An application of a neural network to adaptive control of a servo system

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ABSTRACT
A neural network was applied to adaptive control of a servo system. The neural network was used to learn inverse dynamics of a controlled system. Experimental works were done using an electro-hydraulic servo motor with a digital signal processor. Two types of neural networks were tested. Simulation studies were done to investigate effects of ordering of training data, choice of input signals fed to a neural network, and number of neurons in a hidden layer.

KEYWORDS
Neural network, Adaptive control, Servo system, Inverse dynamics

NOMENCLATURE

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>δ</td>
<td>learning rate</td>
</tr>
<tr>
<td>ε</td>
<td>learning rate</td>
</tr>
<tr>
<td>ω</td>
<td>rotating speed</td>
</tr>
<tr>
<td>ωd</td>
<td>desired rotating speed</td>
</tr>
</tbody>
</table>

INTRODUCTION

Many investigations have been done on applications of neural networks to system control [1][5]. This
paper deals with an application of neural networks as an adaptive controller for an electro-hydraulic servo system. In such applications, to learn inverse dynamics of a controlled system, neural networks are constructed with many neurons, a hidden layer, and a sigmoid function. It is not easy to investigate the performance due to the complex network. A simplified neural network provides another good place to start investigations of the performance. In this paper, attention is focused on a simplified neural network which is used as an adaptive controller. First, experimental works were done using a simplified neural network. Neither hidden layer nor sigmoid function was included. Secondary, slightly complicated neural networks with more neurons, a hidden layer, and a sigmoid function were examined through simulation works.

EXPERIMENTAL WORKS WITH A SIMPLIFIED NEURAL NETWORK

**Servo System**

FIGURE 1 shows an electro-hydraulic servo system with a neural network. The purpose of this servo system was to control rotating speed of an inertial load. Specification of the system is listed in TABLE 1.

**TABLE 1** Specification of the system

<table>
<thead>
<tr>
<th>Component</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Servo Valve</strong></td>
<td></td>
</tr>
<tr>
<td>flow rate</td>
<td>0.000317 m³/s</td>
</tr>
<tr>
<td>(pressure drop)</td>
<td>6.8 MPa</td>
</tr>
<tr>
<td>current</td>
<td>40.0 mA</td>
</tr>
<tr>
<td>time constant</td>
<td>3.0 ms</td>
</tr>
<tr>
<td><strong>Servo motor</strong></td>
<td></td>
</tr>
<tr>
<td>displacement</td>
<td>1.64x10⁻⁶ m³/rad</td>
</tr>
<tr>
<td>maximum speed</td>
<td>2000 rpm</td>
</tr>
<tr>
<td>Load: inertia</td>
<td>8.2x10⁻³ kgm</td>
</tr>
<tr>
<td><strong>Rotary Pulse Encoder</strong></td>
<td>500 pulses</td>
</tr>
<tr>
<td><strong>Amplifier</strong></td>
<td>4.5 mA/V</td>
</tr>
<tr>
<td><strong>DSP</strong></td>
<td>AT&amp;T DSP32C</td>
</tr>
<tr>
<td><strong>Supply pressure</strong></td>
<td>6.86 MPa</td>
</tr>
</tbody>
</table>

![Figure 1 Servo system](image_url)
Simplified Neural Network
Neglecting oil compressibility and servo valve dynamics, a transfer function from the input voltage $u$ to rotating speed $\omega$ is roughly approximated by a first order lag element in discrete-time domain.

$$u(k) = W_1(k)\omega(k+1) + W_2(k)\omega(k)$$ \hspace{1cm} (1)

Here parameters $W_1$ and $W_2$ are assumed to be unknown. These values are estimated through training. If the training is finished, using a demand signal $\omega_d(k+1)$ instead of $\omega(k+1)$, an input $u(k)$ is obtained from eq. (1) so that output $\omega(k+1)$ is equal to $\omega_d(k+1)$. Training is done according to back propagation:

$$\begin{cases} W_1(k+1) = W_1(k) + \varepsilon \delta \omega_d(k+1) \\ W_2(k+1) = W_2(k) + \varepsilon \delta \omega(k) \end{cases}$$ \hspace{1cm} (2)

where

$$\delta = u(k) - v(k)$$ \hspace{1cm} (3)

$u$ is control input for control.
$v$ is control input which is a result of training.

