A RESEARCH AND APPLICATION ON A NEW FNN CONTROL STRATEGIES *

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ABSTRACT

As the precise model of most practical mechatronics system cannot be obtained, the practice of typical control method is limited. Accordingly, numerous AI (Artificial Intelligence) control methods have been used widely. Fuzzy control and Neural Network control have been an important point in the developing process of the field. However, shortcomings exist in each of these methods. For example, the fuzzy control is unable to learn, and the physical meanings of learning result of the Neural Network control are not clear. Combining the strong points of above two methods, a new control method of FNN (Fuzzy Neural Networks) is explored in this paper. Additionally, a problem concerning the traditional network learning is discussed and a solution to such a problem is obtained subsequently. The new control strategy does not depend on the classical model and the algorithm is simple. The results of the experiments applying the new strategies are discussed. Through different researches on control system, which model is unacquainted, the reasonableness, effectiveness and applying universality of the new control strategies is proved.

INTRODUCTION

The mechatronics system becomes more and more complicated. According to the Incompatibility Principle [1], the higher complicacy of the system is, the lower ability to describe becomes. So the typical control methods based on the precise model cannot meet the need. AI offers new strategies for the mechatronics control system.

Since the AI Project was launched at MIT in 1957, it has achieved great success in many fields. It attracts more and more attention to AI and many AI methods have been put forward [2]. Fuzzy and NN (Neural Networks) are important aspects in AI, simulating different functions of the human brain. The former simulates the macroscopical functions, such as syllogisms, but the latter simulates the associatron, classification, memory by way of imitating the microcosmic structure. But the Fuzzy cannot learn and the NN cannot deduce. In addition, the Fuzzy can be understood and the learning results of the NN cannot [3]. The new AI method, FNN , which integrated the good qualities of the two methods, has been the hotspot in AI fields.

Firstly, this paper will discuss a new object function of FNN learning and a problem in NN control system. Then a new FNN control structure will be put forward based on them. Finally, some conclusions will be acquired, supported by related experiments.

THE OBJECT FUNCTION

Object function is very important for the control system. $\int e^2 dt$ is usually taken as the Object function in time fields. The smaller the area, like figure 1, which surrounded by the phase track in the phase space is, the better performance of the system is. So the integrated object function can be defined as

$$J = d\int e^2 dt + b\int |\dot{e}| de \qquad (1)$$

where e is the error between the sysytem's real output and the reference input. $\dot{e}$ is the differential coefficient of e . $\int e^2 dt$ is the general object function, $\int |\dot{e}| de$ is the area. δ and β are the weighted coefficients.

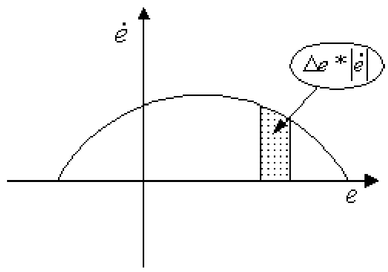

Fig. 1 A example of phase space

On second thoughts

$$|\dot{e}| de = \left|\frac{de}{dt}\right| de = \frac{de}{dt} * \frac{de}{dt} * dt = (\dot{e})^2 dt \qquad (2)$$

$$\int |\dot{e}| de = \int \dot{e}^2 dt \qquad (3)$$

The area surounded by the phase track is the integration of the error's differential coefficient. So the error and its differential coefficient are synthetically considered in the new object.

* The Project Sponsored by ROC, SEM

A PROBLEM IN NN CONTROL

NN control just applies the NN’s approximating ability. A typical NN control system likes figure2.

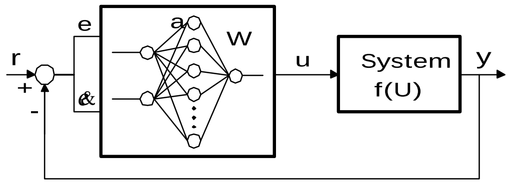

Fig. 2 The typical structure of NN

Where y is the real output, r is the reference input, u is the NN’s output, and e is the system error. The object of the control is made y=r, namely e becomes 0.

The learning method adopted is usually Gradient Search. Obviously, the error is the main parameter in this method.

In theory, the error which is needed by the NN learning is e’, defined as

$$e = u - u_o \tag{4}$$

Where u_o is the NN’s desired output. u_o can be obtained:

$$u_o = f^{-1}(r) \tag{5}$$

So the general object function can be defined as:

$$J_e^{\ *} = (u - f^{-1}(r))^2$$

(6)

Then

$$\frac{\partial J^*_e}{\partial w} = -(u - f^{-1}(r))\frac{\partial f^{-1}(r)}{\partial w}$$

(7)

Because the precise model of the system can not be obtained, even though the precise model is obtained, most practical mechatonics system is very complex. Therefore, the equations cannot be solved. So u_o is not known. Practically, y usually is used to replace u_o, as a result, the object function is defined as

$$J_e = (r - y)^2$$

(8)

So

$$\frac{\partial J_e}{\partial w} = -(r - y)\frac{\partial y}{\partial w}$$

(9)

Generally the following equation is not true.

$$(r - y)\frac{\partial y}{\partial w} = (u - f^{-1}(r))\frac{\partial f^{-1}(r)}{\partial w}$$

(10)

In fact, the signs are different from each other between these at the two sides of the “=”. So the NN can not approach the desired value, even the NN’s astringency can not be guaranteed.

