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Feedforward control design for shaking table by Data driven control considering control input limitation

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Abstract: The burden of control adjustment of shaking table is increasing with the background of lack of skilled operators. With such background, there is a strong demand for a method to achieve desired control performance regardless of the operator's skill. The data-driven control is a promising approach to meet this requirement. However, even though an actual controller has an input limit, the data-driven control cannot handle it. Therefor, we proposed a novel method that considers the input limit based on data-driven prediction and an optimal problem with a penalty function. We verified the effectiveness of the proposed method through experiments using a small shaking test device.

Keywords: Data driven control, Feedforward control, Industrial control, Self tuning control, SISO

1. INTRODUCTION

Shaking tables (Ogawa (2000)) are testing devices used to evaluate the structural vibration-resistance performance and understand the destruction process of the structures. The performance of such a test system largely depends on how accurately the shaking table can reproduce a desired test pattern. In other words, it can be said that the control performance of the shaking table determines the performance of the test system.

Generally, PID control (Ang (2005)) is used to control the conventional shaking table, and operators adjust the parameters to satisfy required performance by trial and error. This adjustment method is based on the experience of each operator, and the know-how is accumulated in individuals. For this reason, there is a problem that the control performance of the shaking table greatly depends on the skill of the operator. Further, since the shaking table is activated many times for control adjustment, it takes time and cost. With such background, there is a strong demand for the development of control methodology that ensures control performance with fewer adjustment steps and does not depend on the skills of the operator. Furthermore, the number of workers with little experience in control design is increasing due to the shortage of workers. Therefore, there is also a strong demand for developing control method that can be applied as simply as possible.

As a general control design, a mathematical model of a control target is derived using first principal modeling or system identification (Ljung (1999)). Then, controller is designed by using this mathematical model. Such a design method is widely known as MBC (Model-Based Control). In some previous studies(Seki (2008, 2009)), mathematical models have been obtained by simplifying the dynamics including a specimen. However, MBC approaches are effective only when accurate models are available. The specimen is selected by the user, so the control designer cannot know physical quantity of specimen in advance. Furthermore, properties such as mass and inertia of the specimen are not always the same. So, MBC approach may not be able to provide sufficient control performance when the mathematical model has some uncertainties. For this reason, we considered that MBC approach was not always the best method for controlling the shaking table.

Therefore, in this research, we decided to control the shaking table not by MBC but by data-driven control (Lecchini (2002); Kaneko (2011, 2013)) that uses experimental data directly for control design. When data-driven control is used, the control parameters are automatically adjusted, so that it is possible to provide control performance that does not depend on operator skill. So, the data-driven control is a promising method. However, it is not easy to apply it directly for controlling the shaking table.

In this paper, we first introduce the operation method of shaking table, and introduce the issues for applying data-driven control based on this. After that, we propose an appropriate shaking table operation to overcome this problem. In addition, the controller of shaking table has input limit, but existing data-drive control cannot handle the input limit. Therefore, we proposed a novel method that considers the input limit based on data-driven prediction (Kaneko (2017)) and an optimal problem with a penalty function. We verify the effectiveness of the proposed method through experiments using a small test-bed driven by an electric actuator.

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2. PROBLEMS ON CONTROLLING SHAKING TABLE

2.1 On shaking table

In this section, we briefly explain the shaking table. Fig.1 shows outline of 1-axis shaking table.

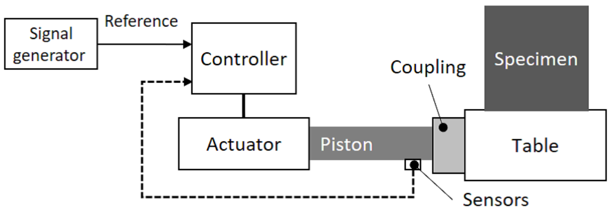

Fig. 1. Outline diagram of shaking table

Shaking table is composed of a piston, an actuator, a coupling, and a table. When conducting the evaluation test, a miniature of structure (a specimen) is placed on the table. The specimen is vibrated with a desired vibration waveform by driving the piston with an actuator and applying a force to the table via the coupling. In the case of a 3-D shaking table, the number of axes increases, but the basic configuration is the same as Fig.1. The purpose of the designing control of shaking table is to control the displacement of the table so that the specimen is vibrated with a desired waveform.

