Neuro-Controller with Simultaneous Perturbation for Robot Arm –Learning of Kinematics and Dynamics without Jacobian

Yutaka Maeda[1], Nobutaka Kitajima[1], Tsubasa Inagaki[1] and Hidenori Onishi[1]

Kansai University, Faculty of Engineering,
Department of Electrical Engineering and Computer Science

Abstract. We report two control schemes for a two-link robot arm system using a neuro-controller. We adopted the simultaneous perturbation learning rule for a neuro-controller. Ordinary gradient type of learning rule uses Jacobian of the objective system in a direct control scheme by a neural network. However, the learning rule proposed here requires only two values of an error function. Without Jacobian or related information of the objective robot arm, the neuro-controller can learn an inverse of robot kinematics and dynamics, simultaneously. Some results are shown.

1 Introduction

Neuro-Controller (NC) by a direct inverse control scheme (see Fig.1) is a promising approach for non-linear control problems. When we use a gradient type of learning rule such as the back-propagation method for the NC, it is essential to know Jacobian or related information on an objective plant[1]. However, it is generally impossible or very difficult to know the Jacobian especially for a nonlinear objective.

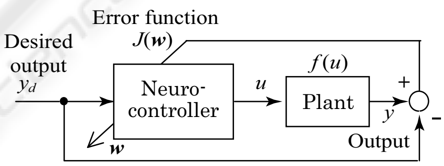


Fig. 1. A basic scheme for a neuro-controller.

In this paper, we propose control schemes by neural networks (NNs) using the simultaneous perturbation learning rule for a two link robot arm system. This learning rule does not directly require a derivative of an error function but only values of the

Maeda Y., Kitajima N., Inagaki T. and Onishi H. (2004).
Neuro-Controller with Simultaneous Perturbation for Robot Arm Learning of Kinematics and Dynamics without Jacobian.
In *Proceedings of the First International Workshop on Artificial Neural Networks: Data Preparation Techniques and Application Development*, pages 16-22
DOI: 10.5220/0001149200160022

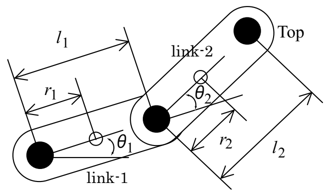


Fig. 2. Two link robot arm system.

error function itself. Therefore, without knowing Jacobian of the objective system, we can design a direct neuro-controller and then the neuro-controller can learn a robot kinematics and a dynamics simultaneously. Moreover, the NC is able to adapt changing environment through learning.

2 Simultaneous Perturbation for Neuro-Controller

The simultaneous perturbation(SP) and its applications are widely reported[1–4]. We explain the SP learning rule with a sign vector for NCs. Now let $\boldsymbol{w}$, $J(\cdot)$ and u be a weight vector of the NC including thresholds, an error function and an input for the robot arm, respectively. The learning rule via the SP is as follows;

$$\boldsymbol{w}_{t+1} = \boldsymbol{w}_t - \alpha \frac{J(u(\boldsymbol{w}_t + c\boldsymbol{s}_t)) - J(u(\boldsymbol{w}_t))}{c} \boldsymbol{s}_t \tag{1}$$

Where, α and c are a positive learning coefficient to adjust a magnitude of a modifying quantity and a magnitude of a perturbation, respectively. $\boldsymbol{s}$ denotes a sign vector whose components are +1 or -1. Moreover, t is iteration.

Note that only two values of the error function $J(u(\boldsymbol{w}))$ and $J(u(\boldsymbol{w} + c\boldsymbol{s}))$ are used to update the weights in the neural network. Any information about the objective plant such as Jacobian does not have to be required in this learning rule. Therefore, this learning rule is easily applicable to the direct control scheme by NCs for a plant including unknown and/or unmodeled factors.

