Gain Tuning Using Neural Network for Contact Force Control of Flexible Arm

Minoru Sasaki, Nobuto Honda, Waweru Njeri, Kojiro Matsushita

Abstract—In this research, contact force control of an one link flexible arm is presented. A simple boundary feedback controller consisting of bending moment at the base of the flexible arm proposed by Endo et al. A gain adjustment control system using a neural network is designed and its control performance examined and compared by numerical simulation and experiment. In this study, we designed the feedback gain to correspond to the coupling coefficient of the neural network, and stabilized the learning by giving the initial value to the coupling coefficient of the neural network, thereby shortening the learning time. Also, in order to adjust the gain value in real time, a sequential correction type (online learning) that repeats learning at every sampling was adopted as the learning scheme of the neural network. As a result, it was confirmed that by using the using the neural network, the value of the feedback gain is adaptively changed and the target contact force converges around 0.35 seconds. Comparing with the fixed gain results, it takes shorter time for convergence to the target value by 0.8 seconds, the proposed controller is confirmed to be more effective for the contact force control of the flexible arm.

Keywords—Flexible arm, contact force control, neural networks, gain tuning

I. Introduction

FOR heavy and highly rigid robotic arms used in factories and the like, it is common to increase the rigidity by increasing the wall thickness of the arm so as to obtain high accuracy in determining the position of the tip. In recent years, however, there has been an increasing demand for weight reduction of robot arms in order to realize high speed operation and energy saving. As the rigidity decreases accordingly, the influence of elastic deformation due to the flexibility of the arm becomes large, so that position error and elastic vibration cannot be ignored [1,2,3]. Against such a background, researches on control of flexible manipulators have been actively conducted.

In addition to the requirement mentioned above in regards to need for lightweight roots, use of nursing care robots and welfare robots under human-contacting environments is on the rise, so it is necessary to control the contact force in addition to the positioning control to work safely together with people[4].

In this paper, we examine the force control problem on the constrained one-link flexible arms. In this conventional study, we propose to extend the simple boundary feedback consisting of a bending moment at the root of the flexible arm and its time derivative against the force control problem of the constrained one-link flexible arm earlier developed by Endo et als [5,6]. In their works, feedback control was used to obtain the exponential stability of the closed loop system. Researchers in [7,8,9] conducted several simulations to examine the effectiveness of feedback techniques involving tuning the feedback gains, but the method of adjusting the performance verification and feedback gain by the experiment of the proposed controller remained a problem.

Therefore, in this research, we developed a one-link flexible arms, first to experimentally verify the controller proposed by Endo et al. and confirmed its effectiveness. Next, we designed a control system using a neural network controller for auto-tuning feedback gains. We experimentally verified compared and examined the control performance of the neuro controller against the fixed gain controller earlier proposed by Endo. Similar work in literature related to the control of flexible manipulator using neural networks includes [10,11,12].

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II. Modelling of One Link Flexible Arm

The model of one link Flexible Bernoulli-Euler Arm in this study is shown in Figure 1. The base of Flexible Bernoulli-

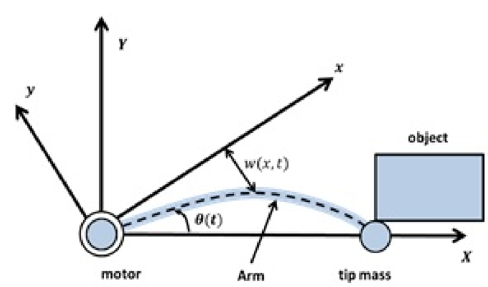

Fig. 1. Flexible Bernoulli-Euler Arm contact with an object

Euler Arm is equipped with a motor to rotate the arm, and rotation is controlled by the actuator. Also, the tip of the arm is in contact with the object. Variables used in the derivation are; length of arm is l, linear density ρ of arm, secondary moment of area I, Young's modulus E, moment of inertia J of the motor, torque of motor $\tau_a(t)$, motor rotation angle $\theta(t)$. Further, $w(x,t)$ is the transverse displacement of the point x on the X axis of the arm at a certain time, the equation of motion and the boundary condition of this model can be obtained as follows.