The network has 2 neurons in an input layer and a neuron in an output layer. To investigate fundamental characteristics of the neural network, neither hidden layer nor sigmoid function is used. In this paper, the simplified neural network is referred to as a first order type neural network.

For a short sampling period, servo valve dynamics can not be neglected. Approximating servo valve dynamics as a first order lag element, the transfer function is written by a second order lag element [6].

$$u(k) = W_1(k)\omega(k+1) + W_2(k)\omega(k) + W_3(k)\omega(k-1) + W_4(k)u(k-1)$$ \hspace{1cm} (4)

These weights are updated by:

$$\begin{cases} W_1(k+1) = W_1(k) + \varepsilon \delta \omega_d(k+1) \\ W_2(k+1) = W_2(k) + \varepsilon \delta \omega(k) \\ W_3(k+1) = W_3(k) + \varepsilon \delta \omega(k-1) \\ W_4(k+1) = W_4(k) + \varepsilon \delta u(k-1) \end{cases}$$ \hspace{1cm} (5)

The network is referred as a second order type neural network.

A reference model was a first order lag element which was discretized using a corresponding sampling period.

$$\frac{\omega_d(s)}{R(s)} = \frac{1650.0}{s+14.27}$$ \hspace{1cm} (6)

Experimental Results
FIGURE 2 shows examples of experimental results. The sampling period was 10 ms. A first order type neural network was used. Learning rate $\varepsilon$ was $10^{-4}$ and number of repeated training within a sampling period $n$ was 1 in the top of FIGURE 2. Sinusoidal wave was used as an input signal.
After the first cycle, the neural network was well trained. Rotating speed $\omega$ followed demand signal $\omega_D$. With more training within a sampling period as shown in the middle of FIGURE 2, transient responses were improved. Increase in learning rate had the same effect shown in the bottom of FIGURE 2.

FIGURE 3 shows an example of experimental results using a second order type neural network with a sampling period of 5 ms. The rotating speed $\omega$ successfully followed a demand signal $\omega_D$.

Both simplified neural networks were successfully applied to an adaptive control of an electro-hydraulic servo system. It has been shown that learning rate and number of repeated training had an influence on the performance.

**SIMULATION STUDY OF A MORE COMPLICATED NEURAL NETWORK**

**Complicated Neural Network**

In this section, a more complicated neural network is examined. Linear threshold model was used. The neural network examined had a hidden layer. The input layer had 2 neuron units and the output layer had a neuron unit. The hidden layer had 10 neuron units. Sinusoidal input signals and rotating speeds of the servo system were sampled. These data were used for training.

**Training Data Ordering**

Training performance of the neural network was examined. FIGURE 4 shows the results for comparison of sequential ordering and random...
ordering. The sequential ordering did not show good performance. In the case of random ordering, output error rapidly converged to zero.

Input Signals
From eq.(1), another equation is obtained.

\[ u(k) = W_1 \omega(k) (\omega(k+1) - \omega(k)) + W_2 \omega(k) \]

(7)

The first member of the left hand side is a differential term of rotating speed. A differential term \( \omega(k+1) - \omega(k) \) and \( \omega(k) \) are fed to a neural network for training. FIGURE 5 shows training performance of an ordinary input which is described above and a differential input described in this section. Sum of squared error of a weight is plotted. There is clear difference between an ordinary input and a differential input. The differential input activated the training. This results encouraged us to use a delta operator.

Hidden Layer
Performance of an adaptive control system was examined. FIGURE 6 shows an example of simulated results. In that instant pointed by arrows, plant parameters were changed. With 10 neurons in a hidden layer, the neural network worked well as an adaptive controller. With 3 neurons, it did not work enough.
CONCLUSIONS

A simplified neural network was examined to investigate fundamental performance of a neural network which was applied to adaptive control of an electro-hydraulic servo system. Through experimental works, both a first order type neural network and a second order type neural network has been proved to work as an adaptive controller. With larger learning rate and more training within a sampling period, the controlled performance was improved. A more complicated neural network was examined through simulation works. Random ordering and differential input improved training performance. With more neurons in a hidden layer, performance of the adaptive control system was improved.

REFERENCES


ACKNOWLEDGEMENTS

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