

# Neural Network Aided Dynamic Parameter Identification of Robot Manipulators

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**Abstract**—This paper addresses issue of dynamic parameter identification of robot manipulators. A new identification approach with neural network based compensation of uncertain dynamics is proposed. Based on this approach, parameter identification process is divided into two steps. The first step is to determine unknown dynamic parameters using inverse dynamics of the robot manipulator and pseudo-inverse matrices. The second step is to establish a dynamic compensator by neural network and learning method for improving accuracy of the dynamic model with parameters given in the first step. A Direct Drive (DD) SCARA type industrial robot arm AdeptOne is used as an application example for the parameter identification. Simulations and experiments are carried out. Comparison of the results confirms the correctness and usefulness of the proposed identification method.

## I. INTRODUCTION

For model-based control and simulation of a robot manipulator, we need to know the dynamic model of the robot with specified parameters. In the past two decades, a large number of research results in modeling and parameter identification have been reported. The intensive research in this area has focused on the torque-controlled robots with the dynamics being formulated on the basis of joint torque vs. joint motion manner [1]~[5]. Practically speaking, except those robot arms used in laboratories as test beds, recently it is not easy to find such the torque-controlled robot manipulator in a huge number of the commercially available industrial robots, because almost industrial robots are equipped with servo-controlled electrical motors and servo control units. Obviously, we need to take the dynamics of the motors, as well as characteristics of the servo control units, into consideration in the parameter identification of the industrial robot manipulator. In recent years, on the other hand, neural networks have received considerable attention in the control and identification fields. It has been demonstrated that neural networks can be used effectively for the identification of nonlinear systems[6]. A large number of reports have been published on dynamics formulation using neural networks for control design of robot manipulators[7] ~ [9].

In this paper, we propose a new identification method for robot manipulators using both a usual parameter identification approach and a dynamic compensator

established based on neural network theory. First, we identify dynamic parameters of the robot to specify robot arm dynamic equation that is derived by Lagrange Formulation [10]. Then, a parallel dynamic compensator is designed with a multi-layer neural network to approximate the unmodeled dynamic characteristics and the Lagrange Formulation based model with the identified parameters. A learning method is used to train the weights of each layer of the neural network in order to minimize output error between a reference input of the robot and the total output of the network and inverted dynamic model of the robot with identified parameters. The whole dynamics of the robot is presented by combination of the dynamics equation and compensator. Identification experiments are carried out using an AdeptOne robot manipulator as a test bed to demonstrate the effectiveness and usefulness of the proposed method. Simulations are carried out on dynamic model of the AdeptOne robot with combination of the Lagrange equations and dynamic compensator. Comparison of both results of the simulations and experiments confirms the correctness of the presented dynamic model.

This paper is organized as follows. Section II presents formulation of the dynamic model. Section III shows the basic idea and problem statements. Parameter identification using a traditional method is given in Section IV. The dynamic compensator design using neural network is designed in Section V. Parameter identification experiments, and validation simulations are given in Section VI. Conclusions and discussions are presented in Section VII.

## II. DYNAMIC MODELING

### A. Dynamic Model of Robot Arm with Servo-Controlled Motors

The torque-based dynamics of robot manipulator is the popular dynamic model that is widely used for control design and simulation of robot manipulators. The dynamic model can be easily derived and expressed from Lagrange equation as follows

$$\mathbf{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \mathbf{H}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) + \mathbf{g}(\boldsymbol{\theta}) = \boldsymbol{\tau} \quad (1)$$

where,  $\boldsymbol{\theta} \in R^n$  and  $\boldsymbol{\tau} \in R^n$  are joint variable and torque,  $\mathbf{M}(\boldsymbol{\theta}) \in R^{n \times n}$  is inertia matrix,  $\mathbf{H}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) \in R^n$  contains Coriolis and centrifugal forces, and  $\mathbf{g}(\boldsymbol{\theta}) \in R^n$  denotes gravitational force. This type of dynamic model has been used in control design for a class of torque control for the

