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DYNAMIC PARAMETER IDENTIFICATION OF ROBOTS USING A NEURAL NETWORK AS A COMPENSATOR

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ABSTRACT

This paper addresses issues of dynamic parameter identification of robot manipulators. A new identification approach with neural network based compensation of uncertain dynamics is proposed. The 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.

KEYWORDS: robot manipulator, neural network, dynamics, identification.

1. Introduction

Model-based control and simulation of a robot manipulator need to know the dynamic model of the robot with specified parameters. In the past two decades, a large number of research results in modelling 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]~[4]. Practically speaking, except those robot arms used in laboratories as test beds, recently it is not easy to find such a torque-controlled robot manipulator in a huge number of commercially available industrial robots, because almost all 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 the 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 [5]. A large number of reports have been published on dynamics formulation using neural networks for control the design of robot manipulators[6] ~ [8].

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 the dynamic parameters of the robot to specify robot arm dynamic equation that is derived by Lagrange Formulation [9]. Then, a parallel dynamic compensator is designed with a multi-layer neural network to approximate the unmodelled 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 an 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 a dynamic model of the AdeptOne robot with combination of the Lagrange equations and a dynamic compensator. Comparison of both results of the simulations and experiments justifies the correctness of the presented dynamic model.

This paper is organized as follows. Sections 2 presents the formulation of the dynamic model. Section 3 shows the basic idea and problem statements. Parameter identification using a traditional method is given in Section 4. The dynamic compensator design using neural network is designed in Section 5. Parameter identification experiments, and validation simulations are given in Section 6. Conclusions and discussions are presented in Section 7.

2. Dynamics

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

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

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 the gravitational force. This type of dynamic model has been used in a control design for a class of torque control for the robots that can be seen in a lot of robotics laboratories. For almost all 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 a dynamic modelling and parameter identification and control design. To do so, we derive dynamics of the motors with servo control units as follows.

$$\mathbf{L}\boldsymbol{\alpha}^{-1}\dot{\boldsymbol{\tau}} + \mathbf{R}\boldsymbol{\alpha}^{-1}\boldsymbol{\tau} + \mathbf{f_v}\dot{\boldsymbol{\theta}} + \mathbf{D}(\dot{\boldsymbol{\theta}}) = \mathbf{v} \tag{2}$$

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 to directly for a servo motor. $\mathbf{v} = diag(v_1, v_2, \cdots, v_n)$ denoting the input voltage of the servo units; $\mathbf{L} = diag(L_1, L_2, \cdots, L_n)$, $\mathbf{R} = diag(R_1, R_2, \cdots, R_n)$ are matrices of inductance and resistance; and $\boldsymbol{\alpha} = diag(\alpha_1, \alpha_2, \cdots, \alpha_n)$ is a matrix containing back electromotive constant of each servo motor as its elements; $\mathbf{f}_v = diag(f_{v1}, f_{v2}, \cdots, f_{vn})$ 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

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

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

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

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

$$\mathbf{Y}(\boldsymbol{\theta},\dot{\boldsymbol{\theta}},\ddot{\boldsymbol{\theta}},\dddot{\boldsymbol{\theta}}) = \begin{bmatrix} \mathbf{y}_1(\boldsymbol{\theta},\dot{\boldsymbol{\theta}},\ddot{\boldsymbol{\theta}},\dddot{\boldsymbol{\theta}}) & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{y}_2(\boldsymbol{\theta},\dot{\boldsymbol{\theta}},\ddot{\boldsymbol{\theta}},\dddot{\boldsymbol{\theta}}) & \mathbf{0} & \mathbf{0} \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{y}_n(\boldsymbol{\theta},\dot{\boldsymbol{\theta}},\ddot{\boldsymbol{\theta}},\dddot{\boldsymbol{\theta}}) \end{bmatrix} \tag{5}$$

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

2. Problem statement

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 modelling of robot manipulators, since they can express the most part of the 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 in that there are some dynamic effects that are difficult to be modelled by using traditional modelling approaches. Among the effects, friction, for example, is a notable factor. So, we need a new method for modelling and identification in order to control and/or simulate the robot system precisely.

Though some approaches of dynamic modelling 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 advantage of both traditional the 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.

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

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

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

To establish such a mathematical model, first, the dynamic parameters of the motion equation (3) are identified using the method given in 4 based on experimental data. Then, a multi-layer neural network is designed and the weights are trained by the back-propagation method, and the details are presented in 5.