Detailed dynamics of the shaking table have been analyzed in the literature Seki (2008, 2009). Even without giving detailed mathematical model, we can easily imagine that the mass and inertia of the specimen have great influences on the behavior of the shaking table. As we described above, since the specimen is selected by the user, the control designer cannot know the value of that. This is why it is difficult to apply MBC approach to control design of shaking table.

2.2 Data acquisition for data-driven control

Data driven control can automatically adjust control parameters using a single set of input/output experimental data. VFRT (Virtual Reference Feedback Tuning (Lecchini (2002))) and FRIT (Fictitious Reference Iterative Tuning(Kaneko (2011, 2013))) are known as control methods classified as data driven control. Both methods use one-shot experimental data to adjust the control parameters so that the difference between the reference output and the output after control adjustment is reduced. Then, the obtained control parameters are applied to the controller to confirm the improvement effect of the control performance. In other words, these methods assume that at least two experiments are possible. However, the shaking table can be used to confirm the destruction process of the specimen. If the specimen is destroyed in the first experiment to obtain experimental data for control adjustment, the second experiment cannot be performed.

Therefore, in order to apply data drive control to the shaking table, the data acquisition method itself needs to be devised.

2.3 Control input limitation

As with many devices, the shaking table has upper and lower limits for control input. And, some models have an interlock function that stops operation to protect the equipment when the control input continues to maintain the limit value. For this reason, control rule that consider the limit of input is required.

MPC (Model predictive control Maciejowski (2000)) is well known as a method that can take into account input limit. However, MPC is one of a MBC approach and requires accurate mathematical model. And, conventional data-driven control cannot consider the upper limit of input. If a saturation function is used for the control input generated by the conventional method, the upper and lower limits of the input are satisfied, but the optimality is not guaranteed. Therefore, we need to develop a new data driven control considering the upper limit of input explicitly.

3. DEVELOPMENT OF NEW CONTROL FOR SHAKING TABLE

3.1 Structure of proposed control system

The conventional controller performs displacement control only by Feed-Back (FB) control as shown in the Fig.2, where r is reference signal, u is control input, and y is output. We assume that plant model $P(s)$ is linear and time-invariant, single-input and single-output(SISO) system. In most cases, FB control, which is defined by $C(s)$, is implemented with PID control.

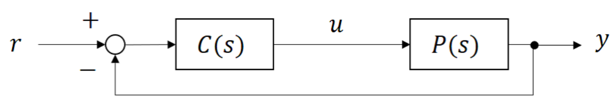

Fig. 2. Conventional controller configuration

Since the actuator receives reaction force from the shaking table, we need to design the FB control to be robust. However, it is not easy to improve both responsiveness and robustness with FB control alone. So, we will consider 2DoF controller shown in Fig.3. $F(\rho, s)$ is Feed-Forward (FF) controller. Following the general design method, we will design FB controller $C(s)$ to improve robustness and FF controller $F(\rho, s)$ to improve responsiveness.

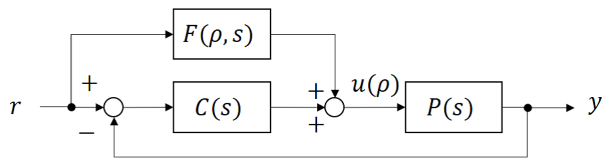

Fig. 3. New controller configuration

FF controller is defined by following

$$F(\rho, s) = \frac{\rho_{n+m}s^m + \cdots + \rho_{n+1}s + \rho_n}{s^n + \rho_{n-1}s^{n-1} + \cdots + \rho_1 s + \rho_0}, \tag{1}$$

where tuning parameter ρ is given by

$$\rho = [\rho_0 \ \rho_1 \ \cdots \ \rho_{n+m}]\,. \tag{2}$$

In this study, we consider a method to adjust the parameters of the FF control in Fig.3 using the experimental data set (u, y) which are obtained with the conventional configuration in Fig.2.

