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System Identification of a Galvano Scanner Using Input-Output Data Obtained from Positioning Control

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***Abstract*— To achieve high-speed and high-precision control, an accurate plant model is required. Since the plant parameters may vary by an environmental change and so on, it is desirable to identify the plant parameters during positioning control. In the system identification, a pseudo random signal is in general used to fully excite the dynamics of the plant. Therefore, when the input-output data obtained from positioning control is used, the identification accuracy may be degraded. In this study, we propose methods to improve the identification accuracy by introducing appropriate pre-processes for the input-output data. Further, a method to identify the mechanical characteristic of the plant is proposed. The effectiveness of the proposed methods is evaluated by using the input-output data obtained from control experiments of a galvano scanner.**

I. Introduction

Laser beam scanners in laser engraving machines require high-speed and high-precision control for more precise laser processing with high throughput [1], [2], [3], and the galvano scanner plays an important role in these systems. The galvano scanner has a mirror to reflect the laser beam and the angle of the mirror is precisely controlled to change the direction of the laser beam [4], [5], [6]. The positioning control system is a semi-closed control system, and the angle of the mirror is indirectly controlled by measuring the angle of the motor shaft detected by an encoder. In order to precisely control the system, an accurate model of the plant is required. However the frequency response of the galvano scanner varies by aging and ambient temperature change [7], [8]. Thus, it is desirable to identify the model during positioning control to know the parameter variations.

An accurate model of the galvano scanner can be obtained from the frequency response of the plant by a curve fitting method [9], [10]. However, a normal operation must be interrupted to measure the frequency response of the plant, and it also takes much time to perform the measurement.

The system identification, deriving the input-output relationship from measured input-output data, is known as a modeling method of dynamical systems [11]. In the system identification, a pseudo random signal is generally used to fully excite the dynamics of the system [12], [13]. However, interruption of the normal operation is required to perform the system identification experiment. If the input-output data during the positioning control can be used to identify the plant, such interruption will be avoided and the productivity can be improved.

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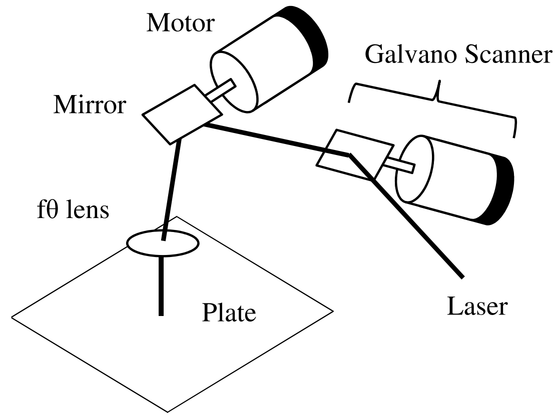


Fig. 1. Laser processing using galvano scanner

The control system of the galvano scanner has an input delay due to calculation time of a digital signal processor (DSP) and a first order lag property of a current amplifier. The system with the input delay tends to be higher order model. Further, the necessity to update the model of the input delay is low because the amount of the input delay does not change by aging and ambient temperature change. The mechanical characteristic of the plant except for the input delay can be obtained by multiplying the inverse of the input delay, however, it requires much computational effort and the order of the obtained transfer function will be higher. Therefore, it is desirable to develop a method to identify the mechanical characteristic of the plant directly from the input-output data.

In this paper, we propose a method to identify the mechanical characteristic of the plant directly from the input-output data based on an equivalent transform of the block diagram. Further, two pre-processing methods for the input-output data are introduced to increase the accuracy of the model. The effectiveness of the proposed method is evaluated by comparing to the curve-fitted accurate model obtained from the frequency response data measured by a servo analyzer.