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

$$\hat{\mathbf{a}}_i = \boldsymbol{\Gamma}_i \hat{\mathbf{v}}_i \qquad (7)$$

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

$$\boldsymbol{\Gamma}_i = (\hat{\mathbf{Y}}_i^T \hat{\mathbf{Y}}_i)^{-1} \hat{\mathbf{Y}}_i^T \qquad (8)$$

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.

5. Design of neural network model

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.

The mathematical model of the neural network is given by

$$\boldsymbol{v}_2 = \mathbf{U}\,\boldsymbol{f}(\mathbf{W}\boldsymbol{q}) \qquad (9)$$

where $\boldsymbol{q}$ denotes input vector with elements being each joint variable, velocity, acceleration and time differentiation of acceleration; $\boldsymbol{v}_2$ is the output vector with the 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 the hidden layer to the output layer; $\boldsymbol{f}(*) \in R^l$ 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 as given by (9) .

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.

$$E = \frac{1}{2}(\boldsymbol{v_d}\text{-}(\boldsymbol{v_1} + \boldsymbol{v}_2))^T(\boldsymbol{v_d}\text{-}(\boldsymbol{v_1} + \boldsymbol{v}_2)) \quad (10)$$

where $\boldsymbol{v_d}$ and $\boldsymbol{v_1}$ 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.

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

and

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

where γ_{jk} and λ_{ij} are the constants of proportionality, to be designed as learning rates.

Using the chain rule and noting that the weights are independent with $\boldsymbol{v}_1$ and $\boldsymbol{v}_d$, 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 jth 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

$$\begin{aligned}\frac{\partial E}{\partial p_j} &= \frac{\partial E}{\partial \boldsymbol{v}_2^T}\frac{\partial \boldsymbol{v}_2}{\partial p_j} \\ &= (\boldsymbol{v_1} + \boldsymbol{v_2}\text{-}\boldsymbol{v_d})^T\boldsymbol{u_j}\end{aligned} \quad (17)$$

where $\boldsymbol{u_j}$ is jth column vector of weight matrix $\mathbf{U}$;

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

where s_i is input of ith node of the hidden layer.

In subsection A, without losing generality, we presented a 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 unmodelled 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 to 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).

6. EXPERIMENTAL EXAMPLES

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.

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 a software and hardware environment.

Fig. 1. AdeptOne robot manipulator

The identification experiments for individual joint were carried out. Since the number of pages is limited, we cannot show all of the experimental results. We carried out identification experiments and identified all the dynamic parameters of the robot. Since it needs a lot of pages to show the experiments and identification results, we give up the idea to show the whole work. Instead, we give the experimental results of the first joint as an example.

The excitation v_d has been chosen as a sine wave shown in Fig.2. The responses of displacement and velocity of joint 1 measured by the sensors of the robot are given in Fig.3 (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.3 (d) and (e).

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

$$v_d = \mathbf{y}_1(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}, \dddot{\boldsymbol{\theta}})\boldsymbol{a}_1 , \tag{19}$$

where the regressor and parameters are given as:

$$\mathbf{y}_1(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}, \ddot{\boldsymbol{\theta}}, \dddot{\boldsymbol{\theta}}) = [\dddot{\theta}_1 \ \ddot{\theta}_1 \ \dot{\theta}_1] \tag{20}$$

$$\boldsymbol{a}_1 = [a_{11} \ a_{12} \ a_{13}]^T \tag{21}$$

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

$$a_{11} = L_1 I_{a1} / \alpha_1 ,$$
$$a_{12} = R_1 I_{a1} / \alpha_1 + L_1 f_1 / \alpha_1 ,$$
$$a_{13} = L_1 f_1 / \alpha_1 + V_{a1}$$

where α_1, L_1, and R_1 denotes the back electromotive constant, inductance, and the resistance of the 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 4, the parameters are identified. Fig.4 shows the typical results of identified parameters against the number of sampling data. It can be seen that each parameter converges to a fixed value, when the number of the sampling data increases. The dynamic compensator is designed and the weights are trained with the methods given in the last section. Fig.5 shows the output of the inverse dynamics. 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 the errors between v_d and v_1 and between v_1 and v_1 respectively. Fig.6 shows the mean squared deviation error between the teaching signal and the output of the inverse system with respect to the learning time. To validate the conrrectness of the identified system, we carried out simulations using the dynamics give by (6). The input of the system is the same sine wave that has been used for the identification experiments.

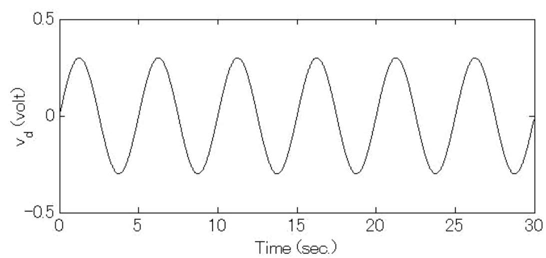

Fig.2. Joint 1 input signal in parameter identification experiment.