It is known that the learning rule has the following property[1]. That is, the learning rule is a kind of stochastic gradient learning rule.

$$E\left(\frac{J(u(\boldsymbol{w}_t + c\boldsymbol{s}_t)) - J(u(\boldsymbol{w}_t))}{c} \boldsymbol{s}_t\right) = \frac{\partial J(u(\boldsymbol{w}_t))}{\partial \boldsymbol{w}} \tag{2}$$

Note that the SP learning rule is not a merely expansion of the ordinary finite difference approximation. In our case, we have to adjust plural parameters, that is, weight values in the NC. The number of the weights is relatively large. If we simply use the finite difference, we have to know many values of the error J for all weights to update. On the other hand, the SP method requires only two values of the error, even if the number of the weights of the NC is large.

3 Control Scheme 1

3.1 Configuration

We consider the two-link robot arm (see Fig.2) as an objective nonlinear plant. Now our problem is to control the end of the link-2 of the robot arm in Fig.2. Then purpose of the NC is to generate proper torque values for the two links.

Fig.3 shows overall configuration of the robot system using a NC. For one trial, the NC with certain weights outputs a series of torque signals to the robot arm. Then we have a locus. Thus we can obtain a value of the error function as follows;

$$J(u(\boldsymbol{w})) = \sum_i \left((x_i - x_{di})^2 + (y_i - y_{di})^2\right) \tag{3}$$

Where, x_i, y_i and x_{di}, y_{di} denote actual position of the top and its desired position, respectively. With the perturbation, we make a trial again and obtain a value of the error. Using these two values and Eq.(1), we update the weights. We repeat this procedure.

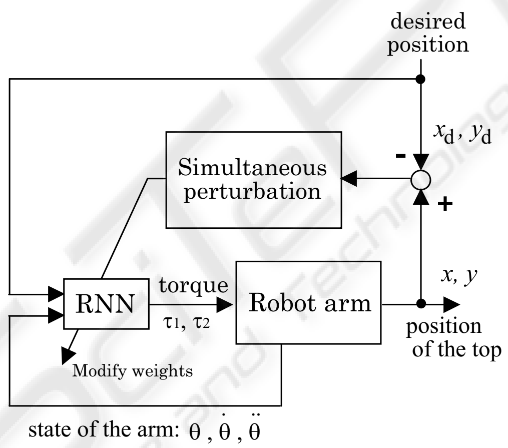


Fig. 3. Overall configuration of control scheme 1.

The objective plant has a dynamics. Therefore, a simple multi-layered neural network cannot control the plant, since the network does not have any dynamics. Basically, the NC consists of two multi-layered neural networks shown in Fig.4. However, the neural networks have time-delayed feedback inputs from outputs of the networks. This feedback gives dynamics to the networks.

Both networks have 14 neurons in input layer, 20 neurons in middle layer, 1 neuron in output layer. The NC uses desired position, angles θ_1 and θ_2, velocities of the angles $\dot{\theta}_1$ and $\dot{\theta}_2$, accelerations of the angles $\ddot{\theta}_1$ and $\ddot{\theta}_2$, time-delayed outputs of the network as inputs. Outputs correspond to torque of the link-1 and the link-2.