II. Plant

A. Galvano Scanner

In this study, the model of the galvano scanner is identified. In the galvano scanner, the angle of the mirror attached

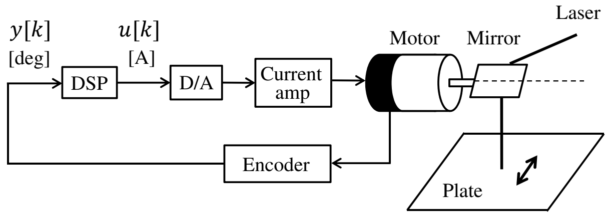


Fig. 2. Control system of galvano scanner

to the tip of the motor is controlled to steer the laser beam. Fig. 1 shows a system configuration. In this figure, a pair of the galvano scanners is used to engrave characters or symbols in two dimensions on a metal plate or a woodblock by laser beam. An F-Theta lens is generally used to convert the rotation of the laser beam deflected by the mirror into a parallel displacement at the target.

In the control system of the galvano scanner (Fig. 2), the DSP is used for calculating the control input at the sampling period of $\tau = 10\ \mu$s. The control input calculated by the DSP is converted to the continuous-time signal through a D/A converter. The current applied to the motor is controlled by the current amplifier to follow the reference current. Then, the torque proportional to the current is generated to rotate the motor shaft. The angle of the motor shaft is measured by the encoder to incorporate the angle information into the DSP. Note that the relation between the angle of the motor shaft and the rotation angle of the laser beam on the plate is linear. When the motor shaft rotates 0.3 deg, the target of the laser beam moves 1.0 mm on the plate.

B. Transfer Function of the Galvano Scanner

Fig. 3 shows that the galvano scanner has three resonant modes at high frequencies. Therefore, the plant model P_{mech} is modeled to have a rigid-body mode and three resonant modes, as shown below:

$$P_{mech}(s) = \frac{k_0}{s^2} + \sum_{i=1}^{3} \frac{k_i}{s^2 + 2\zeta_i\omega_i s + \omega_i^2} \qquad (1)$$

where k_0 is the gain of the rigid-body mode, k_i is the residue of the resonant mode, ω_i [rad/s] is the resonant frequency, and ζ_i is the damping ratio. In this study, a curve-fitted model of $P_{mech}(s)$ from the frequency response data (Fig. 3) measured by the servo analyzer is regarded as the true model, which is referred to as *Reference model*. Table I shows the true value of each parameter of $P_{mech}(s)$.

Fig. 4 shows the block diagram of the galvano scanner model from the current $u(t)$ to the angle of the motor shaft $y(t)$, and it has input delay due to the calculation time of the DSP and the first order lag property of the current amplifier. By defining the input delay as $P_{delay}(s)$, the transfer function $P(s)$ from $u(t)$ to $y(t)$ is expressed as follows:

$$P(s) = P_{mech}(s)P_{delay}(s). \qquad (2)$$

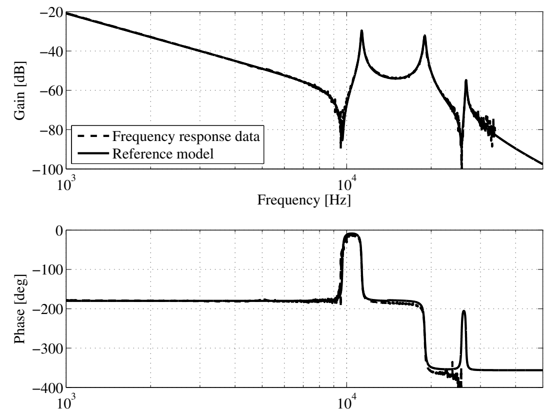


Fig. 3. The frequency response of the galvano scanner

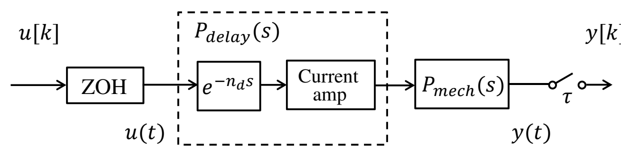


Fig. 4. Effect of phase delay elements

III. System Identification [11]

A. ARX Model

It is assumed that the relation between the input data $u[k]$ and the output data $y[k]$ in Fig. 4 can be described by the following difference equation:

$$\begin{aligned} & y[k] + a_1 y[k-1] + \cdots + a_{n_a} y[k-n_a] \\ & \quad = b_1 u[k-1] + \cdots + b_{n_b} u[k-n_b] + w[k] \end{aligned} \qquad (3)$$

where $w[k]$ is assumed to be white noise. Introduce a column vector θ as

$$\theta = \begin{bmatrix} a_1 & \cdots & a_{n_a} & b_1 & \cdots & b_{n_b} \end{bmatrix}^T$$

and a column vector $\varphi[k]$ as

$$\varphi[k] = \begin{bmatrix} -y[k-1] & \cdots & -y[k-n_a] \\ & & u[k-1] & \cdots & u[k-n_b] \end{bmatrix}^T.$$