THE NEW CONTROL STRUCTURE

Based on the above discussion, a new control structure of FNN can be put forward. It looks like figure 3.

Where the network NN1 is FNN network and NN2 is the RBF network. W is the weight of NN1 and W’ is the weight of NN2. NN1 is employed to obtain the control output u. NN2 is just as the system’s inverse model, it is used to acquire the u_o, u’s desired output.

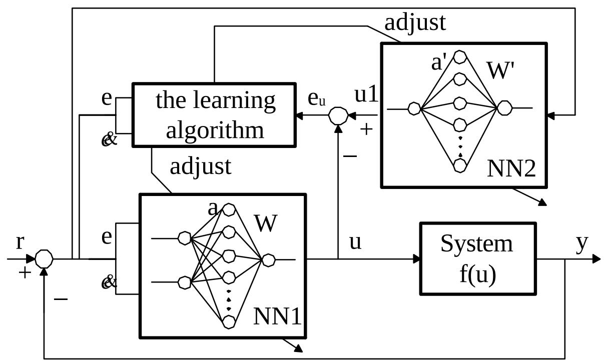

Fig. 3 The structure of the new FNN

There are lots of types of FNN, but generally they can be classified two kinds. One is the NN which directly is constructed by the Fuzzy’s rule,another is the NN which is fuzzied from the unfuzzy NN.

In this paper, The FNN has two layers. Its topical structure is achieved by the Fuzzy, and the fuzzy learning ability becomes strong by taking advantage of NN. The number of NN’s hidden layer’s nodes is just the same with that of the fuzzy’s section and the accept function of the nodes is corresponding to the membership function of the Fuzzy section.

So define the object function again:

$$J = d\int e^2 dt + b\int \dot{e}^2 dt + g\int e_u^{\ 2} dt$$

(12)

THE ALGORITHM

The new algorithm’s detail process is the following:

(1) Partition the fuzzy section according to e and $\dot{e}$

(2) Initial the network

(3) Calculate $u = a * W^T$

where $a = (a_1, a_2, \ldots a_m)$ is the accept function m is the number of the nodes

(4) Modify the weight W and W’

For the j th node, because:

$$grad_{w_j} J = d * grad_{w_j} \int e^2 dt + b * grad_{w_j} \int \dot{e}^2 dt$$
$$+ g * grad_{w_j} \int e_u^2 dt$$

(13)

$$grad_{w_j'} J = d * grad_{w_j'} \int e^2 dt + b * grad_{w_j'} \int \dot{e}^2 dt$$

$$+ g * grad_{w_j'} \int e_u^2 dt$$

(14)

$$e = r - y = r - f(u) = r - f(Wa^T)$$

$$e_u = u1 - u = W'a'^T - Wa^T$$

$$\frac{\partial e_u^2}{\partial w_j} = -(W'a'^T - Wa^T)\frac{a_j}{aa^T}$$

$$\frac{\partial e_u^2}{\partial w'_j} = (W'a'^T - Wa^T)\frac{a'_j}{a'a'^T}$$

$$\frac{\partial e^2}{\partial w_j} = -[r - f(u)] * \frac{\partial f(u)}{\partial u} * \frac{\partial u}{\partial w_j}$$

$$= -[r - f(u)] * \frac{\partial f(u)}{\partial u} * \frac{a_j}{a^T a}$$

$$grad_{w_j} \int e^2 dt = -(y_R - y_j(u)) * \frac{a_j}{aa^T}\frac{\partial y_j(u)}{\partial u}$$

$$\frac{\partial \dot{e}^2}{\partial w_j} = -[\dot{r} - \dot{y}] * \frac{\partial \dot{y}}{\partial w_j} = -[\dot{r} - \dot{y}] * \frac{\partial \dot{y}}{\partial u} * \frac{\partial u}{\partial w_j}$$

$$= -[\dot{r} - \dot{y}] * \frac{\partial \dot{y}}{\partial u} * \frac{a_j}{aa^T}$$

(15)

At the k th sample time:

$$\frac{\partial f(u)}{\partial u} \cong \frac{y(k+1) - y(k)}{u(k+1) - u(k)}$$

$$\frac{\partial \dot{y}}{\partial u} \cong \frac{y(k+1) - 2 * y(k) + y(k-1)}{[u(k+1) - u(k)] * \Delta t}$$

$$\dot{e} = \lim_{\Delta t \to 0} \frac{e}{\Delta t} = \lim_{\Delta t \to 0} \frac{r - y}{\Delta t} = \dot{r} - \dot{y}$$

$$= \lim_{\Delta t \to 0} \frac{r(k+1) - r(k)}{\Delta t} - \lim_{\Delta t \to 0} \frac{y(k+1) - y(k)}{\Delta t}$$

