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# A Study on the Stabilization Force Control of Robot Manipulator

**Yeong Yeun Hwang***

*Division of Electrical and Control Instrumentation Engineering, Pukyong National University, Busan 608-739, Korea*

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**Abstract :** It is important to control the high accurate position and force to prevent unexpected accidents by a robot manipulator. Direct-drive robots are suitable to the position and force control with high accuracy, but it is difficult to design a controller because of the system's nonlinearity and link-interactions. This paper is concerned with the study of the stabilization force control of direct-drive robots. The proposed algorithm is consists of the feedback controllers and the neural networks. After the completion of learning, the outputs of feedback controllers are nearly equal to zero, and the neural networks play an important role in the control system. Therefore, the optimum adjustment of control parameters is unnecessary. In other words, the proposed algorithm does not need any knowledge of the controlled system in advance. The effectiveness of the proposed algorithm is demonstrated by the experiment on the force control of a parallelogram link-type robot.

**Key words :** robot manipulator, accident, stabilization control, neural network

## 1. Introduction

Today, the automatization by industrial robots is merely rely on the simple position repeating works. The position control alone seemed to be insufficient owing to expansion of assembling, grinding and deburring works with industrial robots. Recently, serious damages and accidents are often happened by industrial robots which was mis-controlled unstably. Therefore, both of the position and force control of the robot should be controlled with high accuracy to get a safety. The requirements of the force control research and development which would adapt positively to various restriction works are rising. To meet these new demands, the continuous research and development for hardware design such as mechanical structure of the robot, actuator and sensor are required.

Direct-drive(DD) robots are suitable to the force control with high accuracy. Because DD motor does not use a gear or harmonic drive as a speed reducer, backlash and hysteresis does not exist and it's friction and torque variation is also very small. Also it's dynamic response of torque control is excellent because of small elastic deformation of the power transfer system. The research for the robots manufactured with DD motor have been going on continuously for practical use of DD robot [1~3]. On the other hand, after endowing geometrical constraints, so called natural and artificial constraints, the researches for the force control of the robots have been continued including researches which had founded hybrid control of the position and force [4], cooperative control of two DD robots [5], and robust force control of the pneumatic manipulator [6].

In this paper, a learning control algorithm using neural networks is proposed for the force control by DD robot. The effectiveness of the proposed algorithm is demonstrated by the experiment on the force control of a parallelogram link DD robot with force sensor.

## 2. Dynamics of Parallelogram Link Robot

Fig. 1 is the summary drawing of the parallelogram link robot which is manufactured with two DD motor. The force sensor is attached on the robot tip for the force control. Generally, the dynamics equation of the robot which possess rotational joint can be expressed as following form

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

where, $\boldsymbol{\tau}$ is generated torque at rotational joint, first term at right side is expressing the inertia matrix, sec-

*Corresponding author: yyh@pknu.ac.kr

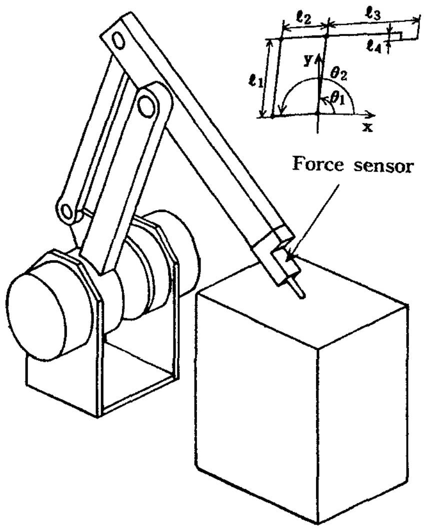



**Fig. 1.** Direct-drive robot with force sensor.

ond term of right side is expressing the centrifugal force and the coriolis force vector, third term is expressing the gravity vector and $\theta, \dot{\theta}, \ddot{\theta}$ express vector of joint angle, angular velocity and angular acceleration respectively.