The output $y[k]$ can then be written as

$$y[k] = \theta^T \varphi[k] + w[k].$$

Also, introduce coprime polynomials $A[q]$ and $B[q]$ of the shift operator q as

$$\begin{aligned} A[q] &= 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a} \\ B[q] &= b_1 q^{-1} + \cdots + b_{n_b} q^{-n_b}. \end{aligned}$$

Then, Eq. (3) is rewritten as follows:

$$A[q]y[k] = B[q]u[k] + w[k]. \qquad (4)$$

The model described in Eq. (4) is referred to as *the ARX (Auto-Regressive eXogenous) model*.

TABLE I

THE PARAMETERS OF $P_{mech}(s)$

k_0	3.564×10^6
k_1	2.069×10^6
k_2	-5.485×10^6
k_3	-4.604×10^5
ω_1	7.108×10^4
ω_2	1.193×10^5
ω_3	1.674×10^5
ζ_1	6.218×10^{-3}
ζ_2	7.723×10^{-3}
ζ_3	4.579×10^{-3}

B. Identification of Model Parameters

In the ARX model, the one-step-ahead prediction of the output is linear with respect to θ. Thus, it can be represented as $\theta^T\varphi$. The prediction error of the linear regression model is given by $y[k]-\theta^T\varphi[k]$. The cost function J_N can then be written as

$$\begin{aligned} J_N(\theta) &= \frac{1}{N}\sum_{k=1}^{N}\{y[k]-\theta^T\varphi[k]\}^2 \\ &= c(N)-2\theta^T f(N)+\theta^T R(N)\theta \end{aligned} \tag{5}$$

where

$$R(N)=\frac{1}{N}\sum_{k=1}^{N}\varphi[k]\varphi^T[k],\ f(N)=\frac{1}{N}\sum_{k=1}^{N}y[k]\varphi[k]$$
$$c(N)=\frac{1}{N}\sum_{k=1}^{N}y^2[k].$$

$R(N)$ is a square matrix of $m\times m$, $f(N)$ is a m-th order vector, $c(N)$ is a scalar, m is the size of θ, and N is the data length of the input-output data. By differentiating J_N in Eq. (5) with respect to θ and putting $\partial J_N/\partial\theta=0$, the simultaneous linear equation for θ called the normal equation

$$R(N)\hat{\theta}(N) = f(N) \tag{6}$$

is obtained. If $R(N)$ is the positive definite matrix, the estimates of the parameters can be obtained as follows:

$$\hat{\theta}(N) = R^{-1}(N)f(N). \tag{7}$$

This identification method is referred to as *the off-line least squares method.*

IV. PRE-PROCESSING METHOD OF INPUT-OUTPUT DATA

In the system identification, a pseudo random signal is generally used to fully excite the dynamics of a system. Therefore, when the input-output data obtained during positioning control is used for the system identification, the accuracy of the model may be degraded. In this section, we examine two pre-processing methods to improve the accuracy of the identified model.

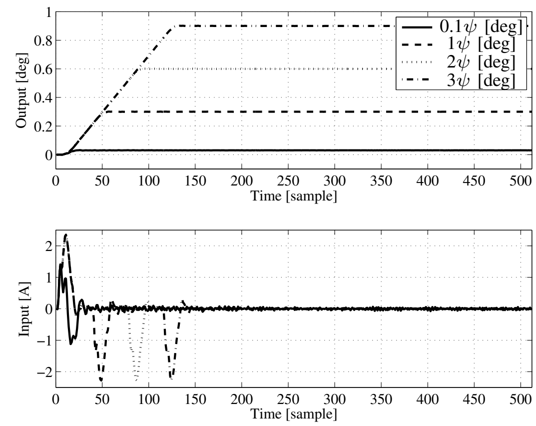


Fig. 5. Input-output data obtained during positioning control for various rotation angles