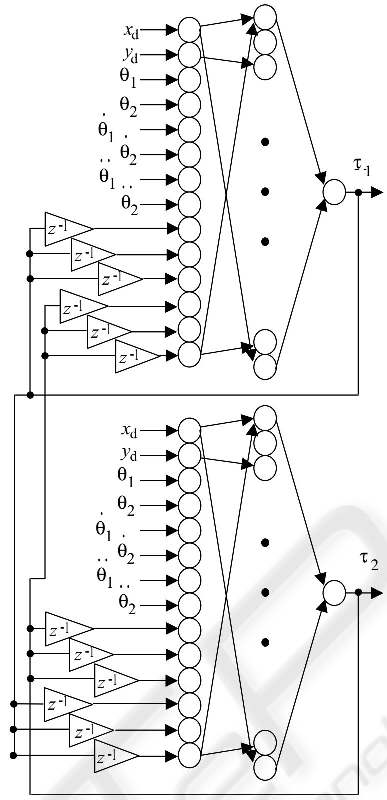


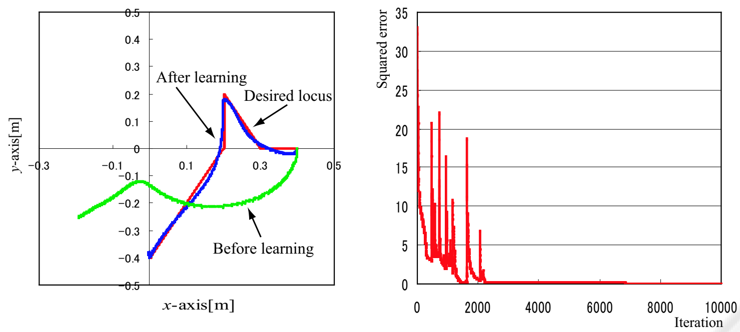
Fig. 4. Neuro-controller used here.

3.2 Result

We consider some practical tasks for the system. Using a proper model of the robot arm, we have a simulation result(see Fig.5) for locus control. Then the learning coefficient $\alpha = 0.0005$ and the perturbation $c = 0.00008$. After 10000 times learning, locus of the top is close to a desired one. The error value decreases as iteration proceeds.

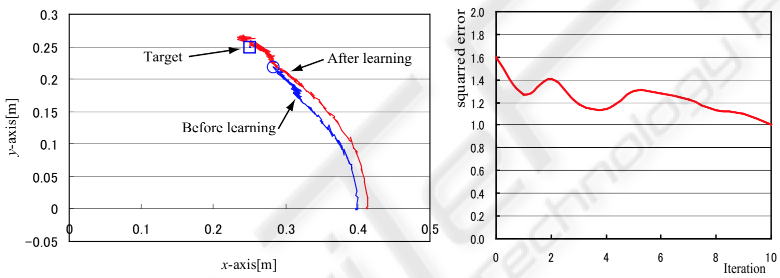
Next, we consider a movement of the top to a certain point. Fig.6 shows a result of the actual robot arm. After pre-training by simulation, the NC is used for the actual system. Then the learning process and operations themselves are carried out simultaneously. $\alpha = 0.01$ and $c = 0.05$. After 10 times learning by the actual system, the top moves to a target point. Before the learning, the top stopped at a point that is different from the target. As is shown in Fig.6(b), the error decreases.

The learning coefficient α and the perturbation c are determined empirically. However, the learning rule is not so sensitive to these values.



(a) Loci before and after learning. (b) Change of squared error.

Fig. 5. Simulation result for a locus.



(a) Loci before and after learning to target point . (b) Change of squared error.

Fig. 6. Experimental result for a target point.

4 Control Scheme 2

4.1 Configuration

Next, we consider more complicated configuration to handle the problem. We prepare two NNs. One neural network is for kinematics. Inputs of the network are desired position of the top of the arm in xy coordinate. Outputs are angles for the two arms. The neural network must learn an inverse kinematics of the robot arm system. The second neural network is a recurrent neural network (RNN). Inputs of the network are the angles of the arm, that is, the outputs of the first network and state of the objective robot arm. Outputs are torque values for the two links. The second network must learn an inverse dynamics of the plant. The configuration is depicted in Fig.7.

In this case, it is difficult to carry out the learning of these two NNs, simultaneously. As same as the previous configuration, if we use an ordinary gradient method to update

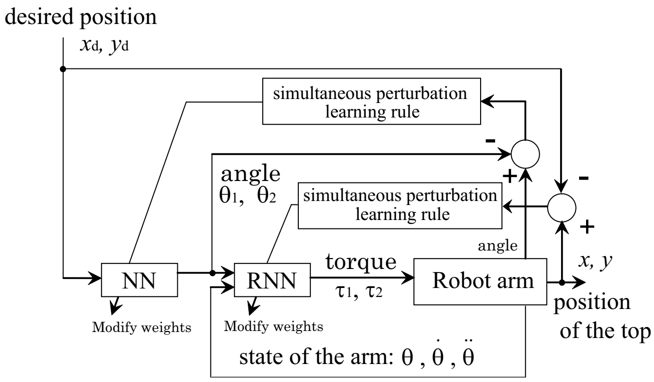


Fig. 7. Overall configuration of control scheme 2.

the weights in these two networks, it is essential to know the Jacobian of the plant. On the hand, our approach does not require the information.

