Self-tuning PD Control of a Flexible Concrete Distributor Arm

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Self-tuning PD Control of a Flexible Concrete Distributor Arm

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This paper is concerned with a vibration suppression of a flexible concrete distributor arm. The distributor arm is characterized as a highly nonlinear system, and then a neural network is applied to synthesize a self-tuning PD controller. The neural network automatically tunes gains of the PD controller to reduce the vibration level. Emulators with neural networks are constructed in place of a conventional numerical model. Effectiveness of the proposed method is demonstrated through numerical simulations.

1. Introduction

Recently, a concrete distributor arm is widely used in construction sites. The distributor which transfers wet concrete with its pump has an arm as long as 30 meters and a pipe along its arm. It also has a multiple joint structure to adapt it to various spots. Figure 1 shows a concrete distributor system.

The arm has a low stiffness. Its natural frequency is 0.3∼0.5 Hz, and thus it is excited by a force caused by a movement of the pump. Vibration levels are very high due to resonance, which deteriorates a working condition. Thus it is important to improve vibration characteristic of the arm from the view point of safety and performance of the construction work, the strength of the arm, and so on. Some studies have been done on the subject[1], [2].

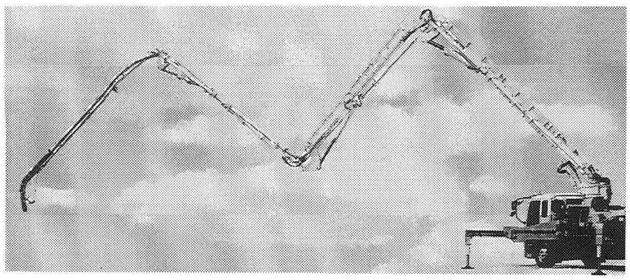

Fig. 1 Concrete distributor arm

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There are some problems associated with the distributor arm. At first, the dynamic characteristic of the system will be changed due to change in its posture. Second, the loss of oil pressure in the pumping system and Coulomb friction existing at its joints make it difficult to build a numerical model because of its nonlinearity. In this study, a neural network is adopted to synthesize a model and a controller of the nonlinear system. Successful results have been reported on various systems[3]−[8], and it is expected that the controller is robust to uncertainties of the system. A self-tuning PD controller is constructed, which automatically determines the control gains to reduce the vibration level. The back propagation algorithm[3], [4] is applied to learning the neural network. It requires a relation between inputs and outputs of the nominal plant. For the purpose, emulators are constructed by using neural networks. They can calculate the same outputs as those of the nominal plant when the inputs are given, and they can also model nonlinearity in the distributor system. Two emulators are constructed in this study. One gives the relation between a movement of the pump and the state of the tip of the arm, while the other gives the relation between the control torque and the state of the tip of the arm.

2. Self-tuning PD Controller

A PD controller is constructed which can automatically tunes feedback gains as shown in Fig. 2. A neural network determines the gains of PD controller so as to minimize a reference function which is

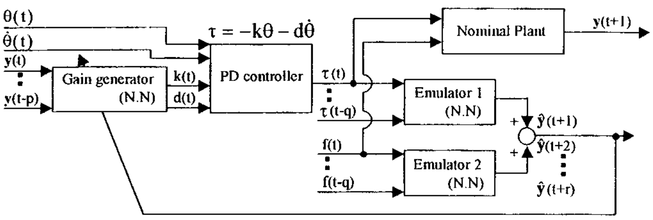


Fig. 2 Control system

given by

$$E=\frac{1}{2}\sum_{r}\hat{y}^{2}(t+r) \tag{1}$$

where $\hat{y}(t+r)$'s are the outputs of the emulators. Connection weights are changed at the output layer by using the steepest descent method[3],[4]:

$$\Delta w_{kj}=-\eta\frac{\partial E}{\partial w_{kj}} \tag{2}$$

Let us introduce the generalized error signal δ_k given by

$$\delta_k\equiv-\frac{\partial E}{\partial net_k} \tag{3}$$

$$net_k=\sum_{j} w_{kj}O_j+\theta_k \tag{4}$$

Hence

$$-\frac{\partial E}{\partial w_{kj}}=-\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial w_{kj}}=\delta_k O_j \tag{5}$$