Δt is the interval of sample time

$$w_j(k+1) = w_j(k) + h * \frac{a_j}{aa^T} *$$

$$\left\{ d * \frac{y(k+1) - y(k)}{u(k+1) - u(k)} * [r(k) - y(k)] + \right.$$

$$b * [\frac{r(k+1) - r(k)}{\Delta t} - \frac{y(k+1) - y(k)}{\Delta t}] *$$

$$\left. \frac{y(k+1) - 2 * y(k) + y(k-1)}{\Delta t} \right\} +$$

$$g * \frac{a'_j}{a'a'^T}(u(k) - u1(k))$$

$$w'_j(k+1) = w'_j(k) + h' * \frac{a'_j}{a'a'^T}(u1(k) - u(k))$$

(16)

In this way, plenty of information is used in the learning process for the NN1, and the damp of the system is increase, which is useful for the stability of the system. This point is proved in the experiments.

(5) If J supplies the demand, then stop, else go to (3).

Experiment

Some experiments using the above methods have been done.

A three order system's open-loop model is the following:

$$G(s) = \frac{4.975^2}{s^2 + 2 * 0.041 * 4.975 * s + 4.975^2} * \frac{1}{1 + 3 * 10^{-3} s}$$

Its step response likes figure 4. The result that is used the new FNN control is also shown as figure 4.

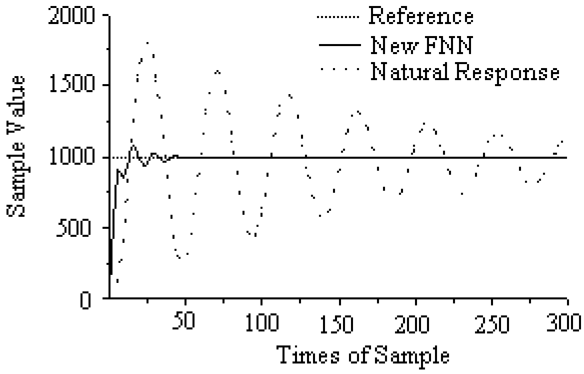

Fig 4. The result of the physical emulational experiment

The result is obtained after six times learning. Apparently it is better than that of PID and BP (The result of PID and BP is not given). It is found in the experiment that δ and β are very important for the result Motor is the typical mechatronics system, but its precise mathematics model cannot be obtained. Regulating the motor's speed is the normal work in the practice, and a lot of methods in such an aspect have been brought forward [4][5][6]. Figure 5 is the result of the experiment about regulating the motor's speed.

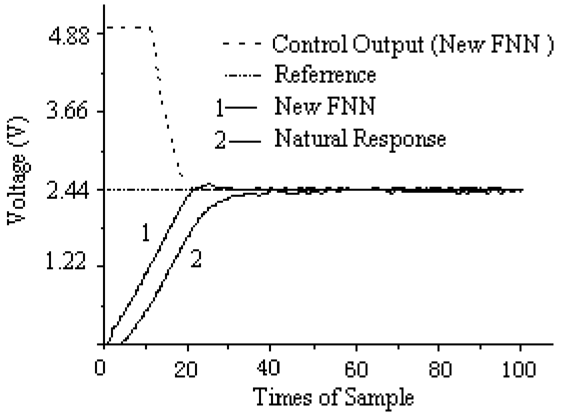

Fig. 5 The result of the experiment about motor

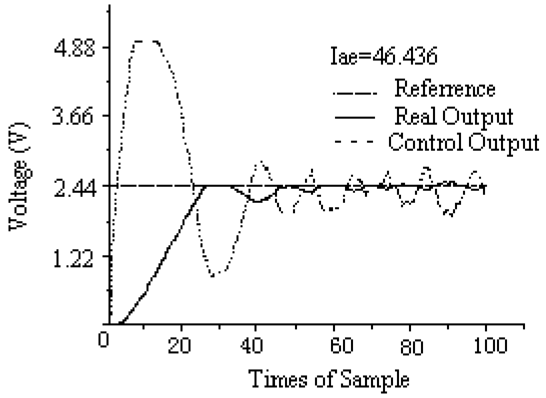

Fig 6. The result of the PID control

The result of the new FNN is obtained after three times learning. Comparing the results of the experiments, the strengths of the new FNN are outstanding. In addition, PID's parameter is confirmed hardly. The PID optimized result shown in Fig.6, which is caused by regulating again and again. According to the experiments, the availability of the new FNN proposed above is proved.

SUMMARY AND OUTLOOK

At first, a new object function based on the phase space is defined, then a problem about NN's learning is discussed and a new FNN control Strategies is proposed, at last two related experiments are practised. Through the experiments, some results can be obtained:

(1) The new FNN is available.

(2) The new FNN does not need the precise mathematics model of the system.

(3) The new object function is valid.

(4) The new FNN is good for overcoming the problem in NN control.

It is very easy for the control rules to be mined from the New FNN. There are some papers concerning this point [7][8].

Finally, we would like to point out that both real time ability of this new control and astringency are the further work we will explore.

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