3.2 FF controller tuning by ERIT

In this subsection, we briefly introduce Estimated Reference Iterative Tuning (ERIT) proposed by Kaneko et. al. (Kaneko (2018)).

Suppose that the transfer function of the desired closed-loop system is given by $T_d(s)$. Then, the desired output y_d is given by

$$y_d = T_d(s)r. \tag{3}$$

ERIT calculates the FF control parameter ρ so as to minimize the following cost function $J_o(\rho)$

$$J_o(\rho) = \|y_d - y(\rho)\|_N^2 , \tag{4}$$

where N is size of the experimental data.

We have to predict $y(\rho)$ without using the plant model $P(s)$ to consider the above optimization problem. From the Fig.2, we can express the output data y obtained by the experiment as

$$y = \frac{P(s)C(s)}{1 + P(s)C(s)} r. \tag{5}$$

On the other hand, we can also express the output data $y(\rho)$ from the Fig.3 as

$$y(\rho) = \frac{P(s)\left(C(s) + F(\rho, s)\right)}{1 + P(s)C(s)} r. \tag{6}$$

Then, we can derive following equation by using eq.(5) and eq.(6),

$$\begin{aligned} y(\rho) &= \frac{C(s) + F(\rho, s)}{C(s)} y \\ &= y + F(\rho, s) \left(\frac{1}{C(s)} \right) y. \end{aligned} \tag{7}$$

We can confirm eq.(7) does not include the plant model $P(s)$. FB control $C(s)$ is known because it is designed by ourselves. As long as FB control is designed with PID control, $1/C(s)$ is a proper transfer function. $F(\rho, s)$ can be also a known transfer function by using ρ which is obtained in each step of optimization. Therefore, we can predict $y(\rho)$ accurately using experimental output data y if there is no observation noise. This technique is called data-driven prediction(Kaneko (2017)).

After predicting $y(\rho)$, optimal FF control parameter ρ^* can be calculated by applying off-line optimization.

3.3 Strategy for applying Data-driven control

ERIT has been proposed assuming that the plant model is linear and time-invariant (LTI) system. If the closed loop dynamics is LTI, when the reference signal r is multiplied by an arbitrary scaling factor S_c, the output is also multiplied by S_c. In other words, the output for the scaled reference $\bar{r} = S_c r$ is given by

$$\bar{y} = S_c y. \tag{8}$$

Using eq.(7) and eq.(8), we can predict scaled output by,

$$\bar{y}(\rho) = \bar{y} + F(\rho, s) \left(\frac{1}{C(s)} \right) \bar{y}. \tag{9}$$

From eq.(4) and eq.(9), we can confirm that the parameter ρ for minimizing the cost function $J_s(\rho)$, which is defined by using scaled experimental data $\bar{y}$, is same for minimizing original cost function $J_o(\rho)$,

$$\begin{aligned} J_s(\rho) &= \|T_d(s)\bar{r} - \bar{y}(\rho)\|_N^2 \\ &= \|T_d(s)\left(S_c r\right) - \{S_c y(\rho)\}\|_N^2 \\ &= S_c^2 J_o(\rho). \end{aligned} \tag{10}$$

In other words, the same ρ can be obtained even with ERIT using scaled data $\bar{y}$. So, all we have to do is collecting experimental data by selecting a scaling parameter S_c that is small enough not to break the specimen.

If the scaling parameter S_c is too small, the dynamic characteristics of the closed loop may not appear in the output data $\bar{y}$. In actual operation of the shaking table, preliminary experiments are performed with an amplitude $1/10 \sim 1/20$ times the maximum amplitude before the actual test. So, we select a scaling parameter as $S_c = 1/10$ in this research.

3.4 ERIT considering input limitation

In previous subsection, we have shown that ERIT can be applied to control the shaking table by using the scaled experimental data. However, ERIT cannot handle the limit of control input u. Therefore, we derive a new ERIT is derived in consideration of the input limit in this section.