A. Input-Output Data Obtained During Positioning Control

For system identification, 100 pairs of input-output data during positioning control were collected each for 19 kinds of rotation angle [deg] as 0.1ψ, 0.2ψ, 0.3ψ, 0.4ψ, 0.5ψ, 0.6ψ, 0.7ψ, 0.8ψ, 0.9ψ, 1ψ, 2ψ, 3ψ, 4ψ, 5ψ, 6ψ, 7ψ, 8ψ, 9ψ, and 10ψ, where $\psi=0.3$. The data length N for each pair of input-output data is 512. As an example, Fig. 5 shows the input-output data when the rotation angles [deg] are 0.1ψ, 1ψ, 2ψ, and 3ψ.

For 100 pairs of collected input-output data, two kinds of pre-processing methods are examined to obtain an accurate model of the galvano scanner.

B. Method (A): Averaging of Input-Output Data

In the method (A), 100 pairs of input-output data for each rotation angle are averaged to obtain a pair of input-output data for system identification as

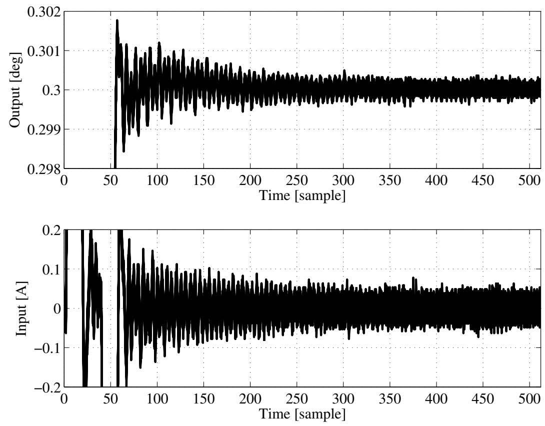
$$u[k]=\frac{1}{100}\sum_{i=1}^{100}u_i[k],\ y[k]=\frac{1}{100}\sum_{i=1}^{100}y_i[k].$$

In this method, the amount of noise in the input-output data will be decreased by averaging.

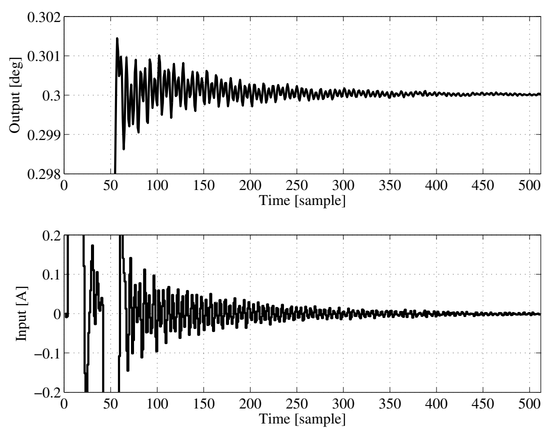
Fig. 6(a) shows 100 pairs of input-output data of rotation angle of 1ψ [deg], and Fig. 6(b) shows the result of averaging. From these figures, it is confirmed that the noise in the input-output data was reduced. It is noted that the data length N of the averaged input-output data is also 512.

C. Method (B): Extension of Data Length

In the method (B), 100 pairs of input-output data are connected in series to extend the data length. Therefore, the data length N of the input-output data obtained by the method (B) is extended to be 512×100. In this method, it is expected that the input-output data includes rich information of the galvano scanner by extending the data length. It is noted that an offset value is added to the output of each pair

