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Plant Identification and Synthesis of Optimal Control by Use of Neural Network with Mixed Strcuture†

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In this paper, firstly we propose a neural network with a mixed structure, which consists of multilayer and recurrent structure, for learning the dynamics of a nonlinear plant. A neural network with a mixed structure can learn time series, therefore, it can learn the plant dynamics without knowing the plant order.

Next, we consider the optimal control synthesis problem using the neural network with a mixed structure, which has learned the plant dynamics completely. Procedures are as follows: (1) the neural network is expanded into an equivalent feedforward multilayer network, (2) it is shown that the gradient of criterion functional to be optimized can be easily obtained from this multilayer network, and then (3) the optimal control is generated by applying any of the existing nonlinear programming algorithms based on this gradient information.

The proposed method is successfully applied to the optimal control synthesis problem of a nonlinear coupled vibratory plant with a linear quadratic criterion functional.

Key Words: neural network, optimal control synthesis, multilayer network, recurrent network, nonlinear plant

1. Introduction

Since Back Propagation algorithm, a learning method for multilayer neural networks, proposed by D.E. Rumelhart et al (1986) [1], various researches have been performed on the application of neural networks (N.N.'s) in various fields. In the field of control engineering, studies on control systems using N.N.'s in various ways have been reported [2].

To control a plant, the construction of a mathematical model representing the plant dynamics, in other words, the identification of the plant, must be performed. Then, the control system is synthesized using an appropriate control theory for the obtained mathematical model. Whether the plant can be identified appropriately, or the mathematical model can represent the plant well, has much effect on the performance of the control system constructed based on it.

The plant identification is generally based on the investigation of characteristics of plant components. However, in case no information is available for the plant characteristics, the identification must be based on only input-output response data of the plant. In practical situations, this condition occurs often. Some assumptions on the plant are necessary to obtain a mathematical model using only input-output data of the plant. In many cases, the linearity of a plant performance or the plant order is usually assumed for the identification. That is, based on the assumption: "the plant characteristic can be represented by a linear X-th order differential equation", its parameters are obtained from input-output response data.

Using the property of a multilayer N. N. that it can learn nonlinear mapping, studies have been performed on the use of the N. N. that has learned the plant dynamics as a plant model of the control. The study [3] shows that the linearity assumption in the identification can be removed, and an effective control can be obtained for a plant with a strong nonlinear property.

In this paper, firstly, a N.N. with a mixed structure is proposed that can learn the time series. For N. N. with a mixed structure, a similar learning algorithm to Back Propagation algorithm is given. N. N. with a mixed structure can learn the time series directly from the input-output response data of the plant, and do not require the plant order. Then, as an example of control using N. N. with a mixed structure learning the plant dynamics as a plant model, a solution method is given that can solve the optimal control problem as a nonlinear programming problem.

2. N. N. with Mixed Structure

2.1 Problems in Multilayer N. N.

Multilayer N. N.'s can learn only input-output relation such as mapping. In applying N. N.'s to the control, this

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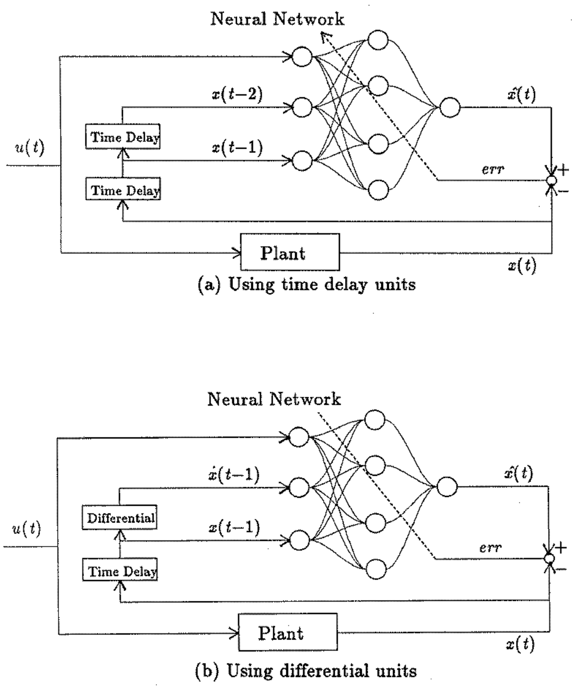

