Neural Network Based Smith Predictor Design for a Time Delay of a Tele-operated Control System

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Abstract: The paper presents a methodology of compensating for time-delayed effects in tele-operated control systems. Compensation can be done by neural network. The tele-operated system consists of a master robot to give commands and a slave robot to work with environment. The positional command by the master robot is transferred to the slave robot, and contact force from the environment back to the master. The structure of the Smith predictor is modified by replacing with neural network. Neural network identifies the slave model to deal with non-linearities in the system. Simulation studies have been conducted.

Keywords: Time-delayed system, Smith predictor, neural network

I. INTRODUCTION

Tele-operation control has become an important technique in robotics research. Recent robotics research focuses more on the development of unmanned systems, but robots are controlled remotely in the space. Most of tele-operated control systems are required to operate under the environment where is harmful to humans, difficult to access, and unexpected environment.

Specially, in the tele-operated robotic systems, haptic is an important terminology to be concerned. The suitable haptic operation requires that the operator feels the same force that the slave feels from the environment. The most popular application of the haptic is the tele-operated surgery. Force feedback from the slave robot has to be delivered to the master robot in a real-time fashion. For stable operation, a time-delay problem has to be solved.

It is well known that there exist time-delays in communication channels when implementing a tele-operated control system. The effect of the time-delay is critical that the tracking performance of the system is poor, even the system becomes unstable if the delay time is severe. Many researches to solve time-delay problems have been presented[1-4].

In linear systems, the time-delay effect has been solved by introducing the Smith predictor that eliminates time-delay terms in the system to make the system stable under the condition that the exact plant model and delayed time are known *a priori*.

However, in nonlinear systems, plant models cannot be exactly modeled and the even delayed time is varying so that control performance by the linear Smith predictor may be degraded. The time varying time-delay has been considered. Nonlinear uncertainties have been estimated by designing disturbance observers.

In this paper, for the nonlinear system, the nonlinear Smith predictor is designed using neural network. The neural network indentifies the slave model, and passes parameters to the master side through communication channels. Simulation results show that the neural network based Smith predictor performs better than that of the linear Smith predictor.

II. SMITH PREDICTOR

The Smith predictor has been known for a cure for the time-delayed systems. The predictor requires the slave plant model and the delayed time to cancel out the delay terms in the characteristic equation. Fig. 1 shows the control block diagram of the linear plant with a time-delay.

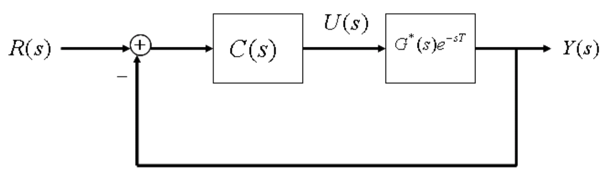


Fig. 1. Time-delayed control system

The closed loop transfer function is

$$T(s) = \frac{G^*(s)C(s)e^{-sT}}{1+G^*(s)C(s)e^{-sT}} \quad (1)$$

where $G^*(s)$ is a nominal plant and T is a delay time. Thus the system becomes easily unstable.

Fig. 2 shows the structure of the Smith predictor. The time delay is fed back to the controller input. Fig. 3 shows another structure of the Smith predictor that gives the same transfer function.

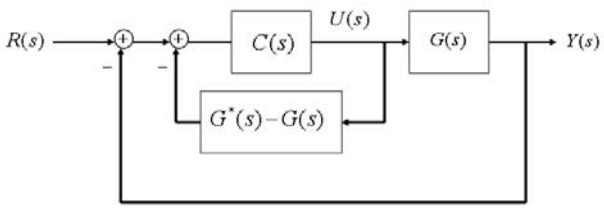


Fig. 2. Smith predictor structure I

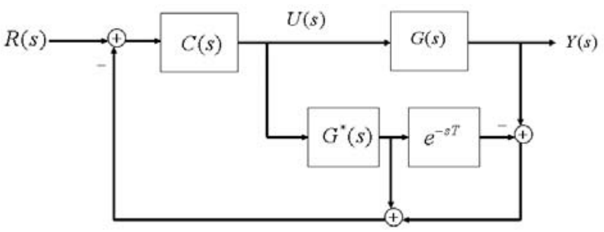


Fig. 3. Smith predictor structure II

The closed loop transfer function for Fig. 2 and 3 is given as

$$T(s) = \frac{G(s)C(s)}{1+G^*(s)C(s)} \tag{2}$$

where the plant has the delay term, $G(s) = G^*(s)e^{-sT}$. The delay term is eliminated and does not appear in the characteristic equation of (2). Thus, a time-delay effect is minimized.