$$\begin{aligned} w(x,t) - x\theta(t) &= y(x,t) \\ y(x,t) + \frac{EI}{\rho} y''''(x,t) &= 0 \\ J\theta(t) = \tau_a(t) - EIw''(0,t) &= \tau(t) \\ y(0,t) = y(l,t) = y''(l,t) = l\theta(t) - w(l,t) &= 0 \\ EIw'''(l,t) &= \lambda(t) \end{aligned}$$

To control the contact force of the tip of the arm, it is necessary to consider boundary control. Here, denoting the target contact force by λ_d and the target values are denoted as $y_d(x)$ and θ_d, the following relational expression is obtained.

$$\begin{aligned} y_d(x) &= \frac{\lambda_d}{6EI} x(2l^2 - 3lx + x^2) \\ \theta_d &= -y_d(0) = -\frac{l^2\lambda_d}{3EI} \end{aligned} \tag{1}$$

The vibration suppression control law is obtained as follows [5].

$$\tau(t) = -k_1 EI[y''(0,t) - y_d''(0)] - k_2 EI\dot{y}''(0,t) \tag{2}$$

Where the feedback gains $\tilde{k}_1$ and $\tilde{k}_2$ are positive constants. In this control law 2, the first item is the bending moment $EIy''(0,t)$ of the base of the arm, we desire that the bending moment will approach the target value $EIy_d''(0,t)$ in a manner that is asymptotic. The second item is a term for vibration suppression.

This section shows that for flexible arms with one end fixed to the control motor and the other end free, this has the effect of suppressing the vibration of the arm [9]. The Laplace transform of the equation of motion, the boundary condition, and the control law is as follows.

$$y(x,s) = w(x,s) - x\theta(s)$$

$$0 = s^2 y(x,s) + \frac{EI}{\rho} y''''(x,s) \tag{3}$$

$$\begin{aligned} Js^2\theta(s) &= \tau_a(s) - EIw''(x,s) = \tau(s) \\ y(0,s) &= y(l,s) = y''(l,s) = l\theta - w(l,s) = 0 \\ \lambda(s) &= EIw'''(l,s) \\ \tau(s) &= -\tilde{k}_1 EI[y''(0,s) - \frac{1}{s} y_d''(0)] - \tilde{k}_2 sEIy''(0,s) \end{aligned} \tag{4}$$

Solving for $y(x,s)$ from equation 3 where $F_1(s)$, $F_2(s)$, $F_3(s)$ and $F_4(s)$ are unknowns and j is the complex operator for imaginary values, yields

$$\begin{aligned} y(x,s) = &F_1(s)e^{-j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} + F_2(s)e^{-j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &+ F_3(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} + F_4(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \end{aligned} \tag{5}$$

and with

$$s^2\theta(s) = \frac{\tau(s)}{J} \tag{6}$$

Substituting 4 into equation 6 and taking $k_1 = \tilde{k}_1/J$, $k_2 = \tilde{k}_2/J$

$$s^2\theta(s) = -k_1 EI[y''(0,s) - \frac{1}{s} y_d''(0)] - k_2 sEIy''(0,s) \tag{7}$$

From 5

$$\begin{aligned} y''(0,s) = &-\frac{F1(s)\sqrt{-s^2E^3I^3\rho}}{E^2I^2} + \frac{F2(s)\sqrt{-s^2E^3I^3\rho}}{E^2I^2} \\ &- \frac{F3(s)\sqrt{-s^2E^3I^3\rho}}{E^2I^2} + \frac{F4(s)\sqrt{-s^2E^3I^3\rho}}{E^2I^2} \end{aligned} \tag{8}$$