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robots that can be seen in a lot of robotics laboratories. For almost cases of control design of industrial robot manipulators, however, this kind of dynamics cannot be used directly because most industrial manipulators are not functionally designed on the basis of torque/force control but servo control. Therefore, we need to take this kind of characteristics of the industrial robot into consideration in dynamic modeling and parameter identification and control design. To do so, we derive dynamics of the motors with servo control units as follows.

$$\mathbf{L}\mathbf{a}^{-1}\dot{\boldsymbol{\tau}} + \mathbf{R}\mathbf{a}^{-1}\boldsymbol{\tau} + \mathbf{f}_v\dot{\boldsymbol{\theta}} + \mathbf{D}(\dot{\boldsymbol{\theta}}) = \mathbf{v} \quad (2)$$

Though rates of amplifiers of the servo units are included in the parameters in the above equation, in the following, we rather like to use the nominal terms of parameters that are often referred directly to a servo motor.  $\mathbf{v} = \text{diag}(v_1, v_2, \dots, v_n)$  denotes the input voltage of the servo units;  $\mathbf{L} = \text{diag}(L_1, L_2, \dots, L_n)$ ,  $\mathbf{R} = \text{diag}(R_1, R_2, \dots, R_n)$  are matrices of inductance and resistance; and  $\mathbf{a} = \text{diag}(\alpha_1, \alpha_2, \dots, \alpha_n)$  is a matrix containing back electromotive constant of each servo motor as its elements;  $\mathbf{f}_v = \text{diag}(f_{v1}, f_{v2}, \dots, f_{vn})$  denotes matrix of viscous friction constants, and  $\mathbf{D}(\dot{\boldsymbol{\theta}})$  is a diagonal matrix with its diagonal elements indicating constants of Coulomb frictions and electrical dead zones of the motors. Combining (1) and (2) together, after some simple manipulations we obtain

$$\hat{\mathbf{L}}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \hat{\mathbf{R}}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}})\dot{\boldsymbol{\theta}} + \hat{\mathbf{H}}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) = \mathbf{v} \quad (3)$$

#### B. Dynamics in a linear form of unknown parameters

In order to derive parameter identification algorithms, we rewrite dynamic model (3) into a set of linear equations of the unknown parameters as follows

$$\mathbf{v} = \mathbf{Y}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}})\mathbf{a} \quad (4)$$

where  $\mathbf{a} \in R^l$  is a vector containing unknown parameters to be identified;  $\mathbf{Y}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) \in R^{n \times l}$  is the regressor, a matrix consisting of non-parametric smooth functions of  $\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}$  and  $\ddot{\boldsymbol{\theta}}$ , which can be formed as

$$\mathbf{Y}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) = \begin{bmatrix} y_1(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) & 0 & 0 & 0 \\ 0 & y_2(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) & 0 & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & y_n(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) \end{bmatrix} \quad (5)$$

Usually  $\mathbf{Y}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}})$  can be determined based on experimental data and calculations.

### III. BASIC CONCEPTS AND PROBLEM STATEMENTS

For identification of a system, a suitable mathematical representation of the system is required. The main objective

for identification of a robot system is to provide specific parameters to the given mathematical representation of the robot. Lagrange and Newton-Euler formulations are the most popular methods for dynamic modeling of robot manipulators, since they can express the most part of dynamic characteristics of the robot and can be easily derived and easily used to control design and simulation. However, the mathematical representation derived from Lagrange formulation or Newton-Euler formulation sometimes cannot describe motion of the robot precisely. The reason lies on that there are some dynamic effects that are difficult to be modeled by using traditional modeling approaches. Among the effects friction, for example, is a notable factor. So we need a new method for modeling and identification in order to control and/or simulate the robot system precisely.