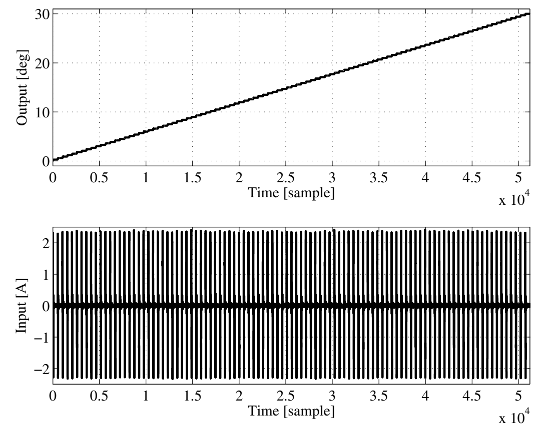


(a) Enlarged view of 100 pairs of input-output data

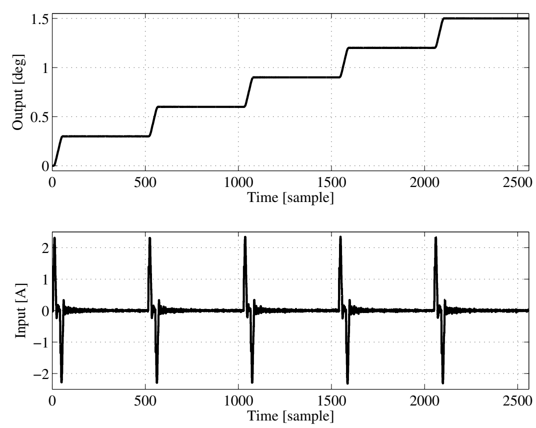


(b) Enlarged view of the averaged input-output data

Fig. 6. Input-output data of rotation angle of 1ψ (=0.3) [deg] obtained by the pre-processing method (A)



(a) Connected input-output data



(b) Enlarged view of Fig. (a)

Fig. 7. Input-output data of rotation angle of 1ψ (=0.3) [deg] obtained by the pre-processing method (B)

of input-output data so that the connected output becomes continuous as follows:

$$\begin{aligned} u[k] &= \big[\ u_1[1]\ \cdots\ u_1[N]\quad u_2[1]\ \cdots\ u_2[N] \\ &\qquad\qquad \cdots\quad u_{100}[1]\ \cdots\ u_{100}[N]\ \big]^T \\ y[k] &= \big[\ y_1[1]\ \cdots\ y_1[N]\quad \Psi + y_2[1]\ \cdots\ \Psi + y_2[N] \\ &\qquad \cdots\quad 99\Psi + y_{100}[1]\ \cdots\ 99\Psi + y_{100}[N]\ \big]^T \end{aligned}$$

where Ψ [deg] is the angle of the motor shaft. As an example, Fig. 7(a) shows the extended input-output data when the rotation angle Ψ is 1ψ [deg], and Fig. 7(b) shows the enlarged view of Fig. 7(a). From these figures, it is confirmed that the output signal is connected to be continuous.

V. Identification Experiment

In this section, we perform the system identification using the input-output data $u[k]$ and $y[k]$ obtained by applying the pre-processing methods described in the previous section, and evaluate the effectiveness of each pre-processing method. The identified ARX model by using the pre-processed input-output data is converted to a continuous-time model by using the zero-order hold conversion method, and the accuracy of the identified model is evaluated. The orders of n_a and n_b of the polynomials $A[q]$ and $B[q]$ of the ARX model are chosen to be 15, respectively. Since the polynomial $A[q]$ describes not only plant characteristic but also disturbance characteristic, it is recommended to choose a higher order polynomial than the order of the plant [11].

A. Identification of the Plant with Input Delay

Fig. 10 shows the frequency responses of the identified models obtained by using the pre-processed input-output data by method (A) and (B). First, in the case of the method (A), it is confirmed that the frequency response of the identified model agrees very much with that of the true model at the primary and the secondary resonance frequencies. On the other hand, in case of the method (B), some errors are observed around the primary resonance frequency. If the

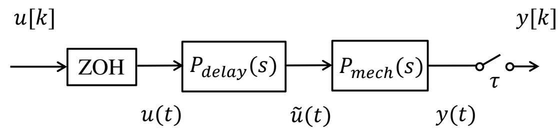


Fig. 8. Input-output relations in the control system

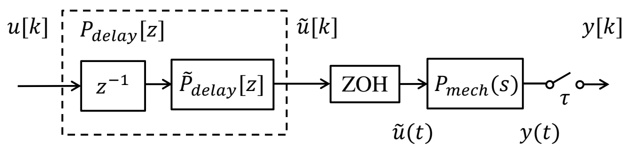


Fig. 9. An approximated system to extract $\tilde{u}[k]$

noise $w[k]$ of the ARX model is white, the accuracy of the model will be improved by increasing the data length of the input-output data, and the method (B) may also achieve the same result as that obtained by the method (A). Thus, it is reasonable to suppose that the noise $w[k]$ is not white, and the method (A) which reduce the noise included in the input-output data by averaging was effective. It should be noted that there are relatively large identification error at the third resonance frequency in both methods, therefore, a large noise might be exist at the high frequency.