From 1

$$y_d''(0) = \frac{\lambda_d l}{sEI} \tag{9}$$

Substituting equations 8 and 9 into the equation 7

$$\begin{aligned} s^2\theta(s) = &-\frac{1}{EIs}(-k_1F_1(s)\sqrt{-s^2E^3I^3\rho}s \\ &+ k_1F_2(s)\sqrt{-s^2E^3I^3\rho}s \\ &- k_1F_3(s)\sqrt{(-s^2E^3I^3\rho}s \\ &+ k_1F_4(s)\sqrt{-s^2E^3I^3\rho}s \\ &+ k_1\lambda_d lEI - k_2\sqrt{-s^2E^3I^3\rho}F_1(s) \\ &+ k_2s^2\sqrt{-s^2E^3I^3\rho}F_2(s) \\ &- k_2s^2\sqrt{-s^2E^3I^3\rho}F_3(s) \\ &+ k_2s^2\sqrt{-s^2E^3I^3\rho})F_4(s)) \end{aligned} \tag{10}$$

$$\begin{aligned} \theta(s) = &\frac{-s(k_1 + sk_2)(-F_1(s) + F_2(s) - F_3(s)}{EIs^3} \\ &+ \frac{F_4(s))\sqrt{-s^2E^3I^3\rho} - k_1\lambda_d lEI}{EIs^3 \text{ Substituting}} \end{aligned} \tag{11}$$

equations 5 and 11 into equation 3

$$\begin{aligned} w(x,s) = &F_1(s)e^{-j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} + F_2(s)e^{-j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &+ F_3(s)e^{-j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} + F_4(s)e^{-j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &- \frac{x(-s(k_1 + sk_2)(F_1(s))\sqrt{-s^2E^3I^3\rho} - k_1\lambda_d lEI)}{EIs^3} \\ &+ \frac{x(-s(k_1 + sk_2)F_2(s)(\sqrt{-s^2E^3I^3\rho} - k_1\lambda_d lEI))}{EIs^3} \\ &- \frac{x(-s(k_1 + sk_2)F_3(s)(\sqrt{-s^2E^3I^3\rho} - k_1\lambda_d lEI))}{EIs^3} \\ &+ \frac{x(-s(k_1 + sk_2)F_4(s)(\sqrt{-s^2E^3I^3\rho} - k_1\lambda_d lEI))}{EIs^3} \end{aligned} \tag{12}$$

$$\begin{aligned} w'''(l,s) = &\frac{1}{E^3I^3}[(-s^2E^3I^3\rho)^{\frac{3}{4}}IF_1(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &- F_2(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} - IF_3(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &+ F_4(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}}] \end{aligned} \tag{13}$$

Substituting equation 13 into equation 4

$$\begin{aligned} \lambda(s) = &\frac{1}{E^2I^2}[(-s^2E^3I^3\rho)^{\frac{3}{4}}(IF_1(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &- F_2(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &- IF_3(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}} \\ &+ F_4(s)e^{j(\frac{s^2E^3I^3\rho}{EI})^{\frac{1}{4}x}})] \end{aligned} \tag{14}$$

By substituting the four unknowns $F_1(s)$, $F_2(s)$, $F_3(s)$, $F_4(s)$ from the simultaneous equations of the equation 4 into 12, we get the general solution of $w(x, s)$. Based on the above, the block diagram of the 1-link Flexible Arm system is shown in Figure 2.

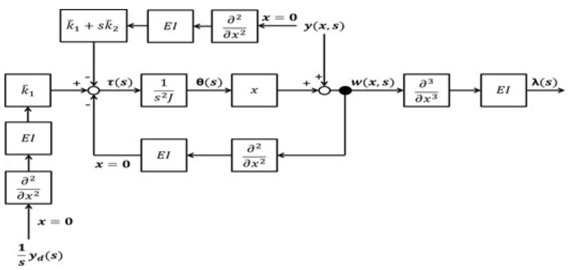

Fig. 2. Block diagram of 1 link flexible Bernoulli-Euler Arm

III. Determination of feedback gains $\tilde{k}_1$, $\tilde{k}_2$ by simulation

In the simulation, the cross sectional area $A = bh$ (m^2), the geometrical moment of inertia $I = \frac{bh^3}{12}$ (m^4), the linear density ρ (kgm^{-1}) is obtained as $\rho = \rho_a bh$. The feedback gain to be used is set to $k_1 = 1.2$ and $k_2 = 0.5$ obtained by trial and error. Hereinafter, assuming that the target contact force $\lambda_d = 1N$, the results of the deflection distance at the arm tip of the model, the rotation angle of the motor, and the time response of the contact force exerted on the object by the arm tip are shows in Figure 3.