III. TELEOPERATED CONTROL SYSTEM

One sided tele-operation control system has no feedback from the slave, which is a one port system. There is one time delay from the master to the slave. The master robot sends the position command to the slave robot to follow.

In a two port system, bilateral transmission is required. There is a force feedback from the slave robot so that the operator can feel the force as he/she operates the slave robot directly. There are two time delays, one from the master to the slave and the other from vice versa.

Fig. 4 shows the simple two port tele-operated control system.

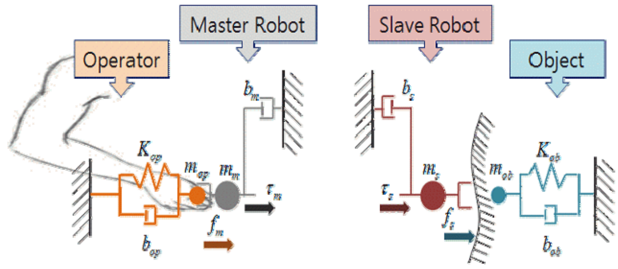


Fig. 4. Tele-operation control

The dynamics of the simple one degrees-of freedom system is given as

$$m_m\ddot{x}_m + b_m\dot{x}_m = f_m + u_m \tag{3}$$

$$m_s\ddot{x}_s + b_s\dot{x}_s = f_s - u_s \tag{4}$$

where m_m, b_m are mass and damping of the master robot, m_s, b_s are mass and damping of the slave robot, and u_m, u_s are nonlinear terms that cannot be modeled. The control block diagram can be described as Fig. 5. The desired force F_h by the operator is an input command to the master robot.

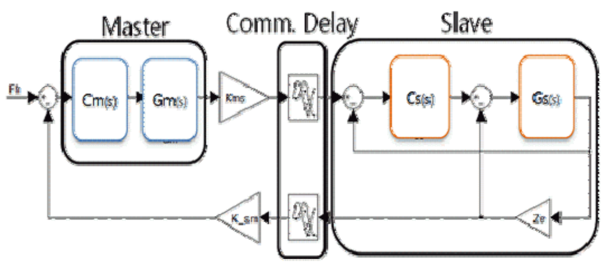


Fig. 5. Tele-operation control block diagram

The transfer function of the slave robot is

$$\frac{X_s(s)}{X_m(s)} = \frac{G_s(s)C_s(s)Z_e}{1+G_s(s)Z_e+G_s(s)C_s(s)}e^{-sT_f} \tag{5}$$

where T_f is the time delay from the master to the slave and Z_e is the impedance of the environment . Let us denote the slave transfer function as

$$\hat{G}_s(s) = \frac{G_s(s)C_s(s)Z_e}{1+G_s(s)Z_e+G_s(s)C_s(s)} \tag{6}$$

Then the transfer function from the master to the slave can be described as

$$\frac{F_e(s)}{F_h(s)} = \frac{G(s)C_m(s)e^{-sT_f}}{1+G(s)C_m(s)e^{-s(T_f+T_b)}} \qquad (7)$$

where $F_e(s)$ is the force feedback from the slave and T_b is the time delay from the master to the slave and $G(s) = G_m(s)\hat{G}_s(s)$.

Thus, the equivalent block diagram of the Fig. 5 is shown in Fig. 6.