In the phase characteristic of the identified model, a large phase lag property is observed. This can be interpreted as the input delay $P_{delay}(s)$ because the phase lag of mechanical characteristics P_{mech} becomes multiples of 180 degrees. The amount of the input delay was estimated to be 1.6τ after some trial and error.

B. Direct Identification of $P_{mech}(s)$

Generally, the order of the plant including a delay tends to be higher because the delay is an infinite dimensional system, and another computational effort is also required to remove the delay from the identified model to obtain $P_{mech}(s)$. Since the input delay does not change normally, it is desirable to identify the mechanical characteristic $P_{mech}(s)$ directly from the input-output data. In this section, we propose a simple method to identify $P_{mech}(s)$ directly by making a fictitious identification input.

Fig. 8 shows the input-output relations of the plant. To identify $P_{mech}(s)$ directly from the input-output data, the input $\tilde{u}(t)$ and the output $y(t)$ are required. However, the system identification based on continuous time signals are not easy, and it is also difficult to recover $y(t)$ from the measurement output $y[k]$. Therefore, we consider to approximate Fig. 8 as shown in Fig. 9. In Fig. 9, $P_{delay}[z]$, which is used to calculate the fictitious identification input $\tilde{u}[k]$, is an discretized model of $P_{delay}(s)$. Using $\tilde{u}[k]$ and $y[k]$, $P_{mech}[z]$ is identified by using the ARX model, and $P_{mech}[z]$ is converted to $P_{mech}(s)$ using the zero-order-hold conversion method. Since the input delay of 1.6τ is not multiples of the sampling period τ, $P_{delay}[z]$ is implemented as

$$P_{delay}[z] \quad = \quad \tilde{P}_{delay}[z]z^{-1}$$

where $\tilde{P}_{delay}[z]$ is a bilinear transform of the third-order Pade approximation of $e^{-0.6\tau s}$. It is expected for this implementation to reduce the discretization error associated with the Pade approximation.

The frequency response of $\tilde{P}_{mach}(s)$ identified using $\tilde{u}[k]$ and $y[k]$ is shown in Fig. 11. In comparison with Fig. 10, it is confirmed that the input delay was removed and only the mechanical characteristic of $P_{mech}(s)$ have been identified correctly.

TABLE II
THE RELATIVE ERRORS [%] OF THE PARAMETERS IN THE IDENTIFIED MODEL $\tilde{P}_{mech}(s)$

Parameters	Method (A)	Method (B)
k_0	-3.638	-3.583
k_1	6.301	0.8503
k_2	-23.13	-25.15
k_3	61.93	-612.4
ω_1	0.5523	0.9544
ω_2	1.053	1.082
ω_3	1.690	2.531
ζ_1	-9.581	136.2
ζ_2	-8.513	5.023
ζ_3	655.4	1216

C. Mode Parameters of the Identified Model $\tilde{P}_{mech}(s)$

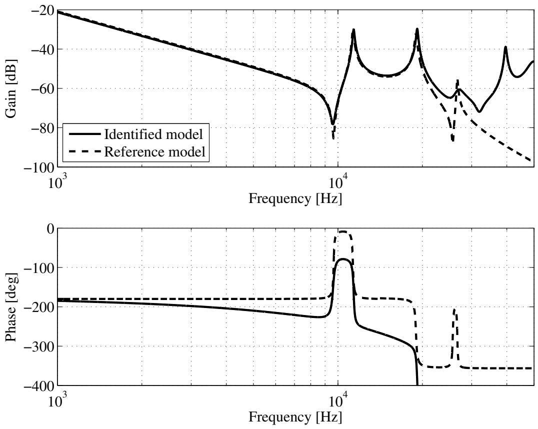
The mode parameters of the rigid-body mode and the 1st, 2nd and 3rd resonance modes in Eq. (1) are retrieved from the identified model $\tilde{P}_{mach}(s)$ by the mode decomposition, and the accuracy of each parameters is evaluated. Table II shows the relative errors [%] of the parameters of the identified model $\tilde{P}_{mech}(s)$.