Fig. 1 Conventional method of learning plant dynamics

property often causes a problem. Especially for the control of plants that can monitor nothing but displacement, a typical problem of this kind arises. In using a multilayer N. N. to learn the dynamics of such a system, time delay elements or derivative elements are conventionally applied as shown in **Fig. 1**, where output data collected some sampling time steps ago or the derivative of output data are used as a feedback to N. N.. For this kind of method to hold, output data sampled at least N time steps ago or N-th order derivative must be utilized for the plant with N-th order. Here, an inconsistent problem arises that its plant order must be given for a plant whose dynamics must be identified.

2.2 N.N. with Mixed Structure

To solve problems described in the previous section, instead of installing an additional element that can deal with time property, N.N.'s by themselves should be able to learn time property in their internal mechanism. N.N.'s with interconnected networks can deal with time series data. Therefore, a N. N. as shown in **Fig. 2** is proposed, which has a multilayer structure and whose hidden layer has recurrent connections. N.N.'s with this structure are called N.N.'s with a mixed structure. A N.N. with a mixed structure has the same processing mechanism as a multilayer N.N., where activation value of each unit at input, hidden, and output layers are calculated sequentially as

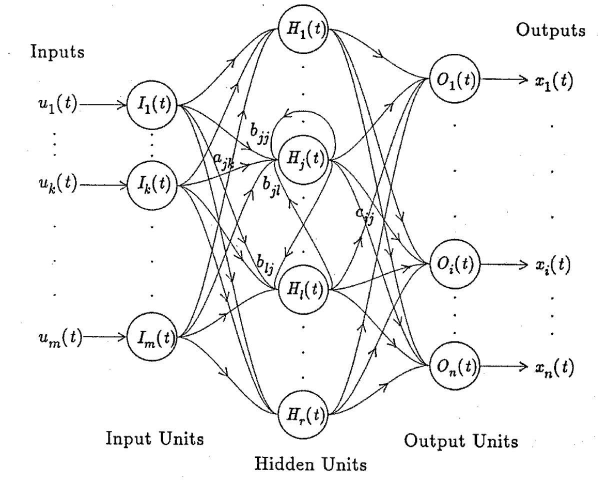

Fig. 2 Neural network with mixed structure

well as synchronously.

For a N.N. in Fig. 2, a unit at the input layer has the following activation value determined from an external input.

$$I_k(t) = u_k(t) \tag{1}$$

Then, a unit at the hidden layer receives input $net_{H_j}(t)$, the sum of output signals from the input layer and signals from the hidden layer one time step ago through recurrent connections, and calculates its activation value $H_j(t)$ as follows:

$$net_{H_j}(t) = \sum_{k=1}^{m} a_{jk} u_k(t) + \sum_{l=1}^{r} b_{jl} H_l(t-1) \tag{2}$$

$$H_j(t) = f_H(net_{H_j}(t)) \tag{3}$$

A unit at the output layer receives output from hidden layer as input $net_{O_i}(t)$, and calculates its activation value as output $x_i(t)$ of the entire N.N.:

$$net_{O_i}(t) = \sum_{j=1}^{r} c_{ij} H_j(t) \tag{4}$$

$$x_i(t) = O_i(t) = f_O(net_{O_i}(t)) \tag{5}$$

In this way, by dividing units based on the layer and calculating activation values of units at each layer synchronously, the input-output relation of the entire N.N. can be obtained as:

$$x_i(t) = f_O\left(\sum_{j=1}^{r} c_{ij} f_H\left(\sum_{k=1}^{m} a_{jk} u_k(t) + \sum_{l=1}^{r} b_{jl} H_l(t-1)\right)\right) \tag{6}$$

2.3 Learning Algorithm for N.N. with Mixed Structure

In considering a learning algorithm for any N.N., it is necessary to obtain the gradient of an error criterion with respect to its connection coefficients. For this purpose, two types of algorithms are considered.