We could get the dynamic equation of the parallelogram link robot with two degrees of freedom as follows,

$$\tau_1 = M_{11}\ddot{\theta}_1 + M_{12}\ddot{\theta}_2 + H_{12}\dot{\theta}_2^2 + G_1 \tag{2}$$

$$\tau_2 = M_{21}\ddot{\theta}_1 + M_{22}\ddot{\theta}_2 - H_{12}\dot{\theta}_1^2 + G_2 \tag{3}$$

If we assume that $I_i$ is the inertia moment of $i$ joint axis, $l_i$ is length of link $i$, $l_{ci}$ is length from joint $i$ to center of link, and $g$ is acceleration of gravity, then $M_{ij}, H_{12}$, and $G_i$ $(i,j = 1,2)$ are respectively given by

$$M_{11} = I_1 + m_1 l_{c1}^2 + I_3 + m_3 l_{c3}^2 + m_4 l_1^2 \tag{4}$$

$$M_{12} = M_{21} = (m_3 l_2 l_{c3} - m_4 l_1 l_{c4}) c_{1-2} \tag{5}$$

$$M_{22} = I_2 + m_2 l_{c2}^2 + I_4 + m_4 l_{c4}^2 + m_3 l_2^2 \tag{6}$$

$$H_{12} = (m_4 l_1 l_{c4} - m_3 l_2 l_{c3}) s_{1-2} \tag{7}$$

$$G_1 = g c_1 (m_1 l_{c1} + m_3 l_{c3} + m_4 l_1) \tag{8}$$

$$G_2 = g c_2 (m_2 l_{c2} + m_3 l_2 - m_4 l_{c4}) \tag{9}$$

where, $c_i = \cos\theta_i$, $s_i = \sin\theta_i$, $c_{1-2} = \cos(\theta_1 - \theta_2)$, $s_{1-2} = \sin(\theta_1 - \theta_2)$.

If we set, inertia of the DD motor $\boldsymbol{J}$, viscosity coefficient friction $\boldsymbol{B}$ and coulomb friction $\boldsymbol{F}$, then the dynamic equation of the DD motor can be expressed as follows,

$$\boldsymbol{\tau} = \boldsymbol{J}\ddot{\theta} + \boldsymbol{B}\dot{\boldsymbol{\theta}} + \boldsymbol{F}(\dot{\theta}) \tag{10}$$

We could get total dynamic equation of the DD robot from dynamic equation (1) of the parallelogram link robot and dynamic equation (10) of the DD motor.

$$\boldsymbol{\tau} = \boldsymbol{R}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \boldsymbol{B}\dot{\boldsymbol{\theta}} + \boldsymbol{V}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) + \boldsymbol{F}(\dot{\boldsymbol{\theta}}) \tag{11}$$

where

$$\boldsymbol{R}(\boldsymbol{\theta}) = \boldsymbol{M}(\boldsymbol{\theta}) + \boldsymbol{J} \tag{12}$$
$$\boldsymbol{V}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) = \boldsymbol{H}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) + \boldsymbol{G}(\boldsymbol{\theta}) \tag{13}$$

First term of equation (11) express inertia, second term express viscosity, third term express nonlinearity with centrifugal and gravity, and fourth term of the equation express coulomb friction. The inertia moment varies in accord with running angle of motor as function of $\theta$. Also nonlinear external disturbance of centrifugal force and gravity affect to operation of motor each other. From this we know that motor is interfering each other dependently.