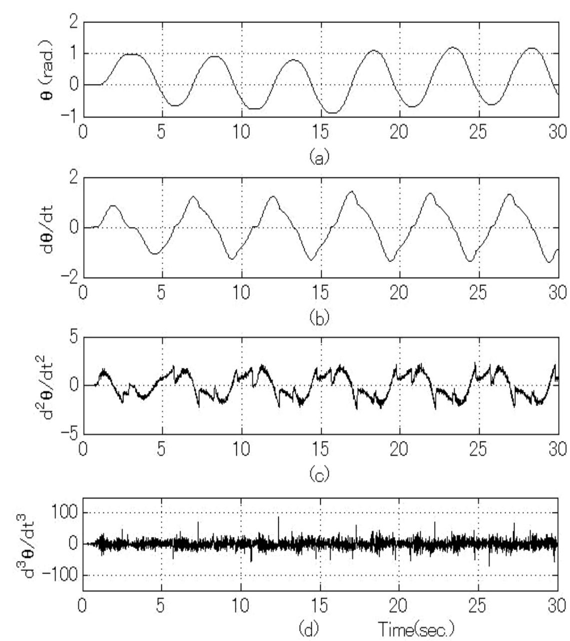

Fig.3. Responses of joint 1 to the input volt shown in Figure5

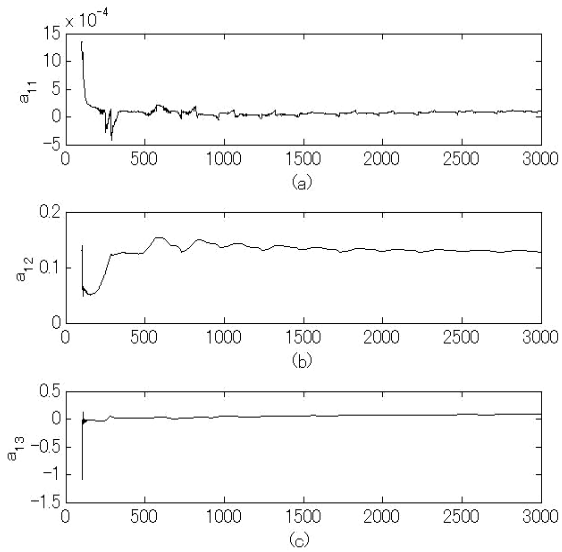

Fig.4. History of identified parameters with respect to the number of the experimental data

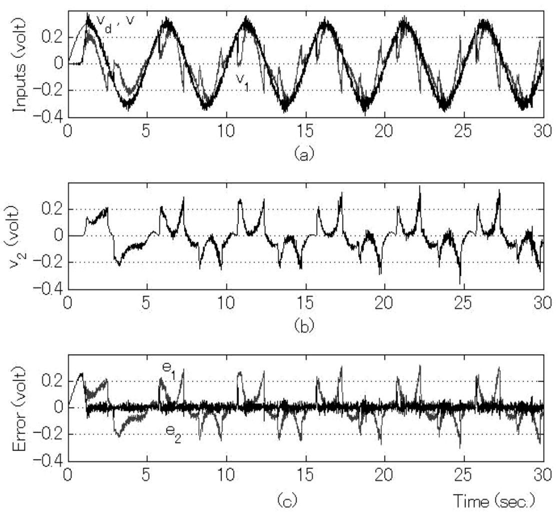

Fig.5. Validation results: output of the inverse system

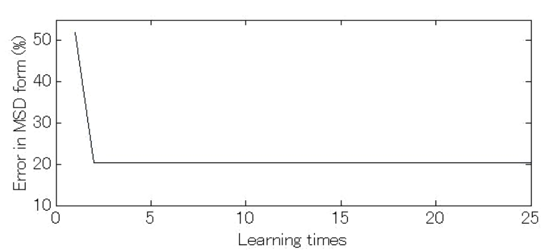

Fig.6. Mean squared deviation error between the teaching signal and the output of the inverse system with respect to the learning time