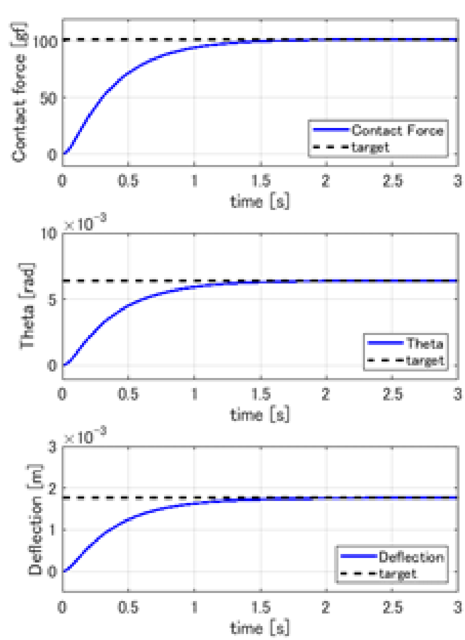

Fig. 3. Numerical result of moment-PD control.

As can be seen from Figure 3, since the contact force at the tip of the arm converges to the target value around 2.3 seconds, the moment-PD control is also effective for this model. From this result, the values of feedback gain used in this research are set to $k_1 = 1.2$ and $k_1 = 0.5$.

IV. Design of control system using neural network

For the purpose of shortening the convergence time from that observed using the feedback gain determined by trial and error as an initial value, we designed a control system that tunes gain adaptively. In this research, we take advantage of the numerous strengths on the artificial neural network, primarily, that it can be used to approximate any nonlinear function. The neural network to be used is a three-layer hierarchical type having three units in the input layer, one hidden neuron and one neuron in the output layer corresponding to the driving torque. Also, the input is the target value and the present value of the bending moment of the base of the arm and the present value of deflection, and the sigmoid function is used for the output function of the hidden layer and the output layer. As the learning method, the error backpropagation method is used and the steepest descent method is used for the updating the coupling coefficient between the units in an online version. Figure 3 shows the block diagram of the control controller.

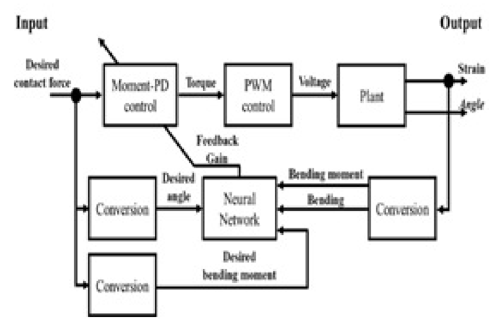

Fig. 4. Neural network control system.

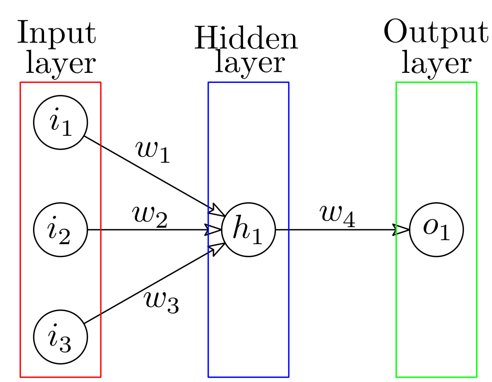

Fig. 5. Three-layered neural network.