As demonstrated by Rumelhart et al[1], for a general recurrent N.N. such as a N.N. with feedback loops, there is a feedforward multilayer N.N. with identical behavior over a finite period of time. Thus, the equivalent multilayer N.N., which is transformed from a N.N. with a mixed structure, can learn the system dynamics over a finite period of time by Back Propagation algorithm to give the gradient of the error criterion. This method is effective if plant dynamics over a finite period of time or some input-output data are available, which can be considered suitable as an off-line learning algorithm.

For the direct solving method using the derivative of a composite function, other than a similar calculation method to Back Propagation method, the use of simultaneous equations of derivatives of input value with respect to connection coefficients can give the gradient of the error criterion with respect to connection coefficient. Here, the derivatives of input with respect to a connection coefficient are defined as:

$$B_{ipq}(t) = \frac{\partial net_{H_i}(t)}{\partial b_{pq}},\ A_{ipq}(t) = \frac{\partial net_{H_i}(t)}{\partial a_{pq}} \tag{7}$$

Using the similar error signals to a feedforward multilayer N.N. defined as:

$$\hat{\delta}_{O_j}(t) = f_O{}'(net_{O_j}(t))\frac{\partial E_r(t)}{\partial x_j(t)} \tag{8}$$

$$\hat{\delta}_{H_j}(t) = f_H{}'(net_{H_j}(t))\sum_{i=1}^{n}\hat{\delta}_{O_i}(t)c_{ij} \tag{9}$$

the gradient is calculated as:

$$\frac{\partial E_r(t)}{\partial c_{pq}} = \hat{\delta}_{O_p}(t)H_q(t) \tag{10}$$

$$\frac{\partial E_r(t)}{\partial b_{pq}} = \sum_{j=1}^{r}\hat{\delta}_{H_j}(t)B_{jpq}(t) \tag{11}$$

$$\frac{\partial E_r(t)}{\partial a_{pq}} = \sum_{j=1}^{r}\hat{\delta}_{H_j}(t)A_{jpq}(t) \tag{12}$$

and, simultaneous equations are given as:

$$\begin{aligned} B_{jpq}(t) &= H_q(t-1)\delta_{pj} \\ &+ \sum_{l=1}^{r} b_{jl} f_H{}'(net_{Hl}(t-1))B_{lpq}(t-1) \end{aligned} \tag{13}$$

$$\begin{aligned} A_{jpq}(t) &= \hat{u}_q(t-1)\delta_{pj} \\ &+ \sum_{l=1}^{r} b_{jl} f_H{}'(net_{Hl}(t-1))A_{lpq}(t-1) \end{aligned} \tag{14}$$

This calculation method is called Simultaneous Error Back Propagation Method[4], which can be considered as one of the most powerful methods as a calculation algorithm of gradient for an off-line learning.

3. Learning of Plant Dynamics Using N.N. with Mixed Structure

3.1 Plant Identification

When some control system should be installed in a plant, the designer must understand the plant dynamics to make a mathematical model. This action to learn the plant dynamics is called "identification of plant". Firstly, by investigating plant components and its environments, a mathematical model of the plant is constructed. However, the plant model can be rarely constructed only through this process. If the plant model cannot be constructed, the designer must estimate a mathematical model based on the input-output data of the plant. To construct a mathematical model from the input-output data, some assumptions are usually necessary.

For example, the linearity of the plant dynamics is among most common assumptions, which assumes that the input-output relation of a plant can be represented in terms of linear differential equations or linear algebraic equations. If the range of variations in an input-output relation is narrow, the plant often shows the linear performance. But, many plants have nonlinear plant dynamics, and show nonlinear performance for a wide range of variations in their input-output relation. Therefore, the use of a mathematical model under the linear assumption often causes a problem.