From the same discussion as in the previous section, we can express the control input data u obtained by FB only experiment as

$$u = \frac{C(s)}{1 + P(s)C(s)} r. \tag{11}$$

we can also express the control input $u(\rho)$ from the Fig.3 as following,

$$u(\rho) = \frac{C(s) + F(\rho, s)}{1 + P(s)C(s)} r. \tag{12}$$

Then, we can derive following equation by using eq.(11) and eq.(12),

$$u(\rho) = u + F(\rho, s) \left(\frac{1}{C(s)} \right) u. \tag{13}$$

Therefore, we can also predict $u(\rho)$ using output data u obtained by the experiment. The above equation also holds when using scaled experimental data $\bar{u} = S_c u$ as

$$u(\rho) = \left(\frac{1}{S_c} \right) \left\{ \bar{u} + F(\rho, s) \left(\frac{1}{C(s)} \right) \bar{u} \right\}. \tag{14}$$

We can predict whether the control input $u(\rho)$ exceeds the limit u_{lim} by using eq.(14) in advance. Therefore, we define a function that gives a penalty when the predicted input $u(\rho)$ exceeds the limit u_{lim} as

$$P_i(u_i(\rho), u_{\mathrm{lim}}) = \begin{cases} 0, & \|u_i(\rho)\| \le u_{\mathrm{lim}} \\ \alpha(u_i(\rho) - u_{\mathrm{lim}})^2 \end{cases}, \tag{15}$$

where i is index number of date and α is tuning parameter. Then, we modified original cost function $J_s(\rho)$ as

$$J_p(\rho) = \|T_d(s)\bar{r} - \bar{y}(\rho)\|_N^2 + \sum_{i=1}^{N} P_i(u(\rho), u_{\mathrm{lim}}). \tag{16}$$

When the control input $u(\rho)$ exceeds the limit u_{lim}, the value of the cost function $J_p(\rho)$ increases abruptly. Therefore, such an adjustment parameter ρ will not be selected. This is the same idea as the penalty function in MPC. If you want to find a parameter ρ that strictly satisfies the constraint condition, you can use a barrier function $B_i(u_i(\rho), u_{\text{lim}})$ instead of eq.(15).

$$B_i(u_i(\rho), u_{\text{lim}}) = \frac{1}{\alpha} \frac{1}{\{u_i(\rho) - u_{\text{lim}}\}^2} \tag{17}$$

4. EXPERIMENTAL TRIAL

4.1 On test-bed

In order to confirm the effectiveness of the proposed method, we build a simple shaking test-bed. Fig.4 shows picture of the shaking test-bed. Although not shown in Fig.4, there is a controller that calculates the control input. This test-bed is configured with only an actuator and a piston, and does not include coupling, table, and specimen. We will implement the table part in future modifications.

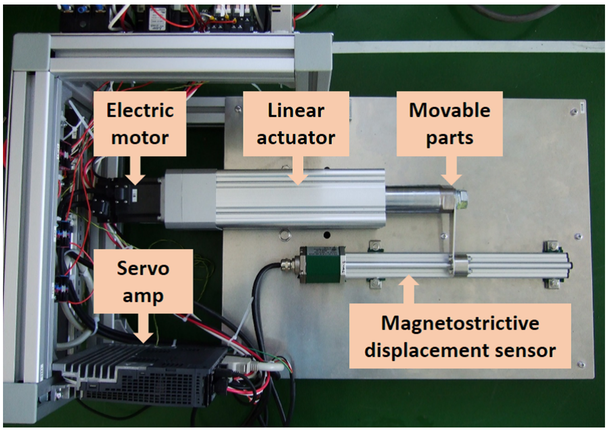

Fig. 4. Picture of test-bed

Fig.5 shows functional diagram of the shaking test-bed.