Though some approaches of dynamic modeling of a robot using neural network technology have been proposed. Complicity of robot dynamics requires complicated structure of neural network if we only use the neural network to express whole dynamics of the robot, and the complicated neural network is difficult to use in real time control. In this work, we take advantages of both traditional dynamic formulation and neural network for the identification of the robot system. The main idea is to combine a dynamic compensator designed using neural network and dynamic model given (3) to express dynamic characteristics of the robot. The mathematical representation of the whole system is given as follows.

$$\hat{\mathbf{L}}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \hat{\mathbf{R}}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}})\dot{\boldsymbol{\theta}} + \hat{\mathbf{H}}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) + \mathbf{N}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) = \mathbf{v} \quad (6)$$

where  $\mathbf{N}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}})$  is the compensator to be designed with neural network later.

In above mathematical model, the terms derived from Lagrange formulation play the main role in representing dynamic behavior of the robot, and the neural network is used for both purposes to approximate the unmodeled part and to compensate the error of dynamics caused by imprecision of identified parameters.

To establish such the mathematical model, first, dynamic parameters of motion equation (3) are identified using the method given in IV based on experimental data. Then, a multi-layer neural network is designed and the weights are trained by back-propagation method, and the details are presented in V.

### IV. APPROACH FOR PARAMETER IDENTIFICATION

Dynamic parameter identification can be done based on the dynamic descriptions shown in (4), (5). There are two approaches for the parameter identification: (a) to identify the unknown parameters with respect to individual link separately; (b) to identify all the unknown dynamic parameters of the robot simultaneously. In this paper, we focus on the former approach. The procedure for individual joint parameter identification is described as below.

- 1) Keep the joints steady except the assigned joint (assuming to be joint  $i$ ) on which the related parameters of the robot are identified;

- 2) Give a periodic excitation, i.e. periodic servo voltage, to the servo unit of joint i;
- 3) Record the excitation  $v_i(k)$  ( $k = 1, 2, \dots, N$ ) and responses of joint i  $\theta_i(k)$ ,  $\dot{\theta}_i(k)$ , and calculate  $\ddot{\theta}_i(k)$ ,  $\ddot{\theta}_i(k)$ , where  $k$  indicates sampling number;
- 4) Calculate the related regressor given by (5) as  $\mathbf{y}_i(k) = \mathbf{y}_i(\theta_i(k), \dot{\theta}_i(k), \ddot{\theta}_i(k), \ddot{\theta}_i(k))$  according to the recorded joint responses on every sampling time to form a matrix as  $\hat{\mathbf{Y}}_i = [\mathbf{y}_i^T(1), \mathbf{y}_i^T(2), \dots, \mathbf{y}_i^T(N)]^T$ , and form the excitation vector  $\hat{\mathbf{v}}_i = [v_i(1), v_i(2), \dots, v_i(N)]^T$  as well;
- 5) Based on (4), the parameters related to joint i are calculated as follows

$$\hat{\mathbf{a}}_i = \Gamma_i \hat{\mathbf{v}}_i \quad (7)$$

where  $\Gamma_i$  is a pseudo-inverse matrix of  $\hat{\mathbf{Y}}_i$  given by

$$\Gamma_i = (\hat{\mathbf{Y}}_i^T \hat{\mathbf{Y}}_i)^{-1} \hat{\mathbf{Y}}_i^T \quad (8)$$

- 6) Repeat the process from 1) to 5) for other joints till all parameters of the robot are identified.

Using the above method, optimal solution of parameter identification based on the experimental result is guaranteed in a sense of least-squares of the mean errors.

## V. DESIGN OF DYNAMIC COMPENSATOR

### A. Neural network design

In this section we give a detail design of dynamic compensator using neural network. The neural network, with two layers as shown in Fig.1, is designed with the form of inverse dynamics for the unmodeled dynamic characteristics. This neural network is consisting of input unites, hidden layer that are designed with nonlinear activation functions, and the linear output layer.

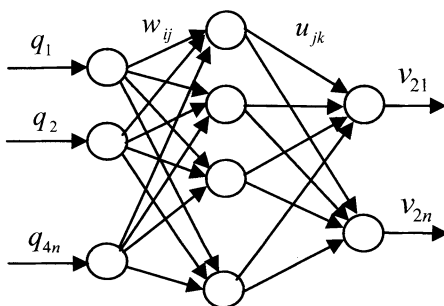


Fig.1. Neural network structure used to establish dynamic compensator.