From the results, it is confirmed that the parameters of the 1st and 2nd resonance modes obtained by the method (A) is in good agreement with the true value. However, the identified damping ratio of the 1st resonance mode by the method (B) has large error. Therefore, we can conclude that the method (A) is appropriate for pre-processing to the input-output data. As for the 3rd resonance mode, both pre-processing methods require further improvements to identify accurate parameters.

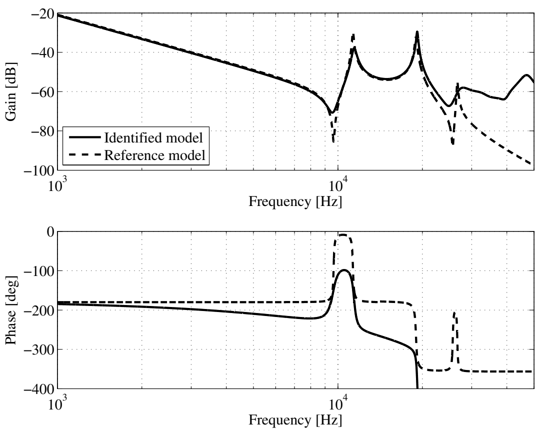
We have shown the results when the rotation angle is 1ψ [deg], though, almost the same results have been obtained for the other rotation angles shown in section IV-A.

VI. CONCLUSION

In this paper, we have proposed the methods to identify the mechanical property $P_{mech}(s)$ directly from the input-output data during positioning control of the galvano scanner. Further, two pre-processing methods for 100 pairs of the input-output data have been proposed to increase the accuracy of the identified model. From the identification experiments, we have confirmed that an accurate model can be obtained by using the method (A). The improvements of the identification accuracy of the 3rd resonance mode will be a future work.

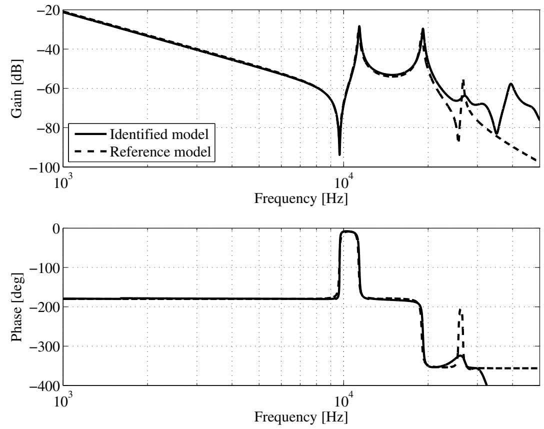


(a) Method (A)

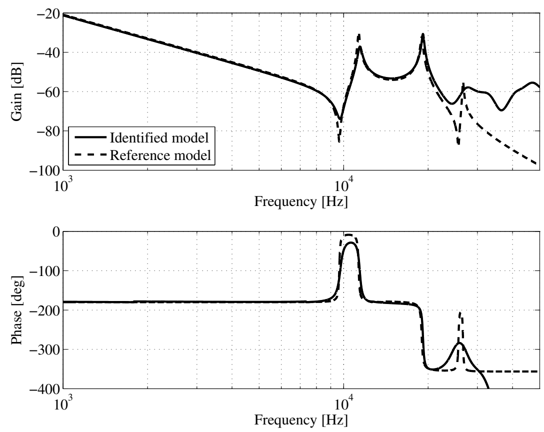


(b) Method (B)

Fig. 10. Frequency response from $u(t)$ to $y(t)$ (solid line)



(a) Method (A)



(b) Method (B)

Fig. 11. Frequency response from $\tilde{u}(t)$ to $y(t)$

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