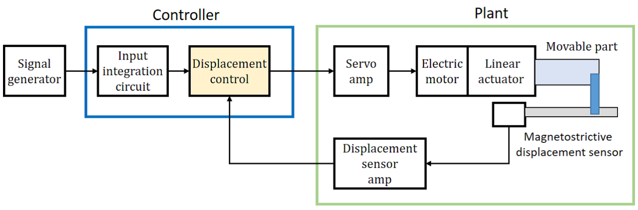

Fig. 5. Functional diagram of shaking test-bed

We explain the configuration of the test-bed using Fig.5. The controller accepts the displacement or acceleration command generated by the signal generator as reference signal r. Generally, a shaking table is driven by displacement control. Therefore, in the case of an acceleration command, it is converted into a displacement command using an input integration circuit that performs second-order integration. The control input u calculated by the controller is transmitted to the servo amp, and the electric motor is driven by the current value output from the servo amp. There are restrictions on the control input to protect the servo amplifier and the electric motor. The linear actuator connected to the electric motor expands and contracts by switching the rotation direction of the electric motor depending on whether the current is positive or negative. This expansion/contraction movement of movable parts corresponds to the piston of the shaking table. A magnet is attached to the tip of the movable part, and the displacement of the linear actuator can be detected by a magnetostrictive displacement meter. The signal detected by the magnetostrictive displacement meter is transmitted to the controller as an output y via the sensor amp.

4.2 Experimental result

In this paper, we decided to use JMA KOBE(JMA (web)) as a test pattern. JMA KOBE is a test pattern commonly used in Japan. JMA KOBE is an acceleration date of a large earthquake that occurred in Hyogo prefecture in 1995, and is widely used to evaluate the seismic performance of structures. In this experiment, we use displacement signal which is converted from JMA KOBE acceleration signal by applying the input integration circuit.

First, we acquired experimental data using only FB control enabled for data-driven control design. FB control is PID control, and PID gain was determined by trial and error. We did not optimize PID control, assuming that an unskilled operator adjusted the control. In this experiment, we set the amplitude to be 1/10 of the maximum excitation, that is, the scaling parameter is designed as $S_c = 1/10$. The upper part of Fig.6 shows the whole experimental result, and the lower part shows an enlarged part of the experimental result. We normalized the experimental result so that the maximum amplitude of the reference r is 100%. The blue line shows the scaled reference $\bar{r} = S_c r$ and red line shows the output $\bar{y}$.

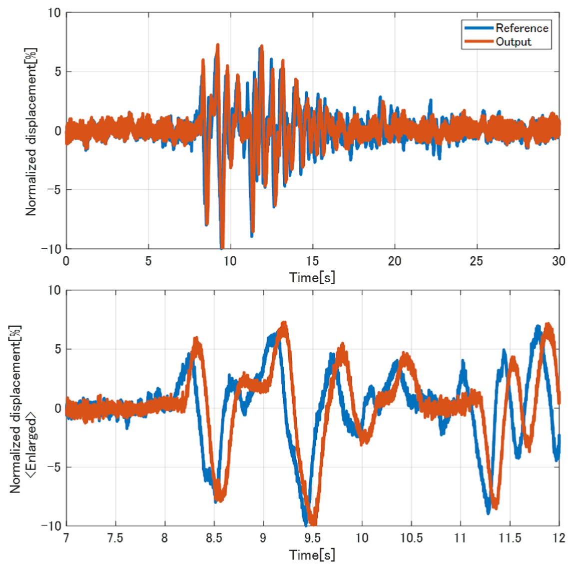

Fig. 6. Experimental result of scaled reference

We can confirm that the displacement response $\bar{y}$ is delayed from reference $\bar{r}$.

We performed following three experiments with actual amplitude($S_c = 1$) :

(1) Only FB control
This is a comparison target to verify the effectiveness of FF control.
(2) Conventional ERIT
This experiment is performed to confirm the output response $u(\rho)$ without considering the input limit.
(3) Proposed ERIT
This experiment is performed to confirm the effectiveness of proposed control.

We set the limit of control input $u_{\rm lim}$ slightly lower than the limit depending on the actual equipment. In addition, we disabled the interlock function in order to conduct the experiment (2).