The mathematical model of the neural network is given by

$$\mathbf{v}_2 = \mathbf{U} \mathbf{f}(\mathbf{W} \mathbf{q}) \quad (9)$$

where  $\mathbf{q} = [q_1, q_2, \dots, q_{4n}]^T \in R^{4n}$  denotes input vector with elements being each joint variable, velocity, acceleration

and time differentiation of acceleration;  $\mathbf{v}_2 = [v_{21}, v_{22}, \dots, v_{2n}] \in R^n$  is output vector with unit of torque;  $\mathbf{W} \in R^{4n \times l}$  and  $\mathbf{U} \in R^{l \times n}$ , with their elements being expressed by  $w_{ij}$  and  $u_{jk}$ , are weight matrices from input nodes to the hidden layer and from hidden layer to the output layer;  $\mathbf{f}(\cdot) \in R^l$  is an activation function vector of the hidden layer with elements being sigmoid functions;  $l$  is the number of hidden nodes.

For a system that its dynamic characteristics can be expressed with a dynamic model precisely, and if the system is invertible, with an input of the invert system being the output of the original system, output of the invert system will repeat the input of the original system precisely. We combine an inverted dynamics as given by (4) and the neural network given by (9) and Fig.1 together to describe the inverse system. The relation between the robot manipulator and the inverse system is shown in Fig.2.

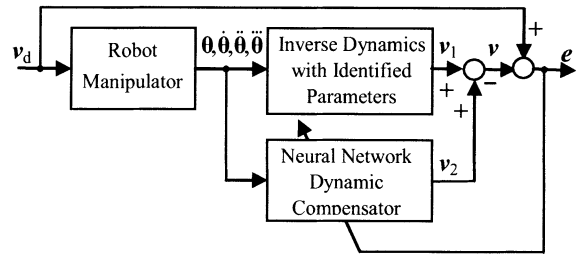


Fig. 2. Dynamic compensator using a Neural Network and a dynamic model with identified parameters

To train the weights such that the neural network can approximate the unmodeled dynamics of the robot, we use the input of the original system (the robot manipulator) as a desirable input and adjust the weights by a learning algorithm so that the error between the desired input and output of the inverse system would converge to zero. The learning algorithm is derived based on the back-propagation approach. In so doing, firstly we define the error as follows.

$$E = \frac{1}{2} (\mathbf{v}_d - (\mathbf{v}_1 + \mathbf{v}_2))^T (\mathbf{v}_d - (\mathbf{v}_1 + \mathbf{v}_2)) \quad (10)$$

where  $\mathbf{v}_d$  and  $\mathbf{v}_1$  are the desired input and output of the inverse dynamics.

The learning algorithm is to make a change in the weight proportional to the negative of the gradient of the quadratic error with respect to the weights, i.e.

$$\Delta u_{jk} = -\gamma_{jk} \frac{\partial E}{\partial u_{jk}} \quad (j=1, 2, \dots, l; k=1, 2, \dots, n) \quad (11)$$

and

$$\Delta w_{ij} = -\lambda_{ij} \frac{\partial E}{\partial w_{ij}} \quad (i=1, 2, \dots, 4n; j=1, 2, \dots, l) \quad (12)$$

where  $\gamma_{jk}$  and  $\lambda_{ij}$  are the constants of proportionality, to be designed as learning rates.

Using the chain rule and noting that the weights are independent with  $\mathbf{v}_1$  and  $\mathbf{v}_d$ , the derivative of (11) can be expressed as follows,

$$\frac{\partial E}{\partial u_{jk}} = \frac{\partial E}{\partial v_{2k}} \frac{\partial v_{2k}}{\partial u_{jk}} \quad (13)$$

In detail,  $\partial E / \partial v_{2k}$  and  $\partial v_{2k} / \partial u_{jk}$  can be given as

$$\frac{\partial E}{\partial v_{2k}} = v_{1k} + v_{2k} - v_{dk} = -e_k \quad (14)$$

and

$$\frac{\partial v_{2k}}{\partial u_{jk}} = p_j \quad (15)$$

where  $p_j$  is the output of  $j$ th node of the hidden layer.