On the other hand, the plant order is often assumed. That is, it is assumed that the plant is governed by some specific order of differential equations, or the plant output at the present time is affected by the input and output over a certain period of time. This assumption causes a serious problem, because such an assumption is based on the experience and subjective judgment of the designer.

3.2 Application of N.N. to Plant Identification

N.N.'s can learn the nonlinear plant dynamics. Using this property, many studies have been done on the identification of nonlinear plant dynamics, in other words, making N.N.'s learn the nonlinear plant dynamics. Using a N.N. as a plant model, the linear assumption in the identification can be removed. However, since feedforward multilayer N.N.'s with their established learning algorithm have been used, the learning method as shown in Fig. 1 must be applied for the plant identification. But, on the other hand, using a N.N. with a mixed structure, the plant dynamics can be learned simply as a temporary relation between input and output data without feedback of plant output data. Thus, the assumption of plant order in the plant identification can be removed.

3.3 Example of Learning Plant Dynamics

As an example of nonlinear plant, consider a hypothetical second order nonlinear vibration system obtained from Rayleigh equation representing a typical nonlinear vibration system.

[Plant A]

$$\begin{aligned} \ddot{x}_1 + 2.5\dot{x}_1 - \dot{x}_2 + 0.3\dot{x}_1^3 + 0.8x_1 - 0.3x_2 &= 0 \\ \ddot{x}_2 - \tfrac{2}{3}\dot{x}_1 + \tfrac{2}{3}\dot{x}_2 + 0.2\dot{x}_2^3 - 0.2x_1 + \tfrac{8}{15}x_2 &= u \end{aligned} \quad (15)$$

This system is asymptotically stable at steady point($x_1 = x_2 = 0$)[(1)]. Further, since a N.N. with a mixed structure represents a discrete system, the subject system is transformed into a discrete system with sampling time equal to 0.1.

Since plant A has 1 input variable and 2 output variables, a N.N. with a mixed structure used in this example has 1 input unit, 2 output units, and 15 units at its hidden layer. As the learning method, the off-line learning with 500 sampled data is applied with BFGS(Broyden-Fletcher-Goldfarb-Shanno) method [5] as a gradient method. Using input time series $\{u(0), \cdots, u(500)\}$ and output time series $\{x_1(0), \cdots, x_1(500)\}$ & $\{x_2(0), \cdots, x_2(500)\}$, the error function is defined as:

$$E = \sum_{t=0}^{500} \left\{ (x_1(t) - \tilde{x}_1(t))^2 + (x_2(t) - \tilde{x}_2(t))^2 \right\}$$

Using BFGS method, the error function is to be decreased so that its value is less than sufficiently small specific value ε. This procedure is called one batch of off-line learning in this paper. The off-line learning is applied, because quasi Newton method or method of conjugate gradients does not work well in on-line learning. Input signals for learning is random step signal as shown in **Fig. 3**. **Figure 4** shows how the error function decreases as the off-line learning proceeds.

Let N.N.1 denote a N.N. which learns off-line once with $\varepsilon = 0.001$ using 500 sampled data, and let N.N.2 denote a N.N. which learns off-line twice. To investigate how well these N.N.'s learn the plant dynamics, examine the frequency response for each N.N.. **Figure 5** shows the frequency responses of x_1 of the plant, N.N.1 and N.N.2 to a sine wave input signal with amplitude = 0.3. From Fig. 5, it is clear that the difference between the plant and N.N.'s appears more clearly in high-frequency area rather than low-frequency area. And, naturally, N.N.2 is more consistent with the plant response than N.N.1. Thus, when a N.N. with a mixed structure learn a plant dynamics, the input-output responses in low-frequency area are easier to learn, while those in high-frequency area are more time-consuming. Thus, it is shown to be useful to use high-frequency response as the criterion to evaluate the process of learning.