We design a conventional ERIT, which does not consider input constraints. We design the FF control $F(\rho, s)$ by using scaled experimental output $\bar{y}$ and cost function $J_s(\rho)$. We use the following third-order transfer function for FF control

$$F(\rho, s) = \frac{\rho_0 s^3 + \rho_1 s^2 + \rho_2 s + \rho_3}{s^3 + \rho_4 s^2 + \rho_5 s + \rho_6}, \tag{18}$$

where $\rho_i (i = 0, \cdots, 6)$ is designed by conventional ERIT. We used "`fminsearch`" command of Matlab®to calculate optimal ρ.

We design proposed ERIT, which can deal with control input limit. We decided to use the same form of FF control (18) in order to make a fair comparison. Then, we design the FF control $F(\rho, s)$ by using scaled experimental dataset $(\bar{u}, \bar{y})$ and cost function $J_p(\rho)$. In order to increase the penalty cost when the control input u exceeds the input limit $u_{\rm lim}$, we set the tuning parameter $\alpha = 10$.

Fig.7 shows experimental result of FB control only test. The upper part of figure shows the normalized displacement output y of an enlarged part of the experimental result, and the lower part shows the normalized control input u.

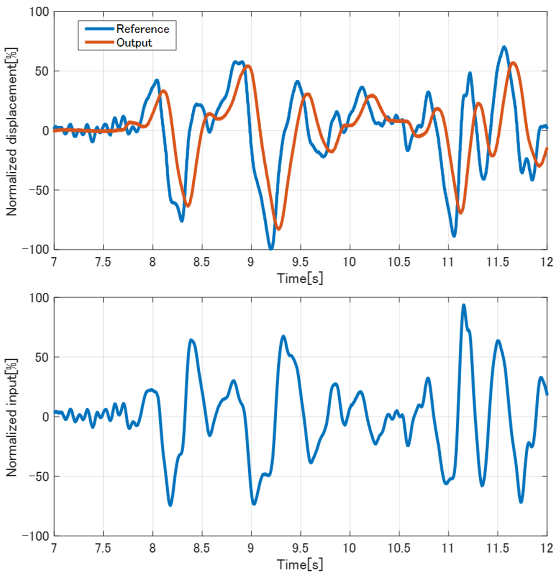

Fig. 7. Only FB control

We can confirm that the displacement response y is delayed from reference r. We can also confirmed that waveform of Fig.6 and Fig.7 are almost similar. From this result, we can confirm that dynamics of the test-bed can be assumed as LTI. Furthermore, we can confirm that the control input u has not reached the input limit ($\pm 100\%$).

Fig.8 shows experimental result of conventional ERIT. The filled part at the lower part of the figure indicates where the control input u reaches the input limit ($\pm 100\%$).

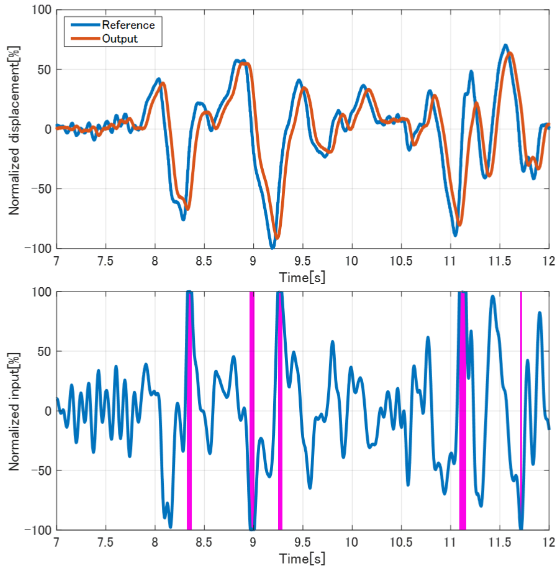

Fig. 8. Conventional ERIT

From Fig.8, we can confirm that delay of displacement response y has been improved. However, the control input u reaches the limit in some time. Therefore, a controller with this FF control may not be applicable to an actual vibration table.