Similarly, we adopt the chain rule to (12) to obtain

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial p_j} \frac{\partial p_j}{\partial w_{ij}} \quad (16)$$

In detail,  $\partial E / \partial p_j$  and  $\partial p_j / \partial w_{ij}$  can be given as

$$\begin{aligned} \frac{\partial E}{\partial p_j} &= \frac{\partial E}{\partial \mathbf{v}_2^T} \frac{\partial \mathbf{v}_2}{\partial p_j} \\ &= (\mathbf{v}_1 + \mathbf{v}_2 - \mathbf{v}_d)^T \mathbf{u}_j \end{aligned} \quad (17)$$

where  $\mathbf{u}_j$  is  $j$ th column vector of weight matrix  $\mathbf{U}$ ;

$$\begin{aligned} \frac{\partial p_j}{\partial w_{ij}} &= \frac{\partial p_j}{\partial s_i} \frac{\partial s_i}{\partial w_{ij}} \\ &= \frac{\partial f_j(\sum s)}{\partial s_i} q_i \end{aligned} \quad (18)$$

where  $s_i$  is input of  $i$ th node of the hidden layer.

### B. An implementation issue

In subsection A, without losing generality, we presented dynamic compensator design based on a neural network that is formulated using not only joint variables, velocities, but also accelerations and time differentiation of the accelerations as its inputs. With the whole variables as its inputs, the compensator will have better performance in approximating the unmodeled dynamics. In real time control, however, the neural network will be difficult to be adopted since joints' accelerations and time differentiation of the accelerations are not available in sensor systems of most industry robot manipulators. Although control issue is not directly addressed in this work, we have to take this issue into consideration in the design of the compensator because our objective is to design a better control system using the identified dynamic model. Therefore, there should be a trade-off between more accurate approximation and easier implementation. In this paper, we prefer to choose the later and to design the neural network only with joint variables, velocities as its inputs. The simplified dynamic compensator has a two-layer neural network and the weights of the network are trained based on the algorithm given in expressions (10) – (18) and the system shown in Fig.3.

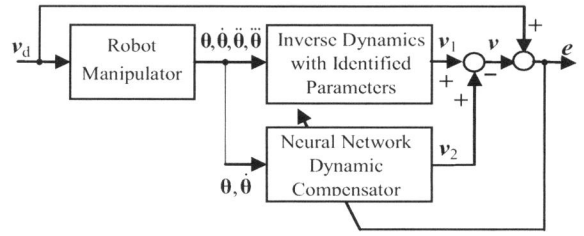


Fig. 3. Simplified dynamic compensator using a Neural Network and a dynamic model with identified parameters

## VI. PARAMETER IDENTIFICATION EXPERIMENTS

### A. The experimental facility

AdeptOne XL robot manipulator is a high performance industrial robot as shown in Fig.1. It is a SCARA type Direct Drive (DD) robot that possesses 4 joints. Except the third joint being a prismatic joint, other joints are revolute.

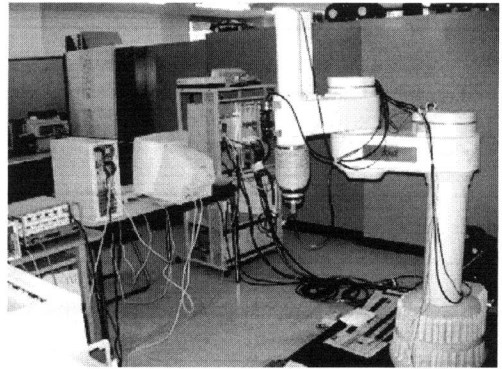


Fig. 4. AdeptOne robot manipulator.