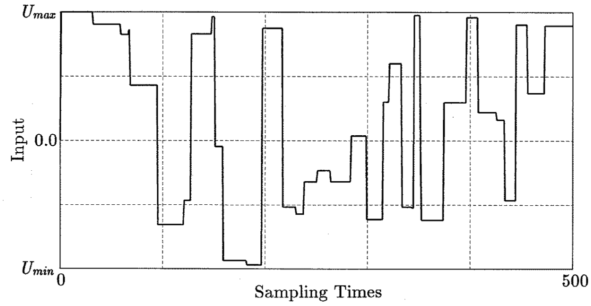

Fig. 3 Random rectangle wave used in learning of plant dynamics

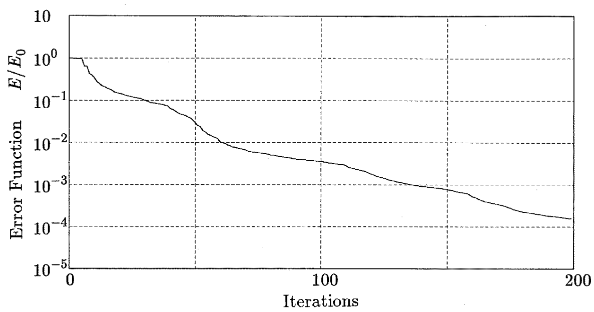

Fig. 4 Convergence properties of error function

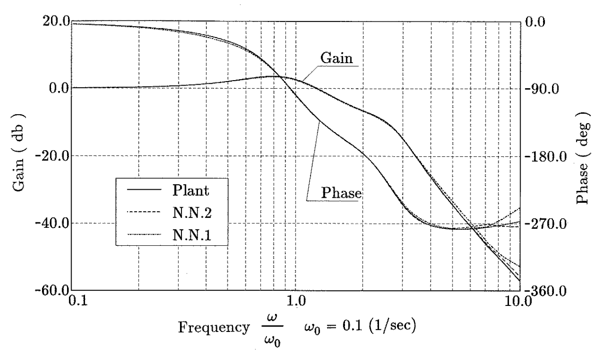

Fig. 5 Frequency response of N.N.1, N.N.2, and plant for 0.3 sin ωt

(1) Transforming Eq. (15) into a vector differential equation such as $\frac{dx}{dt} = Ax + f(x)$ where the first term denotes a linear part and the second term denotes a nonlinear part, the real part of any eigenvalue of A is negative and $\|f(x)\| \to 0$ when $\|x\| \to 0$. Thus, point $x = 0$ is stable.

4. Determination of Optimal Control Input

4.1 Optimal Control Problem

It is proven that using the N.N. with a mixed structure that has learned a plant dynamics, the optimal control problem for the plant can be solved. Generally, the optimal control of a nonlinear plant can be solved as follows.
1. Construct a mathematical model of a plant.
2. For the mathematical model obtained at the previous step, formulate an optimal control problem and solve it using the calculus of variation or differential dynamic programming method.
3. Control the plant using the optimal control input obtained.

For the plant whose mathematical model is exact, the application of such a optimal control procedure causes no problem. However, if a mathematical model is constructed under an uncertain condition, this method will cause a severe problem. Generally, the exactness of a mathematical model plays an important role as the control becomes complex. In this sense, the optimal control requires a high accuracy of the mathematical model.

4.2 Problem Formulation

Consider the optimal control problem of a plant represented by the following difference equations:

[Problem *]

Assume that the plant to be controlled is represented by:

$$\vec{x}(0) = \vec{x}_0$$
$$\vec{x}(t) = \vec{f}(\vec{u}(t), \vec{x}(t-1), \vec{x}(t-2), \cdots) \quad \text{for } t = 1, \cdots, T \tag{16}$$

Let the criterion functional represented as follows in terms of $\vec{x}(t)$ and $\vec{u}(t)$:

$$E = E\left(\vec{x}(t), \vec{u}(t)\right) \tag{17}$$

Obtain the optimal time series of control inputs that minimize E:

$$\vec{u}_{opt}(t) \quad t = 1, \cdots, T \tag{18}$$

Here, the different point from the conventional optimal control problem is that the difference equation, Eq. (16), representing the plant dynamics is unknown. Instead, a N.N. with a mixed structure which has learned the plant dynamics is given.

