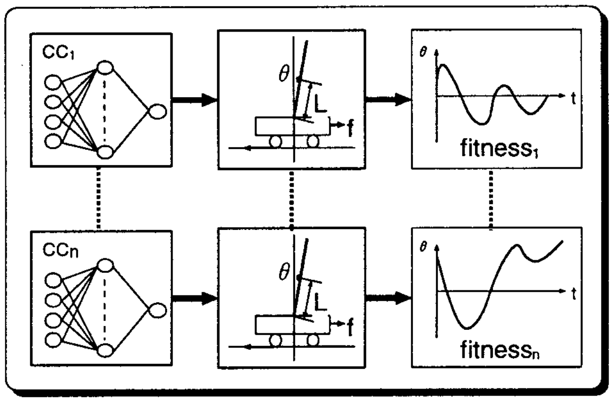


Fig.7. Evaluation of controllers.

The output of the neural network is continuously vary between -1.0 and 1.0, where -1.0 represents a pushing force of 50(N) to the right. The value of the synapse weight are optimized by Genetic Algorithm(GA). GA is one of the useful method to solve an optimization problem.

Genetic Algorithm(GA) [10] is used to optimize the control performance of neural networks by evolving their weights. A flowchart of the process which generates candidate controllers is shown in Fig.6. In evaluation process, each candidate controllers' fitness is calculated by controlling cart-pole system(Fig.7). We use the fitness to select candidate controllers.

3.3 Generated Controllers

We generate candidate controllers 5 times to evaluate settling time of candidate controllers. In MNN, preprocessing module transforms input signals by Chebyschev polynomials which has degree one term and has degree three term.

We generate candidate controllers for 0.5m pole. The number of candidate controllers is 50. Settling time(s) means a period from the start of control to the state of settling(Fig.8). The result is shown in Tab.2. 'ave' means average settling time of the popu-

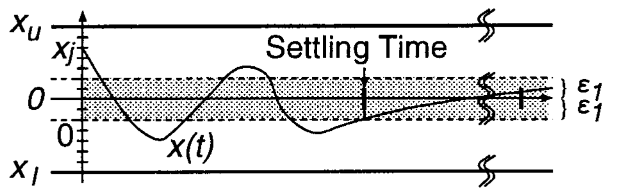


Fig.8. Settling time.

lation and 'min' means the minimum settling time in the population. 'AVE' in the bottom column of Tab.2 means the average settling time of 5 trials.

Tab.2. Settling time.

	NN		MNN	
	ave	min	ave	min
1	3.23	2.86	3.41	2.73
2	4.95	4.65	2.75	2.53
3	3.70	2.89	3.12	2.89
4	3.01	2.82	3.12	2.79
5	4.77	4.49	3.12	2.75
AVE	3.93	3.52	3.10	2.73

According to Tab.2, both average and minimum settling time of MNN are shorter than NN. It represents that controllers using MNN is superior to NN's for $0.5m$ pole.

We have discussed the pole with the middle($0.5m$) length. We have also examined a shorter($0.1m$) one and a longer($1.0m$) one in order to confirm the effectiveness of making candidate controllers based on MNN. Tab.3 shows that settling time of MNN is shorter than that of NN in terms of 'ave' and 'min'. It shows that candidate controllers using MNN is superior to that using NN in settling time for different length of poles.

Tab.3. Settling time of poles with different length.

	NN		MNN	
	ave	min	ave	min
0.1	5.16	3.41	3.11	2.50
0.5	3.93	3.52	3.10	2.73
1.0	5.16	4.67	4.28	3.84

4. CONCLUSIONS

We propose a construction method of candidate controllers which is using MNN which consists of preprocessing module and NN module. Preprocessing module transforms input signals by Chebyschev polynomials into spectra which are used as input of the following NN module. We confirmed that MNN can approximate a complicated nonlinear function in enough accuracy. We applied MNN to making candidate controllers which control the cart-pole balancing system. We show that candidate controllers using MNN are superior to that using NN in the settling time.

Direction for future research is the construction of candidate controller which can control the poles with several length.

5. ACKNOWLEDGMENT

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