The closed-loop servo system is built-in by Adept Technology Corporation based on servo units and servo motors. Using the Advanced Servo Library, however, the user is allowed to access the D/A converter directly to release the close-loop servo system for developing more advanced control system by V+ language. We developed control and parameter identification software on such the software and hardware environment.

### B. Parameter Identification experiments and results

The identification experiments for individual joint were carried out. Since the number of pages is limited, we cannot show all of the experimental results. As an example, we give the experimental results of the first joint. The excitation  $v_d$  has been chosen as a sine wave shown in Fig.5. The responses of displacement and velocity of joint 1 measured by the sensors of the robot are given in Fig.6 (a) and (b). The acceleration and time derivative of acceleration are calculated accordingly using the Finite Difference Method, and the results are shown in Fig.6 (d) and (e).

The dynamic model for parameters is a restricted version of equations (4), and given as follows.

$$\mathbf{v}_d = \mathbf{y}_1(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}, \dddot{\boldsymbol{\theta}}) \mathbf{a}_1 \quad (19)$$

where the regressor and parameters are given as

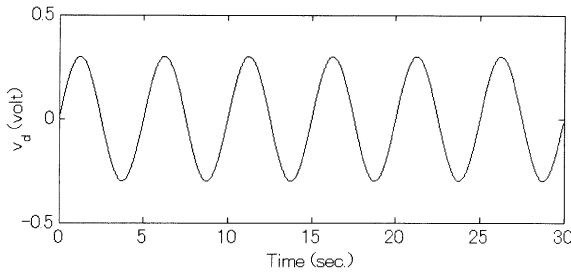


Fig.5. Joint 1 input signal in parameter identification experiment.

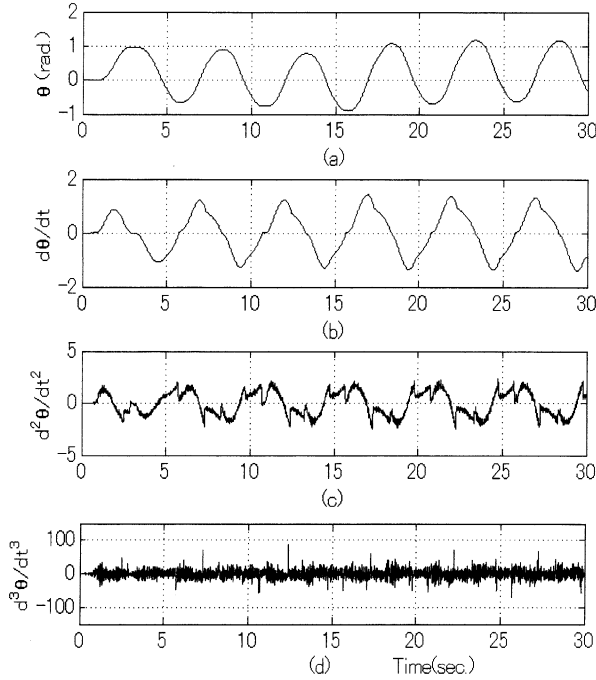


Fig.6. Responses of joint 1 to the input volt shown in Figure 4.

$$\mathbf{y}_1(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}) = [\ddot{\theta}_1 \quad \dot{\theta}_1 \quad \theta_1]^T \quad (20)$$

$$\mathbf{a}_1 = [a_{11} \quad a_{12} \quad a_{13}]^T \quad (21)$$

In detail, the elements of  $\mathbf{a}_1$  are given as follows.

$$a_{11} = L_1 I_{a1} / \alpha_1, \quad a_{12} = R_1 I_{a1} / \alpha_1 + L_1 f_1 / \alpha_1,$$

$$a_{13} = L_1 f_1 / \alpha_1 + V_{a1}$$

where  $\alpha_1$ ,  $L_1$ , and  $R_1$  denote the back electromotive constant, inductance, and resistance of motor of joint 1;  $I_{a1} = m_1 l_{g1}^2 + m_2 (l_1^2 + l_{g2}^2) + (m_3 + m_4)(l_1^2 + l_2^2) + I_1 + I_2 + I_3 + I_4$  is the total moment of inertia of the manipulator with respect to joint 1.