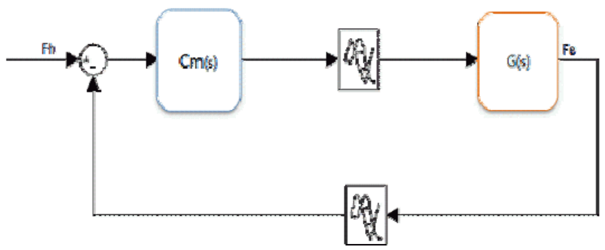


Fig. 6. Equivalent block diagram of Fig. 6

IV. SMITH PREDICTOR WITH NEURAL COMPENSATION

1. Neural network based Smith predictor

Now, we apply the Smith predictor to Fig. 6. However, as in Fig. 2 and 3, the model cannot be known exactly if the plant is nonlinear. To model a nonlinear plant, a nonlinear estimator is preferred. Neural network has been used as a powerful nonlinear estimator. Fig. 7 shows the neural network based Smith predictor. Two neural networks are used, one for estimating a slave model and the other for copying the estimator.

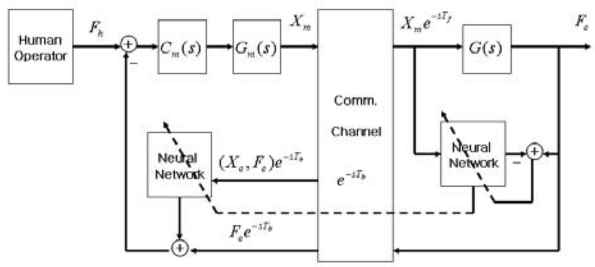


Fig. 7. Neural compensation for the Smith predictor

2. Learning

The radial basis function network is used for the neural network. The back-propagation learning algorithm is used for updating parameters. Fig. 8 shows the learning structure.

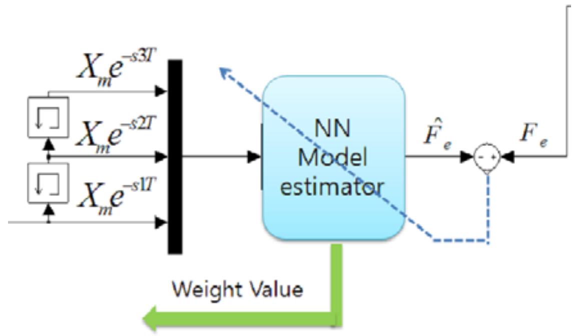


Fig. 8. Neural estimator learning

The structure of the radial basis function network is shown in Fig. 9.

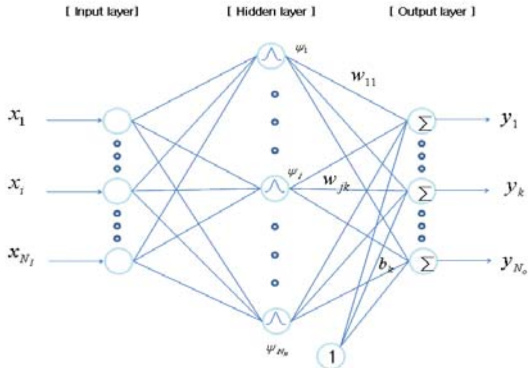


Fig. 9. RBF neural network structure

The nonlinear function $\psi_j(X_{IN})$ is given by

$$\psi_j(X_{IN}) = \exp\left(-\frac{\| X_{IN} - \mu_j \|^2}{\sigma_j^2}\right), \qquad (8)$$

where X_{IN} is the input vector, μ_j is the center value, and σ_j is the width of the jth neuron in the hidden layer.

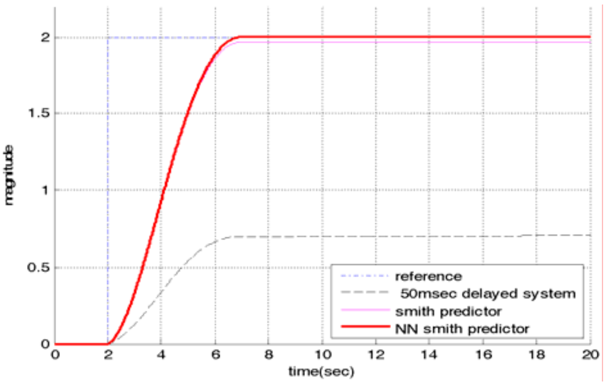
$$y_k = \sum_{j=1}^{N_H} \psi_j w_{jk} + b_k, \qquad (9)$$