## 3. Control System

### 3-1. Learning by Neural Network

Consider the neural network with an input layer, a hidden layer and an output layer, which is shown in Fig. 2. In Fig. 2, there is no connection between the neurons in the same layers, and the signal flow from left to right. The input-output relationships of the input

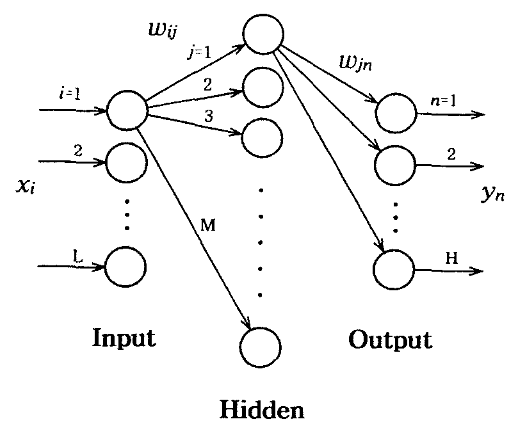



**Fig. 2.** Neural network.

layer are linear. The outputs of the hidden and the output layers are governed by a sigmoid function $f(x)$, bounded by $-1<f(x)<1$.

Error backpropagation method is used as learning algorithm of the neural network controller. If we assume actual output of the neural network as $y_n$, target output as $v_n$, then union weight between each layer $w_{jn}$ and $w_{ij}$ shall be calculated by the following equation.

$$w_{jn} = \sum_{n=1}^{H} \eta \delta_n y_n \tag{14}$$

$$w_{ij} = \sum_{j=1}^{M} \eta \delta_j y_i \tag{15}$$

where $\eta$ is learning rate, $\delta_n$ and $\delta_j$ are given as follows,

$$\delta_n = \{1-(y_n)^2\}(v_n - y_n) \tag{16}$$

$$\delta_j = 0.5\{1-(y_j)^2\} \sum_{n=1}^{H} \delta_j w_{jn} \tag{17}$$

**3-2. Control System of the DD Robot**

The block diagram for the force control system of the DD robot is shown in Fig. 3. The tip position of the force sensor $\boldsymbol{r}$ can be written as follows by the kinematic function $\boldsymbol{\Lambda}(\boldsymbol{\theta})$.

$$\boldsymbol{r} = \boldsymbol{\Lambda}(\boldsymbol{\theta}) \tag{18}$$

If we set the length of link $l_i$ ($l_1$ = 0.4 m, $l_2$= 0.2 m, $l_3$ = 0.545 m, $l_4$ = 0.062 m), as showed on Fig. 1, $\boldsymbol{r}$, $\boldsymbol{\theta}$ and $\boldsymbol{\Lambda}(\boldsymbol{\theta})$ could be defined as follows,

$$\boldsymbol{r} = [r_x \ \ r_y]^T \tag{19}$$

$$\boldsymbol{\theta} = [\theta_1 \ \ \theta_2]^T \tag{20}$$

$$\boldsymbol{\Lambda}(\boldsymbol{\theta}) = \begin{bmatrix} l_1c_1 - l_3c_2 - l_4s_2 \\ l_1s_1 - l_3s_2 + l_4c_2 \end{bmatrix} \tag{21}$$

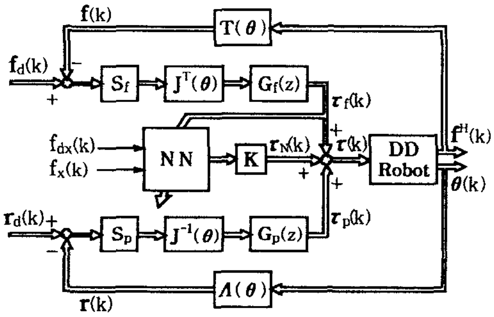



**Fig. 3.** Control system of robot.

The contact force $\boldsymbol{f}^H$ expressed in the sensor coordinates can be transformed into $\boldsymbol{f}$ as follows,

$$\boldsymbol{f} = \boldsymbol{T}(\boldsymbol{\theta})\boldsymbol{f}^H$$

where, $\boldsymbol{f}$ and $\boldsymbol{T}(\boldsymbol{\theta})$ are respectively given by

$$\boldsymbol{f} = [f_x \ f_y]^T \tag{23}$$

$$\boldsymbol{T}(\boldsymbol{\theta}) = \begin{bmatrix} -c_2 & s_2 \\ -s_2 & -c_2 \end{bmatrix} \tag{24}$$