Using the approach given by section IV, the parameters are calculated. Fig.7 shows the typical results of identified parameters against number of sampling data. It can be seen that each parameter converges to a fixed value when number of the sampling data increases.

### C. Identification with compensator and validation

The dynamic compensator is designed and the weights are trained with the methods given in last section. Fig.8 shows output of the inverse dynamics described by Fig. 3.  $v_d$  is the reference input of the sine wave as teaching signal;  $v$  and

$v_1$  are the outputs of the inverse system with and without the dynamic compensator,  $v_2$  is the output generated by the compensator,  $e_1$  and  $e_2$  are errors between  $v_d$  and  $v_1$  and between  $v_1$  and  $v_1$  respectively. Fig.9 shows the mean squared deviation error between the teaching signal and output of the inverse system with respect to learning time.

To validate the correctness of the identified system, we carried out simulations using dynamics give (6). The input of the system is the same sine wave that has been used for identification experiments. Fig.10 shows one of the results of simulation together with the corresponding experiment carried out for parameter identification of joint 1. In Fig.10 (a) and (b),  $\theta_{s1}$ ,  $\theta_{s2}$  and  $\theta_e$  are responses of joint 1 with respect to

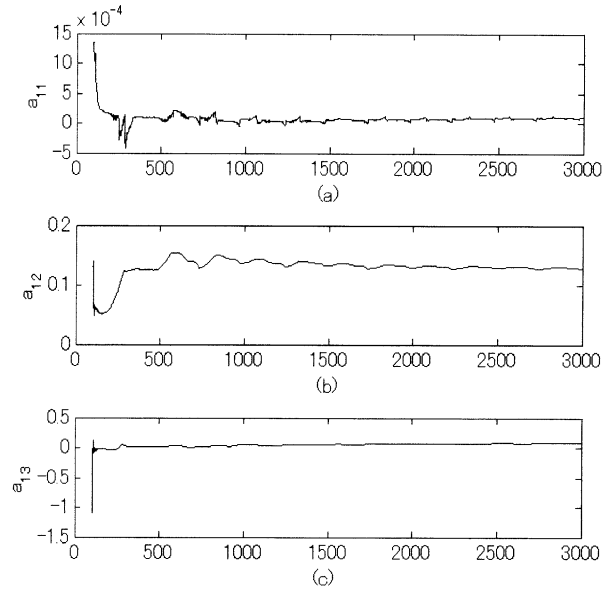


Fig.7. History of identified parameters with respect to number of the experimental data.

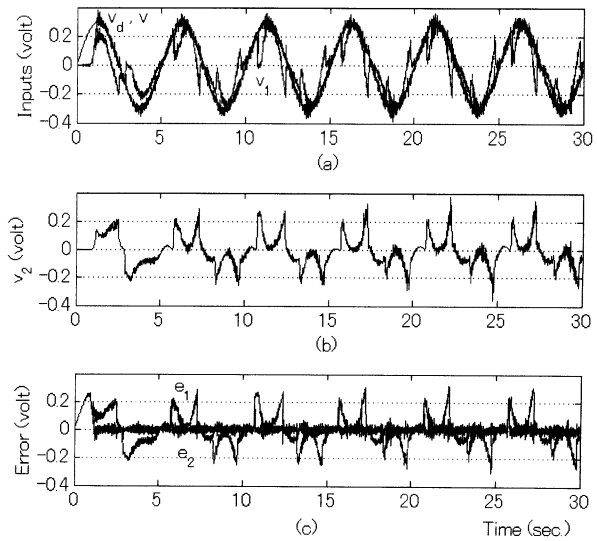


Fig.8. Validation results: output of the inverse system.