V. SIMULATION RESULTS

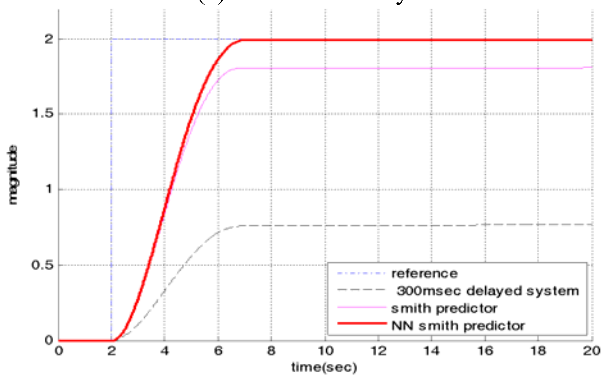
The first simulation study is to test the response when the Hunt-Crossley impedance model is used as an input command.

$$F_h = kx^n + \lambda x^n \dot{x} \qquad (10)$$

where k, λ, n are 110, 40, and 1.2, respectively. Fig. 10 shows the responses of different time delays. We see that tracking performances by the neural network based Smith predictor are better than those of the linear Smith predictor. As the delay time is getting larger, the deviation error of the linear Smith predictor also becomes larger as shown in Fig. 10 (b).



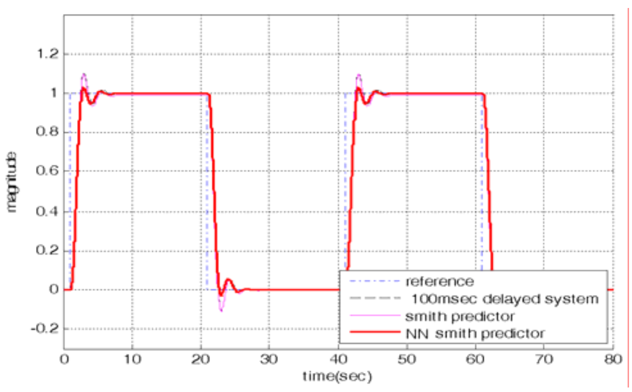
(a) 50ms time delay



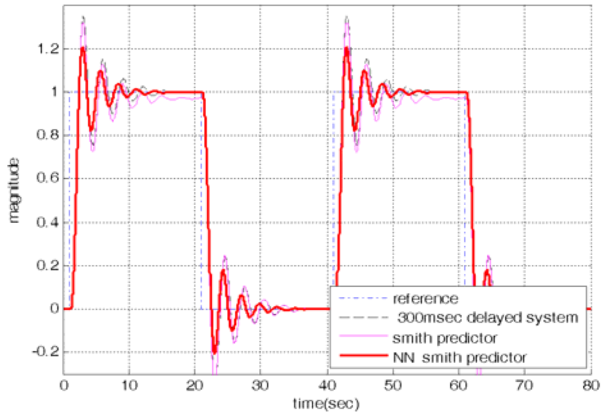
(b) 300ms time delay

Fig. 10. The response to Hunt-Crossley model

The other simulation test is when the force step command is given to the master robot. The force step responses are obtained with different time-delays, 100ms and 300ms. We see from Fig. 11 that performances of both Smith predictors are getting worse as the delay time is longer. Comparing performance between two predictors, the performance of the neural network based Smith predictor is better than that of the linear predictor.



(a) 100ms time delay



(b) 300ms time delay

Fig. 11. The force step response

VI. CONCLUSION

Neural network is used as a nonlinear estimator to identify the slave plant model by forming the Smith predictor structure to deal with time-delays in tele-operated system. Simulation results show that performances of the neural network based Smith predictor is better than that of the linear predictor because the modeling error due to the nonlinearity degrades the performance. Future research is to confirm the neural network based predictor by conducting experiments.

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