Using the chain rule yields

$$\delta_k=-\frac{\delta E}{\partial net_k}$$
$$=-\sum_{r}\left\{\frac{\delta E}{\partial e(t+\tau)}\frac{\partial e(t+\tau)}{\partial u(t)}\right.$$
$$\left.\cdot\frac{\partial u(t)}{\partial o_k}\frac{\partial O_k}{\partial net_k}\right\} \tag{6}$$

Then

$$\frac{\partial E}{\partial e(t+\tau)}=e(t+\tau) \tag{7}$$

$$\frac{\partial O_k}{\partial net_k}=f'(net_k)=1 \tag{8}$$

$$\frac{\partial u(t)}{\partial O_k}=\begin{cases}-\theta(t);\ k=1\\-\dot{\theta}(t);\ k=2\end{cases} \tag{9}$$

Thus, the adjusting rule of the connection weights at the output layer is given by

$$\Delta w_{kj}=-\eta\,\delta_k O_j \tag{10}$$

$$\delta_k=-\sum_{\tau}\left\{e(t+\tau)\frac{\partial y(t+\tau)}{\partial u(t)}\right.$$
$$\left.\cdot\frac{\partial u(t)}{\partial O_k}\right\} \tag{11}$$

Using the steepest descent method at the hidden layer yields

$$\Delta w_{ji}=-\eta\frac{\partial E}{\partial w_{ji}} \tag{12}$$

$$-\frac{\partial E}{\partial w_{ji}}=-\frac{\partial E}{\partial net_j}\frac{\partial net_j}{\partial w_{ji}} \tag{13}$$

Then

$$net_j=\sum_{i} w_{ji}O_i+\theta_j \tag{14}$$

and hence

$$\delta_j\equiv-\frac{\partial E}{\partial net_j}$$
$$=-\sum_{k}\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial O_j}\frac{\partial O_j}{\partial net_j}$$
$$=\sum_{k}\delta_k w_{kj}f'(net_j)$$
$$=\sum_{k}\delta_k w_{kj}(1+O_j)(1-O_j) \tag{15}$$

Thus, the adjusting rule of the connection weights at the hidden layer is given by

$$\Delta w_{ji}=\eta\,\delta_j O_i \tag{16}$$

$$\delta_j=\sum_{k}\delta_k w_{kj}(1+O_j)(1-O_j) \tag{17}$$

It is noted that $\partial y(t+i)/\partial u(t)$ need to be determined for calculating δ_k. It is evaluated by using emulators with neural networks, where the emulators are treated as the nominal plant.

3. Emulator

An emulator is a neural network which gives the same outputs as those of the nominal plant. Two types of emulators are constructed. One gives position and velocity at the tip of the arm when a control torque is given at the first joint. The other gives position and velocity at the tip of the arm when it is excited at the tip of the arm. Vibration excitation is mainly caused by the movement of the pump which distributes wet concrete. Hence, the excitation can be estimated. Both of the emulators are constructed by using time history data as input vectors of those emulators. In order to estimate some future outputs of the nominal plant, position and velocity of the tip of the arm at the following time of 0.05, 0.2, 0.6, 1.2, and 1.9 seconds are introduced into the reference function of the learning process:

$$E=\frac{1}{2}e^t \cdot e \tag{18}$$

$$\begin{aligned} e = \{&y(t+0.05s),\ \dot{y}(t+0.05s),\\ &y(t+0.2s),\ \dot{y}(t+0.2s),\\ &y(t+0.6s),\ \dot{y}(t+0.6s),\\ &y(t+1.2s),\ \dot{y}(t+1.2s),\\ &y(t+1.9s),\ \dot{y}(t+1.9s)\}^t \end{aligned} \tag{19}$$

The accuracies of the emulators thus constructed are illustrated in Figs. 3 and 4.