4.3 Expansion of N.N. with Mixed Structure into Equivalent Feedforward Multilayer N.N.

Before solving the optimal control problem, consider a feedforward multilayer N.N. as shown in **Fig. 6**. This N.N. is a N.N. obtained by the same type of multilayer expansion from time 0 to time T, where input units at the input layer are connected to a uniform input source by weights $\vec{u}(1), \cdots, \vec{u}(T)$, sequentially. The outputs at the output layer of the N.N. in Fig. 6 are proven to be equal to time series of outputs $\vec{x}(0), \cdots, \vec{x}(T)$ given time series of input $\vec{u}(1), \cdots, \vec{u}(T)$.

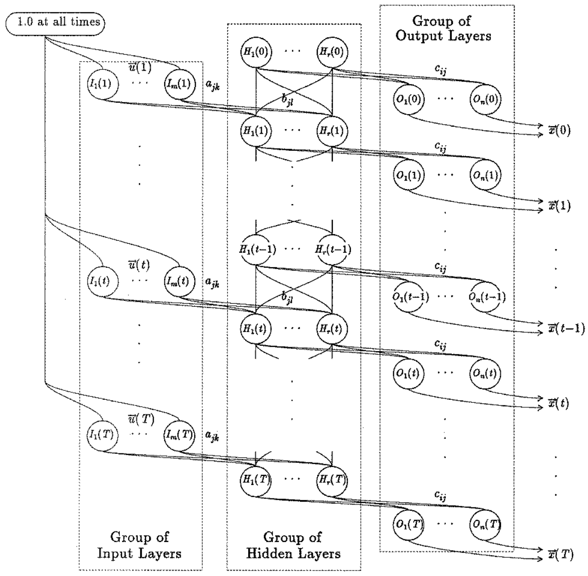

Fig. 6 Equivalent multilayer N.N. representation of N.N. with mixed structure

4.4 Determination Method of Optimal Control Input

Using the feedforward multilayer N.N. in Fig. 6, the solution of [Problem *], that is, the optimal control input can be obtained.

Error Back Propagation method can be considered as the algorithm to obtain the gradient of the error criterion with respect to weights so that the error criterion can be minimized. Though error functional E is usually set as the sum of square errors, any form of function for E can be assumed if E is a function of output $x_i(t)$. Now, assume that for a general feedforward multilayer N.N., units at its output layer receive the following signal as the error back propagation signal:

$$\delta_{O_i}(t) = f'_O\left(net_{O_i}(t)\right) \frac{\partial E\left(\vec{x}(\tau)\right)}{\partial x_i(t)} \tag{19}$$

In Back Propagation method, let δ_i denote an error signal feeded back to unit i of the hidden layer, and let a_j denote active value (or output) of unit j which sends signal to unit i through a connection with weight w_{ij}. Then, the derivative of error function $E(\vec{x}(\tau))$ with respect to weight w_{ij} is represented as:

$$\frac{\partial E\left(\vec{x}(\tau)\right)}{\partial w_{ij}} = \delta_i a_j \tag{20}$$

Here, the error function is allowed to have weights explicitly in its form. For example, consider the following error function:

$$E = E\left(\vec{x}(\tau), w_{ij}\right) \tag{21}$$

In this case, according to the formula for the derivative of a composite function, the following equation holds.

$$\frac{\partial E\left(\vec{x}(\tau), w_{ij}\right)}{\partial w_{ij}} = \frac{\partial E}{\partial w_{ij}}\left(\vec{x}(\tau), w_{ij}\right) + \sum_i \frac{\partial E}{\partial x_i(t)}\frac{\partial x_i(t)}{\partial w_{ij}} \tag{22}$$

The first term in the right hand side of Eq. (22) shows the partial derivative of error criterion E with respect to $w_i j$ which is explicitly included in E, and can be obtained easily. When an error back propagation signal to a unit at the output layer is given as:

$$\delta_{O_i}(t) = f'_O\left(net_{O_i}(t)\right)\frac{\partial E\left(\vec{x}(\tau), w_{ij}\right)}{\partial x_i(t)} \tag{23}$$

the second term can be obtained as follows using error signal δ_i given by Error Back Propagation method:

$$\sum_i \frac{\partial E}{\partial x_i(t)}\frac{\partial x_i(t)}{\partial w_{ij}} = \delta_i a_j \tag{24}$$

Thus, the derivative of error function with respect to weights represented by Eq. (22) can be obtained.