If we set selective matrix of the position and force control as $\boldsymbol{S}_p$, $\boldsymbol{S}_f$, the error between the target position $\boldsymbol{r}_d$ and the actual position $\boldsymbol{r}$, and the error between the target contact force $\boldsymbol{f}_d$ and the actual contact force $\boldsymbol{f}$ can be converted to joint coordinates based $\boldsymbol{\Delta\theta}$ and $\boldsymbol{\Delta\tau}$ as follows by the jacobian matrix $\boldsymbol{J}(\boldsymbol{\theta})$,

$$\boldsymbol{\Delta\theta} = (\boldsymbol{r}_d - \boldsymbol{r})\boldsymbol{S}_p\boldsymbol{J}^{-1}(\boldsymbol{\theta}) \tag{25}$$

$$\boldsymbol{\Delta\tau} = (\boldsymbol{f}_d - \boldsymbol{f})\boldsymbol{S}_f\boldsymbol{J}^T(\boldsymbol{\theta}) \tag{26}$$

where, $\boldsymbol{J}(\boldsymbol{\theta})$, $\boldsymbol{S}_p$ and $\boldsymbol{S}_f$ are respectively given by

$$\boldsymbol{J}(\boldsymbol{\theta}) = \begin{bmatrix} -l_1s_1 & l_3s_2 - l_4c_2 \\ l_1c_1 & -l_3c_2 - l_4s_2 \end{bmatrix} \tag{27}$$

$$\boldsymbol{S}_p = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{28}$$

$$\boldsymbol{S}_f = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \tag{29}$$

If we set output of the neural network as $\boldsymbol{\tau}_N$, output of the force controller as $\boldsymbol{\tau}_f$ and output of the position controller as $\boldsymbol{\tau}_p$, the operational torque of the robot $\boldsymbol{\tau} = [\tau_1 \ \ \tau_2]^T$ is given as follows,

$$\boldsymbol{\tau} = \boldsymbol{\tau}_f + \boldsymbol{\tau}_p + \boldsymbol{\tau}_N \tag{30}$$

**3-3. Force Control of the DD Robot**

The number of neuron on each layer of the neural network are 2 on input layer ($f_{dx}, f_x$), 10 on the middle layer and 2 on the output layer. The constant $\boldsymbol{K}$ is used for adjusting to output of the neural network.

$$\tau_N = Ky_n \tag{31}$$

Only the feedback control is used for the force control on 1st learning and the sum of output of the feedback control $\boldsymbol{\tau}_p$ and output of the neural network $\boldsymbol{\tau}_N$ is applied as operational torque $\tau$ from 2nd learning on. After setting $\tau_p$ as error signal, continue to correct union weight so as this error signal reach to zero at each step of sampling time. Due to large error at the beginning of learning, the feedback controller would function as main controller and the output of neural network is nearly equal to zero. But the error would get smaller as learning continue on and finally learned neural network would become as main controller. The proposed control algorithm in this research is neural network added to feedback controller and possess a character of improving performance of controller by learning.

## 4. Experimentation

### 4-1. Force Sensor and Controlled Object

The force sensor which is manufactured to measure force at tip of robot is constructed with combination of strain gauge attached bronze plate and sub material plate. The mass of force sensor is 0.25 Kg, standard load is ±10 N and maximum load is ±15 N. Two kind of material whose solidity is different to each other (object 1 : styrofoam, object 2 : plastic plate) are used at the contact surface of the force control. Sampling period is 5 ms, total number of sampling is 400. Also value of $\eta$ = 0.1 for learning rate of neural network, the gains of the feedback controller are respectively given by $K_P$=200, $K_D$=10, $K_P^f$=1.5, $K_D^f$=0.2.