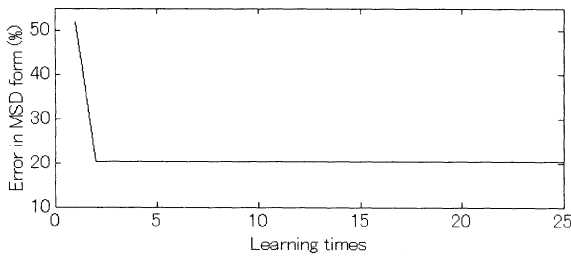


Fig.9. Mean squared deviation error between the teaching signal and output of the inverse system with respect to learning time.

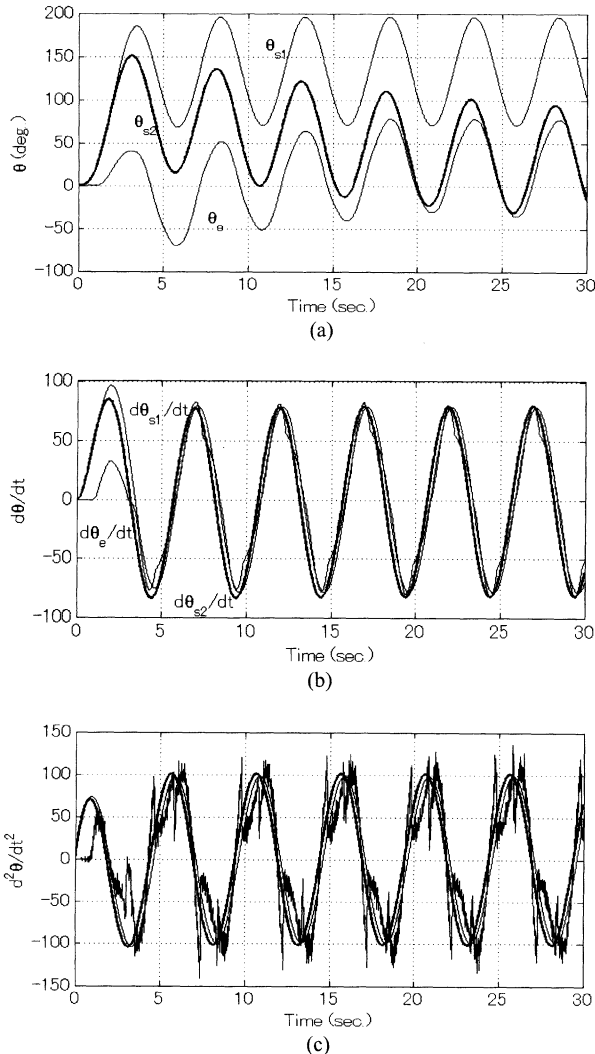


Fig.10. Comparison of experimental results and simulations' results

simulation without dynamic compensator, simulation with the dynamic compensator, and experiment;  $\dot{\theta}_{s1}$ ,  $\dot{\theta}_{s2}$ , and  $\dot{\theta}_e$  are their velocity. Fig. 10 (c) shows the related accelerations.

The bold line and thin line indicate the accelerations of the joint in the simulations with and without the dynamic compensator, as while the line with noise is joint acceleration calculated based on the experimental data.

Comparing with responses of joint angle, velocity, and acceleration, though it exhibits some degrees of differences between the simulations and the experiment, it is seen that the

simulation results with dynamic compensator more effectively converge to their experimental counterparts, therefore the correctness of system with neural network dynamic compensator is confirmed.

## VII. CONCLUSIONS

This paper proposed dynamic identification of robot manipulators using a neural network compensator. Using a pseudo-inverse matrix consisting of the regressors, parameter identification was formulated, and it guaranteed the optimal solution in a sense of least-squares of the mean errors. A neural network was designed to compensate the unmodeled dynamics. Based on back propagation approach, the weights of the neural network were trained using sine wave input volt of the robot as its reference signal and the output of the inverse system consisting of inverse dynamic model of the robot that was formulated by Lagrange Equation and the neural network compensator. The parameter identification and the dynamic compensator with respect to individual link were implemented for a commercially available industrial robot manipulator AdeptOne XL. Comparison of simulation and experiment results of open loop control under the sine wave excitation validated the dynamic identification.

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