The first NN for the kinematics updates their weights based on the error defined by the output angles and the actual angles of the two links of the robot arm. Moreover, the second RNN learns the dynamics using the error defined by the actual xy position of the robot arm and the corresponding desired position.

4.2 Simulation result

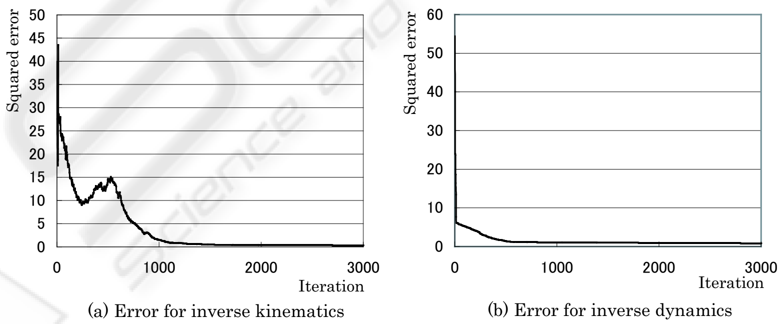


Fig. 8. Change of errors.

We consider a task to move the top of the arm to a certain point using the control scheme 2.

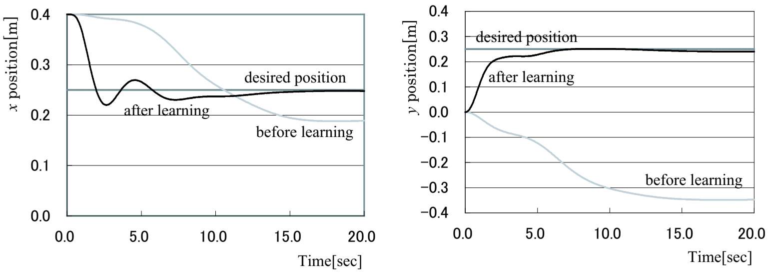


Fig. 9. Simulation result.

Fig.8 shows changes of the errors for the kinematics and the dynamics. This simulation result reveals that 1000 learning gives proper accuracy to move the top of the arm to the desired position. Then, $\alpha = 0.0008$ and $c = 0.0003$.

Fig.9 is xy position of the top. After 3000 learning, the top moves to the desired position. This shows that the first NN and the second NN learn the inverse kinematics and the inverse dynamics properly.

5 Conclusion

This paper describes two control schemes for the two link robot arm. In these control schemes, the NNs learn the inverse of the kinematics and the dynamics of the objective robot system without Jacobian of the plant. The simultaneous perturbation learning rule makes this possible.

Acknowledgement

This work was financially supported by Grant-in-Aid for Scientific Research(No.16500142) of the Ministry of Education, Culture, Sports, Science and Technology of Japan.

References

1. Maeda, Y., deFigueiredo, R.J.P.: Learning Rules for Neuro-Controller via Simultaneous Perturbation. IEEE trans. on Neural Networks, **8** (1997) 1119–1130
2. Spall, J.C.: Multivariable stochastic approximation using a simultaneous perturbation gradient approximation. IEEE Trans. Autom. Control, **AC-37** (1992) 332–341
3. Cauwenberghs, G.: A fast stochastic error-descent algorithm for supervised learning and optimization. in S.J.Hanson, J.D.Cowan and C.Lee(eds.), Advances in neural information processing systems 5, Morgan Kaufmann Publisher. (1993) 244–251
4. Maeda, Y., Hirano, H., Kanata, Y.: A learning rule of neural networks via simultaneous perturbation and its hardware implementation. Neural Networks, **8** (1995) 251-259