In the N.N. of Fig. 6, $\vec{u}(t)$ is set as weights to input layer. Thus, the error criterion functional in [Problme *] can be represented in terms of weights and outputs of the N.N. in Fig. 6. Therefore, using the result obtained above, the derivative of criterion functional with respect to $u_p(\tau)$ is given as:

$$\frac{\partial E}{\partial u_p(\tau)} = \frac{\partial E}{\partial u_p(\tau)}\left(\vec{u}(\tau), \vec{x}(t)\right) + \sum_{t=0}^{T}\sum_{i=1}^{n}\frac{\partial E}{\partial x_i(t)}\frac{\partial x_i(t)}{\partial u_p(\tau)} \tag{25}$$

Let $\hat{\delta}_{lp}(\tau)$ denote the error signals obtained at the input layer by Back Propagation method when the following error signals $\hat{\delta}_{O_i}(t)$ is given at the output layer of the N.N. in Fig. 6:

$$\hat{\delta}_{O_i}(t) = \frac{\partial E}{\partial x_i(t)} f'_O\left(net_{O_i}(t)\right) \tag{26}$$

Using error signal $\hat{\delta}_{lp}(\tau)$, the second term of Eq. (25) reduces to:

$$\sum_{t=0}^{T}\sum_{i=1}^{n}\frac{\partial E}{\partial x_i(t)}\frac{\partial x_i(t)}{\partial u_p(\tau)} = \hat{\delta}_{lp}(\tau) \tag{27}$$

Thus, the derivative is given by:

$$\frac{\partial E}{\partial u_p(\tau)} = \frac{\partial E}{\partial u_p(\tau)}\left(\vec{u}(\tau), \vec{x}(t)\right) + \hat{\delta}_{lp}(\tau) \tag{28}$$

This equation shows that for any form of criterion functional, its derivatives with respect to parameters can be obtained through simple arithmetic calculation and Error Back Propagation method. Using the obtained derivatives, the input signal that minimizes the criterion functional can be obtained. That is, the optimal control problem can be solved for a general criterion functional given by `[Problem *]`.

4.5 Calculation Example

Using N.N.1 and N.N.2 obtained in Section 3 that have learned the dynamics of plant A, the solution obtained for the optimal control problem is shown below. The optimal control input is obtained for the case where the initial state is given as:

$$\begin{array}{ll} x_1(0) = 0.4 & x_2(0) = 1.0 \\ \dot{x}_1(0) = 0.0 & \dot{x}_2 = 0.0 \end{array} \tag{29}$$

and the criterion functional is given as:

$$\begin{aligned} &E(\vec{x}_1(t), \vec{x}_2(t), \vec{u}(t)) \\ &= \sum_{\tau=0}^{100}\{x_1(\tau)^2 + x_2(\tau)^2 + 0.2u(\tau)^2\} \\ &+100.0(x_1(100)^2 + x_2(100)^2) \end{aligned} \tag{30}$$

If eq. (15) representing the plant dynamics is given, the optimal control input can be obtained using differential dynamic programming method [6](DDP). **Figure 7** shows the optimal control inputs obtained using N.N.1, N.N.2, and DDP. It is clear from this figure that the input obtained by N.N.2 is the same as the input obtained by DDP, but the input obtained by N.N.1 has a little deviation from that obtained by DDP. The optimal value of the criterion functional for each case is obtained as: 6.70 for N.N.1, and 6.68 for N.N.2. Thus, the solution obtained by N.N.2 is better. Similarly to the solution obtained by other methods, the quality of the solution obtained by a N.N. with a mixed structure depends on the quality of the mathematical model obtained in the identification process.