Fig.9 shows experimental result of proposed ERIT.

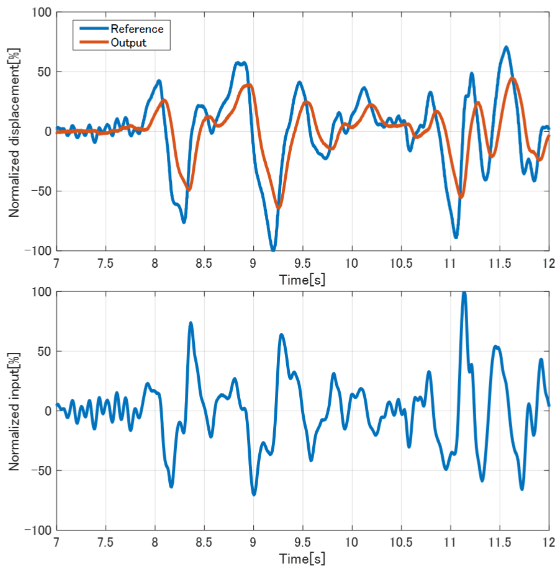

Fig. 9. Proposed ERIT

We can confirm that the displacement response y is improved compared to the experimental results of FB control only test. From the bottom of the Fig.9, it appears that the normalized input u has reached 100% around 11.1 seconds, but in reality the normalized input u remains at about 99%. We confirmed that the control input u did not reach the limit u_{lim} by applying modified cost function $J_p(\rho)$ which contains the penalty function. Therefore, the controller that implements the proposed FF control can be applied in practice.

Table 1 shows root mean square error (RMSE) and maximum overtime (MOT) of each experiment. RMSE is a criterion given by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - y_i)^2} \tag{19}$$

where N is the number of experimental data. MOT is the time that the normalized control input maintains the limit value ($\pm 100\%$).

Table 1. RMSE of each control

	PID	Conventional ERIT	Proposed ERIT
RMSE	14.49	9.37	11.15
MOT(s)	-	0.08	-

We can confirm that the conventional ERIT shows the best control performance. We can also confirm that the control performance of the proposed ERIT is inferior to that of the conventional ERIT. However, as we mentioned above, the conventional ERIT cannot be applied in practice because of the control input limitation. On the other hand, the proposed ERIT can be applied in practice. So, our proposed method can provide the best possible control.

It is clear from the results of this experiments, if a large control input is allowed, the responsiveness is greatly improved. However, such control may not be implemented because the control input reaches the upper limit. The proposed method solves this trade-off and is one of the promising solutions that can be used easily by unskilled operators.

5. CONCLUSION

In this research, we considered a technique of applying data-driven control to a 1-axis shaking table with limited control inputs. First, we proposed data acquisition technique using scaling parameter S_c. We have shown that even when using the scaled experimental data $(\bar{r}, \bar{y})$, it is possible to calculate the same parameters ρ as when using the actual experimental data (r, y). Next, we proposed a new ERIT considering the limit of control input. The proposed method is formulated by the optimal problem using penalty function $Pe(u(\rho), u_{\mathrm{lim}})$, where $u(\rho)$ is predicted by data driven prediction. The proposed method has an advantage in that the limits of the control input can be considered even though the plant model $P(s)$ is not used explicitly. Finally, we confirmed the effectiveness of the proposed method by experiments. We have confirmed that the proposed method can improve the control performance without the control input u reaching the limit u_{lim}.

Our future task is to confirm robustness against sensor noises because scaled experimental date $(\bar{u}, \bar{y})$ can be more subject to noise than non-scaled data (u, y). In addition, it is necessary to verify the influence of the reaction force from the table by modifying the test-bed. Furthermore, we plan to verify the effectiveness of the proposed method using a large shaking table driven by hydraulic actuators which can be nonlinear system. Finally, since the 3-D shaking table is not SISO, our proposed method cannot be directly applied. Therefore, we need to develop a control method that can be applied for MIMO.

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