4. Numerical Simulations

The concrete distributor arm is a structure in which some booms are linked by shafts of rotation, and the respective shafts are restrained from rotation by oil pressured cylinders. A test model of the arm simulating the actual system is set up as shown in Fig. 5. Some numerical simulations are carried out for the test model. Table 1 shows the specification of the test model. The excitation by the pump is generated at the tip of the arm. The vibration is suppressed by giving a torque of a self-tuning PD control to the first joint. The first joint is assumed to have a stiffness of spring constant 20 N/rad and a damping of 0.1 Ns/rad.

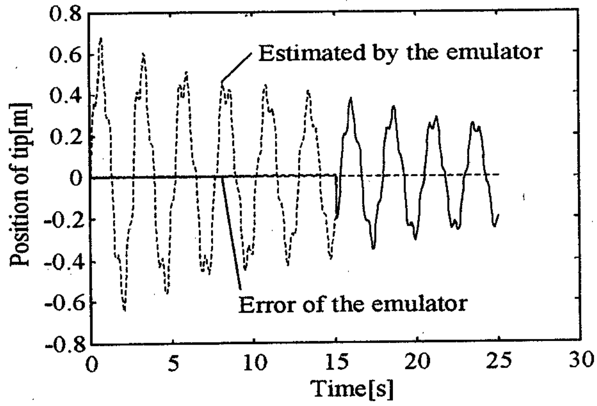


Fig. 3 Accuracy of an emulator estimating a state of the following time 0.05s

Table. 1 Specification of test model

Elem.No.	Length(m)	Mass(kg)	Moment of Inertia(kg/m²)	Area(m²)
1	0.075	1.480	1.00e-7	200e-5
2	0.360	0.483	2.85e-10	171e-6
3	0.140	0.494	1.00e-8	500e-6
4	0.360	0.343	1.045e-10	121e-6
5	0.140	0.474	1.00e-8	500e-6
6	0.375	0.262	3.80e-11	87.5e-6
7	0.375	0.144	5.40e-12	45.6e-6
8	0.070	0.136	1.045e-10	121e-6

4.1 Frequency Response

Figure 6 shows a frequency response when the self-tuning controller is used. It gives a relation between the excitation and the tip of the arm, where the tip of the arm is excited by sinusoidal forces. The optimum gains are estimated for the excitation of each frequency.

Change in the gain of the position makes the resonance frequency shift while increase in the gain of the velocity makes damping increase. These two op-

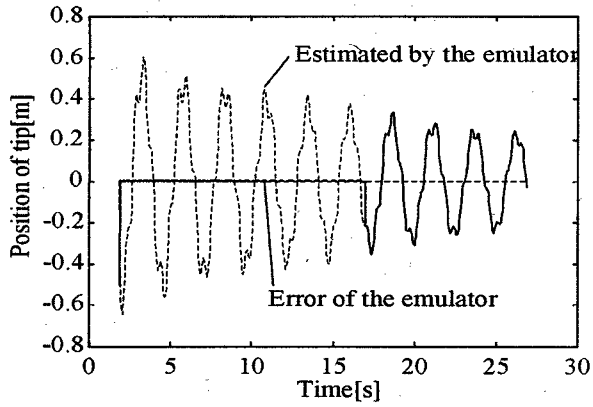


Fig. 4 Accuracy of an emulator estimating a state of the following time 1.9s

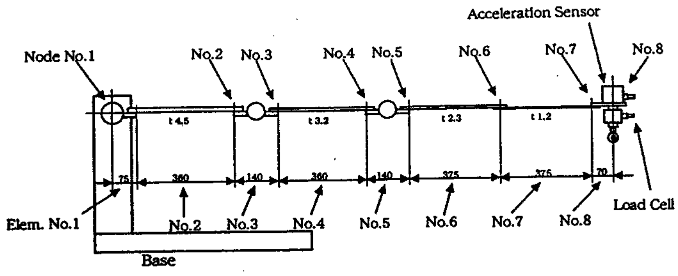


Fig. 5 Test model

erations in the neural network make the vibration be satisfactorily suppressed by the self-tuning PD controller.