V. Design experimental setup

Figure 4 shows the overall view of the 1-link flexible arm to be controlled. The material of the arm is aluminum (3003), the sectional shape is a rectangle, the distance from the root is $l = 0.275$ m. A brushed DC motor equipped with a metal gearbox with a gear ratio of 50:1 and equipped with an integrated type orthogonal encoder is attached at the root of the arm to provide the driving torque. The resolution of the encoder is 64 counts

TABLE I
SYSTEM PARAMETERS

Parameter	Symbol	Dimension
Height	h	0.02 m
Breadth	b	0.00447 m
Length	l	1.05 m
Density	ρ_a	7874 kgm-3
Mass moment of inertia	I_ρ	2.79×10^{-4}kgm
Young's modulus	E	2.06×10^{-11} Pa

per rotation of the motor shaft (corresponding to 3200 counts per shaft rotation of gearbox output). In order to measure the elastic deformation in the direction of rotation of the motor, the strain gauge is attached in a 2-gauge method. The parameters used in this study are shown in Table I.

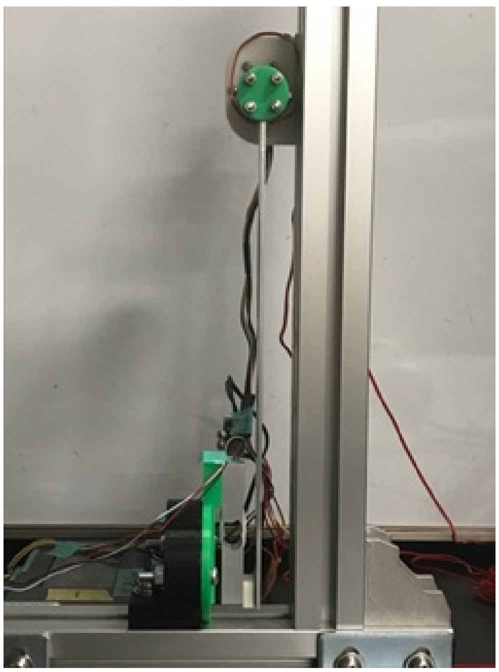

Fig. 6. link flexible arm.

Figure 7 shows a conceptual diagram of the system configuration used in this study.

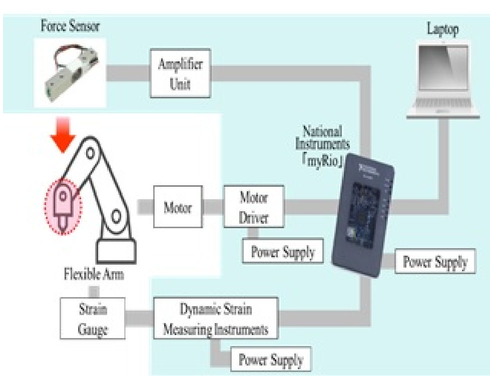

Fig. 7. Experiment system.

A control system consist of Laboratory Virtual Instrumentation Engineering Workbench(LabVIEW) manufactured by National Instrument installed on a PC running Microsoft Windows 7 operating system. LabVIEW makes it easier to express complex logic on a diagram by using a graphical programming approach to visualize every aspect of an application. Designing a distributed test, measurement and control system can be performed efficiently. For the controller, NI myRIO (manufactured by National Instrument Corporation) embedded hardware device for education is used. For the force sensor, 2 kg of load cell single point (beam type) manufactured by Sensor and Control is amplified by an amplifier circuit and used. It is placed so that it will be in vertical contact with the tip of the arm. Experiment is conducted with a dynamic strain measuring instrument (DPM 713 B made by Kyowa Denki) with the low pass filter set at 100 Hz, the measurement range set at $500\mu\Omega$, and the configuration value set at $500\mu\varepsilon$/2V. W_1 = 1.7, W_2 = 1.2, W_3 = -1.0 are given to the initial value of the coupling coefficient of the neural network, and a random number is used for W_4. Learning is performed at every sampling time of 2milliseconds, and the experiment is performed with the target value contact force λ_d set to $1N$. Figure 8 shows temporal changes of the feedback gain (k_1, k_2), Figure 9 shows the distortion of the base of the arm, deflection of the arm tip, the rotation angle of the motor, and the contact force.