Initial operation prior to the force control is bringing of the tip of the robot slowly toward the restricting surface while applying the feedback control to $x$ direction. Force control should be started soon as detected contact force from sensor reach to 2 N on touching restricting surface with tip of the robot. The experimental results indicated on Fig. 4~7 are values taken after initial operation.

### 4-2. Experimental Results

Fig. 4 is experimental results for object 1(styrofoam). When only the feedback controller was used, Fig. 4(a) is response of first trial. Left side of the figure indicates target contact force $f_{dx}$ and sensor detected actual response $f_x$ . These values are not reaching to the target value since suitable feedback gain was used to find out learning effect. Right side of the figure indicates output of the neural network $\tau_N$ and the actual torque

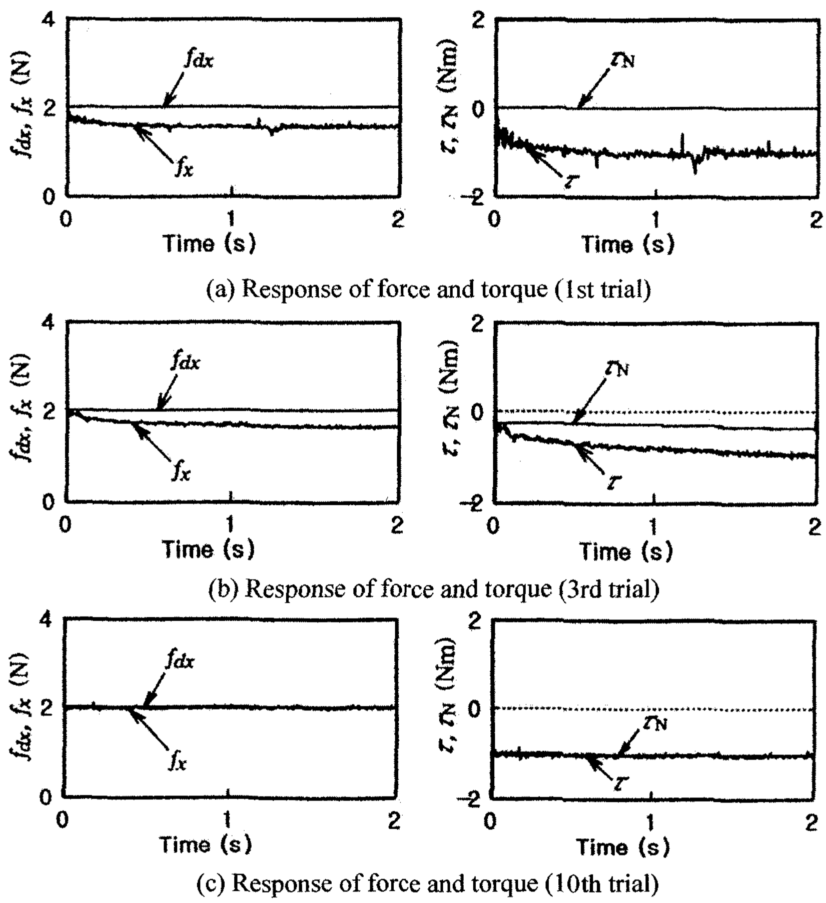



**Fig. 4.** Experimental results for object 1.

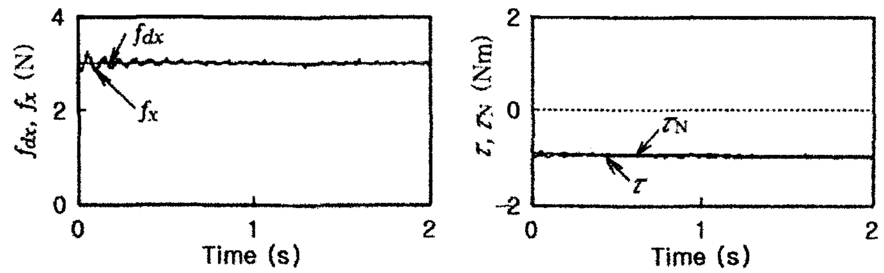
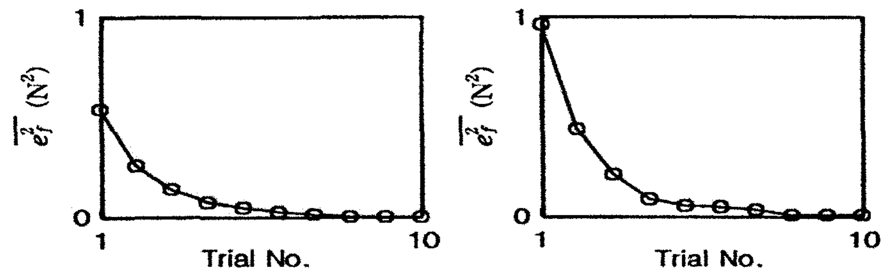


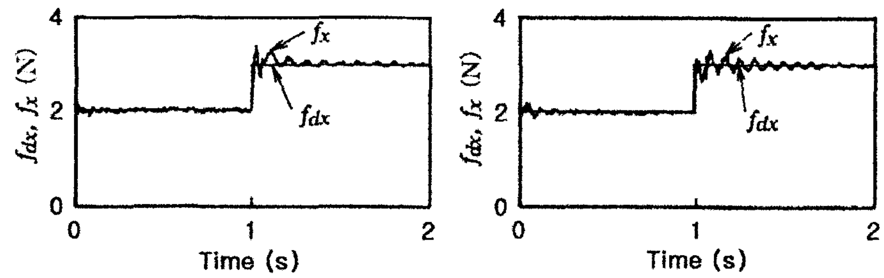

**Fig. 5.** Experimental results for object 2 (10th trial).




(a) In case of object 1

(b) In case of object 2

**Fig. 6.** Learning process.




(a) In case of object 1

(b) In case of object 2

**Fig. 7.** Experimental results for change of force (10th trial).

of the robot $\tau$. There are two actual torque $\tau_1$ and $\tau_2$, however the actual operational torque of $y$ direction $\tau_2$ is omitted because it is so small, and only $x$ directional force is mainly controlled. The output $\tau_N$ of the neural network is zero because only the feedback controller is used on first trial. Fig. 4(b) is the response of third trial and Fig. 4(c) is the response of 10th trial.