Figure 7 illustrates a result when a normal PD control is applied. It is recognized that the self-tuning PD controller is better than the normal one. A resonance happens in case of the normal PD with fixed gains while no resonances occur in case of the self-tuning PD controller.

4.2 Self-tuning Capability

Some discussions are made on how the vibration is damped with the self-tuning controller when the system is subjected to various excitations. The vibrations are supressed within a few seconds for any case of simulations including a rectangular pulse excitation. Patterns of the excitation are given as follows:

1. Sin curve: frequency 0.375Hz
2. Sin curve: frequency 0.39Hz(the first frequency of resonance)
3. Sin curve: frequency 0.45Hz
4. Rectangular pulse: frequency 0.39Hz, rectangular width 1.23s

The time histories of the vibration damping are illustrated in Fig. 8

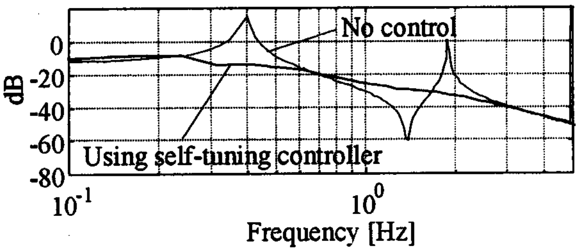
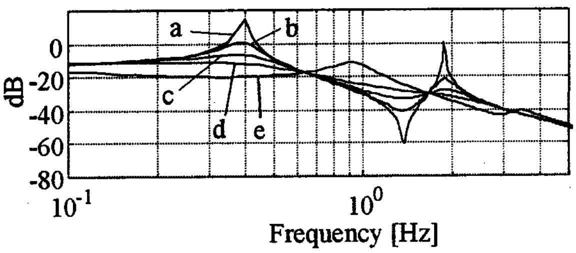


Fig. 6 Frequency response in case of self-tuning PD control



a: k=20.0N/rad, d= 0.1Ns/rad
b: k=20.0N/rad, d= 2.0Ns/rad
c: k=20.0N/rad, d= 5.0Ns/rad
d: k=20.0N/rad, d=10.0Ns/rad
e: k=20.0N/rad, d=50.0Ns/rad

Fig. 7 Frequency response in case of normal PD control

4.3 Robustness

Frequency responses using the self-tuning controller are discussed when the characteristics of the nominal plant is changed, e.g., change in the posture and some parameters. Here, the emulators don't learn the new characteristics of the changed plants. Patterns of the change in the nominal plant are given below:

1. The change in posture as in Fig. 9
2. The change in posture as in Fig. 10
3. Increase in mass of 0.1 kg at the tip of the arm

The frequency responses and change in the control gains are given in Figs. 11 through 16, respectively. It is recognized that the controller is adapted to the change of the posture, and a good performance is attained. However, it cannot be adapted so well to the change of mass at the tip, as shown in Fig. 15.

5. Conclusion

A self-tuning PD controller using the neural network has been proposed to suppress the vibrations of the concrete distributor arm. The effectiveness of the method has been demonstrated through numerical simulations. The neural networks estimate the best gain to suppress the vibration and to prevent the arm from resulting in resonance. The proposed controller can also suppress the vibration even if the characteristis of the distributor arm is changed in its posture. In short, the proposed controller has robustness.