BFGS method is applied as a gradient method to decrease the criterion functional. **Figure 8** shows the convergence property of the criterion functional, while **Figure 9** shows the convergence property of the corresponding control input.

5. Conclusions

By the use of N.N.'s with a mixed structure in the plant identification, assumptions on the linear property of the plant and the plant order becomes unnecessary. Further, using the N.N. with a mixed structure that has learned the

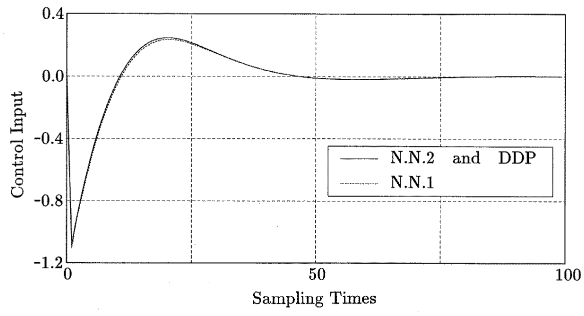

Fig. 7 Comparison of optimal control input

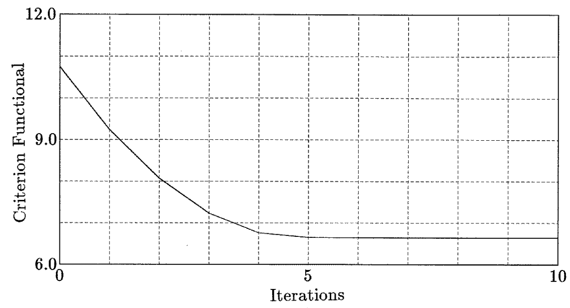

Fig. 8 Convergence property of criterion functional

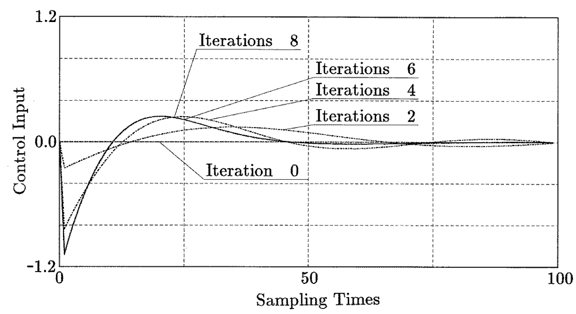

Fig. 9 Convergence property of control input

plant dynamics as the plant model, the optimal control problem can be solved. And, simulation results confirm that the proposed method can be applied to nonlinear plants, can learn the plant dynamics, and can obtain the optimal solution.

Learning of the plant dynamics thorough the conventional feedforward multilayer N.N. can obtain only a functional relation between plant input space and output space. If the functional relation between input and output is stored as a teaching signal, the learned N.N. is essentially equivalent to the functional representation of the entire function by interpolation of outputs corresponding to representative inputs in the input space. However, using a N.N. with a mixed structure in learning the plant dynamics, not only the input and output relation, but also its relation in the time domain can be obtained. The internal mechanism of a N.N. with a mixed structure can interpret and learn the relation in the time space. That is, only the input-output relation given as a teaching signal is sufficient for a N.N. with a mixed structure to learn its temporary relation.

Making a N.N. learn a temporary relation is essential for the control requiring the time concept. And, the use of N.N. with mixed structure could make it relatively easy to obtain the optimal control input which was considered difficult for the conventional N.N..

As points to be considered further in the proposed method, the following problems exist. Firstly, more computation is necessary compared with the conventional multilayer N.N., because the structure of a N.N. with a mixed structure is more complex. Secondly, a plant still exist whose dynamics N.N.'s with a mixed structure cannot learn. For a N.N. with a mixed structure to learn any plant dynamics, introduction of units which can calculate the sum of products may be necessary. However, this introduction will make the structure of a N.N. more complex, and also make it difficult to verify its effectiveness in using computers of Von Neumann type.

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