$\tau_N$ and $\tau$ concurs as indicated on right side of Fig. 4(c). This indicates that output of neural network is concurring with operational torque of the robot and this means that output $\tau_p$ of the feedback controller is nearly equal to zero. In other words, this is indicating that neural network is functioning as main controller by producing operational torque of the robot directly.

Fig. 5 is the experimental results for object 2 (plastic plate) and target contact force is 3 N on this case. It can be seen there is time difference in reaching target value compared to case of object 1 due to initial vibrating component which is caused by a high hardness.

Fig. 6 shows the variation of the mean squared errors $\overline{e_f^2}$ against the contact force. That is, Fig. 6(a) is drawn by the experimental result of Fig. 4 and Fig. 6(b) is drawn by the experimental result of Fig. 5 respectively.

Fig. 7 shows response after 10th trial of learning when the target force was changed from 2 N to 3 N. From Fig. 7, we can conclude that the proposed algorithm is also effective when the target force is changed.

## 5. Conclusion

This research is the study related to the force control to surrounding environment of the robot. A learning control algorithm using neural networks is proposed for the stabilization force control of DD robot. The proposed algorithm is the feedback controller on which the learning controller of neural network is added and improve controller's efficiency by learning. Experimentally, it is confirmed that the output of the feedback controller is nearly equal to zero after the completion of learning, and the neural networks play an important role. Therefore, the optimum adjustment of control parameters is unnecessary. Thus, we showed the proposed algorithm does not require any knowledge of the controlled system in advance.

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