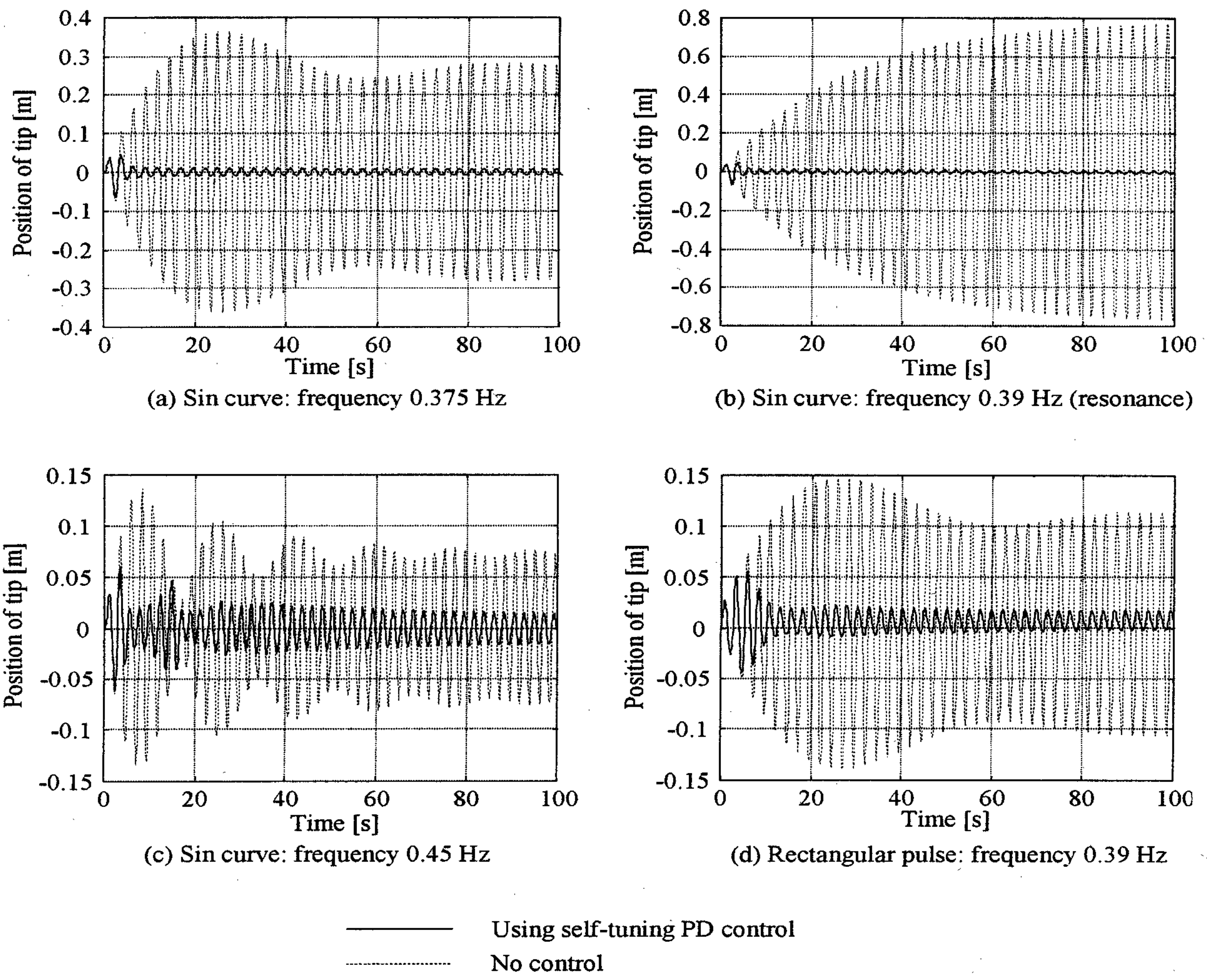


Fig. 8 Damping of the vibration for various excitations

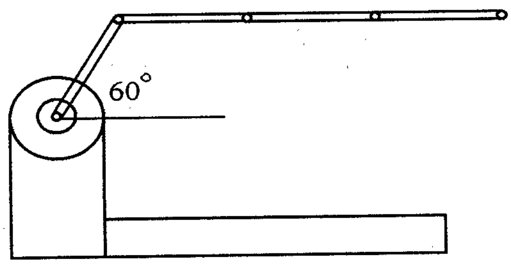


Fig. 9 Change in posture (1)