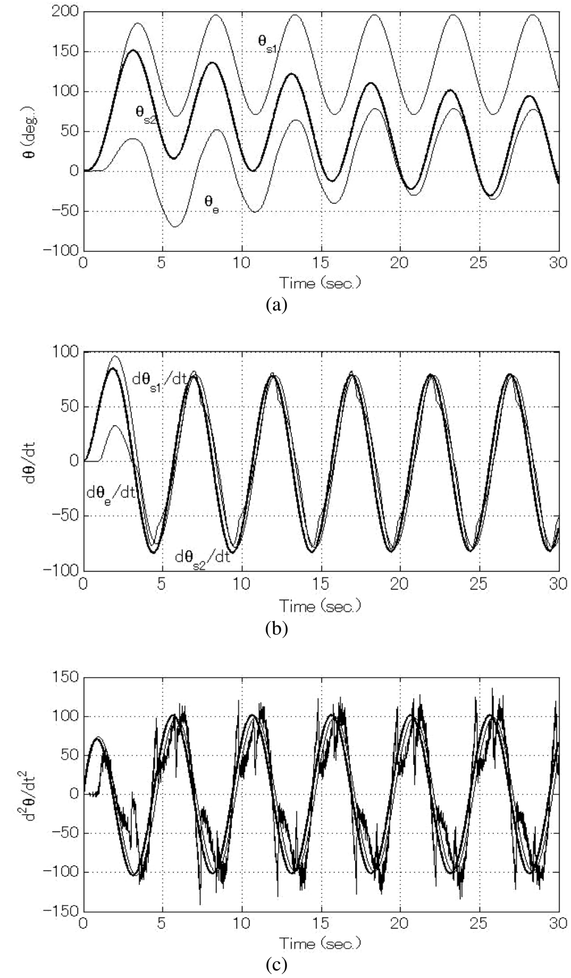

Fig.7. Comparison of experimental and simulation results

Fig.7 shows one of the results of simulation together with the corresponding experiment carried out for the parameter identification of joint 1.

In Fig.9 (a) and (b), θ_{s1}, θ_{s2} and θ_e are responses of joint 1 with respect to the simulation without the dynamic compensator, simulation with the dynamic compensator, and experiment; $\dot{\theta}_{s1}$, $\dot{\theta}_{s2}$, and $\dot{\theta}_e$ are their velocity. Fig. 7 (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 the line with noise is the joint acceleration calculated based on the experimental data. Comparing it with the 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 the dynamic compensator more effectively converge to their experimental counterparts, therefore, the correctness of the system with neural network dynamic compensator is confirmed.

7. Conclusions

This paper proposed a 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 for the unmodelled dynamics. Based on the 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 an 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 the 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.

Refrences

[1] **W, Verdonck, J. Swevers, J-C Samin**, *Experimental Robot Identification: Advantages of Combining Internal and External Measurements and of Using Periodic Excitation*, ASME Journal of Dynamic Systems, Measurement, and Control, Vol.123, pp.630-636, 1992.

[2] **G. Liu, K. Iagnemma, S. Dubowsky, and G. Morel, A Based** *Force-Torque Sensor Approach to Robot Manipulator Inertial Parameter Estimation*, Proceedings of IEEE International Conference on Robotics and Automation, pp.3316-3321, 1998.

[3] **B. Armstrong,** *On Finding Excitation Trajectories for Identification Experiments Involving Systems with Nonlinear Dynamics*, International Journal of Robotics Research, Vol.8, No.6, pp.28-48, 1989

[4] **H. Hahn, M. Niebergall**, *Development of a Measurement Robot for Identifying all Inertia Parameters of a Rigid Body in a Single Experiment*. IEEE Transaction on Control Systems Technology, Vol.9, No.2, pp.416–423, 2001.

[5] **K. S. Narendra, K. Parthasaraphy**, *Identification and Control of Dynamical Systems Using Neural Network*, IEEE Transaction on Neural Network, Vol.1, No.1, pp.5-27, 1990

[6] **S. Jung and S. B. Yim**, *Experimental Studies of Neural Network Impedance Control for the Robot Manipulators*, Proceedings of IEEE International Conference on Robotics and Automation, pp.3453-3458, 2001.

[7] **W. S. Yu, and G. C. Wang**, *Adaptive Control Design Using Delayed Dynamical Neural Network for a Class of Nonlinear Systems*, Proceedings of the IEEE International Conference on Robotics and Automation, pp.3447-3452, 2001.

[8] **B. Baachi, A. Benallegue and N. K. M'Sirdi**, *A Stable Neural Adaptive Force Controller for a Hydraulic Actuator*, Proceedings of IEEE International Conference on Robotics and Automation, pp.3465-33470, 2001.

[9] **Z. H. Jiang, H. Senda**, *Dynamic Parameter Identification of Robot Arms with Servo-Controlled Electrical Motors*, Proceedings of The International Conference on Mechatronics and Information Technology, 1-14-3 JRHI6, 2005.