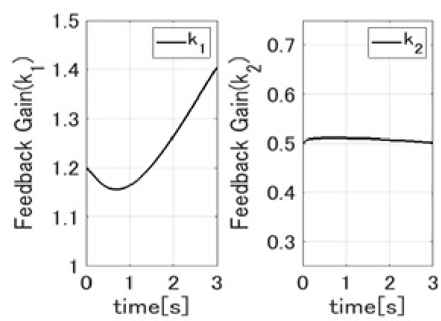

Fig. 8. Time response of feedback gain.

From Figure 9, the blue line is the moment-PD control and the red line is the NN-moment-PD control and is smoothed using the median filter to make comparison easier. From this result, it is understood that the time required for convergence is 0.8 seconds earlier for the NN-moment-PD control that adaptively changes the gain than the fixed moment-PD control. In addition, it can be seen that the control system to which the NN-moment-PD control is applied stably converges to the target value. From the above, it is confirmed that by designing the control system using the neural network as the gain adjustment method, it is possible to adaptively change the value of the gain and to quickly converge to the target value of the contact force, and the controller proposed in the actual machine. These results confirms the effectiveness of this study in terms of enhancing the speed of convergence.

VI. CONCLUSION

In this research, focusing on force control by a constrained one link flexible arm, we fabricated a one-link flexible arm and

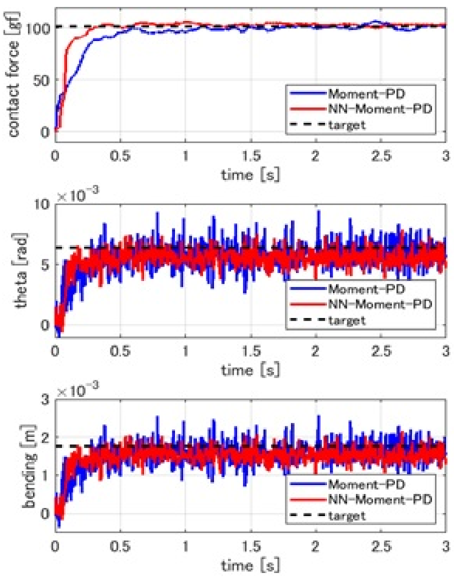

Fig. 9. Transient responses; blue line: Moment-PD; red line: NN-Moment-PD

developed a simple boundary feedback controller (Moment-PD control) consisting of bending moment at the base of the arm proposed by Endo et al. A control system using a neural network was designed as a gain adjustment method, and comparison and examination of control performance by numerical simulation and actual machine were performed. First, regarding moment-PD control, general solutions are derived from the model by formulating a theoretical expression from the model, and the value of the feedback gain to be used in this research is determined using numerical simulation. Thereafter, using those values on an experimental laboratory flexible arm, it was confirmed that the target contact force converged about 1.15 seconds. From this, we confirmed the effectiveness of the moment-PD control proposed by Endo et al. Next, we designed the control system applying the neural network as the gain adjustment method to enhance the performance obtained with fixed gains. Weight updating scheme adopted in this work is the online error backpropagation in which learning is repeated for each sampling for learning timing of the neural network. Analyzing the experimental results, it was confirmed that by using the control system employing the neural network, the value of the feedback gain is adaptively changed, and the target contact force converges around 0.35 seconds. Relative to the control law having fixed gains, we succeeded in enhancing the time it takes for convergence to the target value by 0.8 seconds confirming the effectiveness of the controller proposed in the actual machine. The learning rate employed in this is fixed, as a future prospect, we propose to enhance learning by the introduction of adaptive learning rate. This way, the learning rate will be set to higher values when the error is high and to smaller values when the error decrease to lower values. The learning will gradually decay as the network learns and approach the target values. We also plan to compare the performance of this scheme with other popular machine learning schemes like support vector machine and deep learning.

VII. Acknowledgement

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