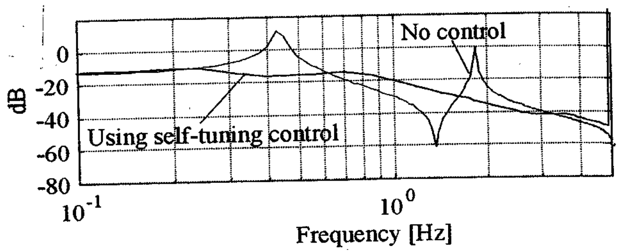


Fig. 11 Frequency response corresponding to posture change of Fig. 9

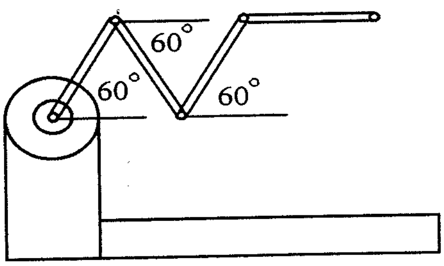


Fig. 10 Change in posture (2)

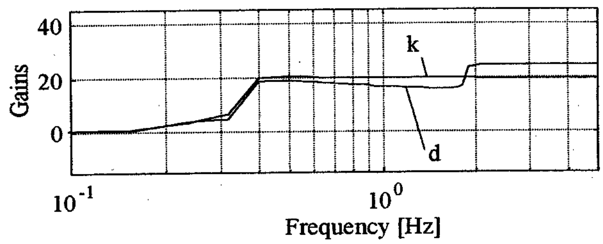


Fig. 12 Change in control gains corresponding to posture change of Fig. 9

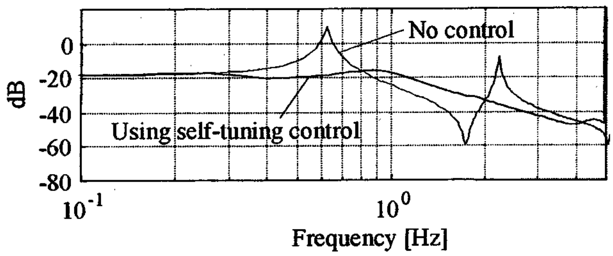


Fig. 13 Frequency response corresponding to posture change of Fig. 10

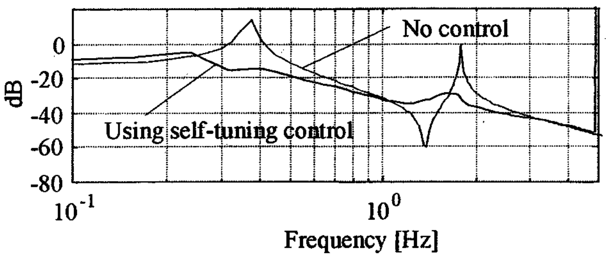


Fig. 15 Frequency response when mass at the tip is increased

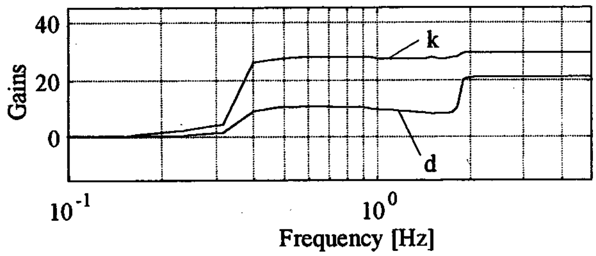


Fig. 14 Change in control gains corresponding to posture change of Fig. 10

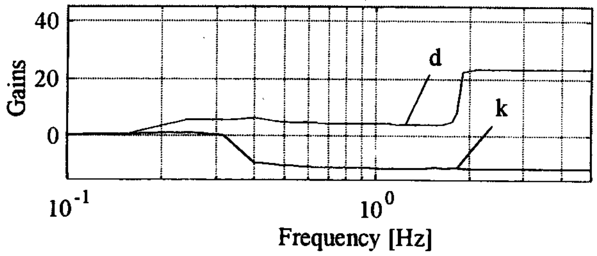


Fig. 16 Change in control gains when mass at the tip is increased

The future work is to apply the proposed method to a real plant with a highly nonlinear characteristics and to examine the effectiveness of the method.

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