RECURSIVE SIMULTANEOUS ESTIMATION OF A TWO-LINK DIRECT DRIVE MANIPULATOR WITH GREAT VARIATION OF PAYLOAD

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ABSTRACT

In this paper, the simultaneous identification strategy for estimating adaptively the basic parameters on two-link direct drive (D.D) robot manipulator with great variation of the payload is proposed. The estimated value is efficiently updated by means of the recursive algorithm of the scalar type appropriately selected from linear relation of the vector type. The identification algorithm is verified by using D.D manipulator of SICE standard.

1. INTRODUCTION

This paper reports the result of the adaptive simultaneous identification based on the recursive least-squares method on a two-link D.D manipulator shown in Fig.1. The recursive estimation occupies an important part in order to design the adaptive control system [1], [2]. The selecting method of the regressor vector for estimation is considered in order to realize the efficient parameter identification. Two recursive identification approaches are compared with respect to the measurement signal used for the estimation deriving good performance.

The SCARA-like D.D manipulator was developed by SICE in order to evaluate the control performance of D.D arm. The SICE standard D.D manipulator has length of same 200[mm] concerning both links and is constructed by means of the direct drive A.C motors of the outer rotor type, driven in torque control mode. Maximum voltage of the torque command signal is same ± 8 volt to both of joints and maximum torques to both actuators of first and second joint are 70 [Nm] and 15 [Nm], respectively. The resolutions of optical encoder for position detection are 614400 and 507904 [pulse/rev] with respect to first link and second link, respectively. Furthermore, the weight of steel disk can be set on the top end of the second link in order to provide the variation of payload. The recursive identification is implemented by using DELL Dimension V400c (Intel celeron processor 400MHz) together with interface board providing 2-channel 12 bits D/A for torque command, 2-channel 24 bits 2-phase encoder pulse counter for position detection and 4-channel 12 bits A/D for current and velocity detection.

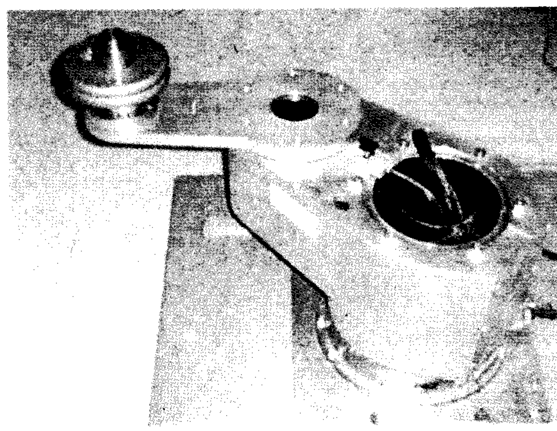

Fig.1 Direct drive manipulator "SR-402DD".

2. MANIPULATOR DYNAMICS

The manipulator called the open kinematic chain is modeled by an articulated chain of the moving rigid bodies with one end fixed the base and the other end free [3]. The vector equation of motion of such manipulator can be written in the general form

$$M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + F(\dot{\boldsymbol{q}}) + G(\boldsymbol{q}) = \boldsymbol{\tau} \ , \quad \boldsymbol{q} \in R^n \quad (1)$$

where $\boldsymbol{\tau}$ is the vector of joint torques by the actuators, and $M(\boldsymbol{q}) \in R^{n\times n}$ is the inertia matrix, and $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$ and $\ddot{\boldsymbol{q}}$ are the joint angles, velocities and accelerations, respectively. The vector $C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}}$ represents torques arising from centrifugal and Coriolis forces. The vectors $F(\dot{\boldsymbol{q}})$ and $G(\boldsymbol{q})$ represent the friction torques acting at rotational joints, and the gravitational torques, respectively.

In the case of neglecting the friction term of (1), the dynamic equation can be usually separated with respect to the link parameters by the property of linear parameterizability as

$$M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + G(\boldsymbol{q}) = \Phi(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})\boldsymbol{\sigma} \ . \quad (2)$$

where $\Phi(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}}) \in R^{n\times p}$ is a signal matrix called the regressor and $\boldsymbol{\sigma} \in R^p$ is the vector of link parameters.

2.1 Dynamics of the SICE D.D arm

Fig.2 shows the schematic drawing of D.D arm. In the case of horizontal plane arm setting, the gravitational term $G(\boldsymbol{q})$ of (2) is identically zero.

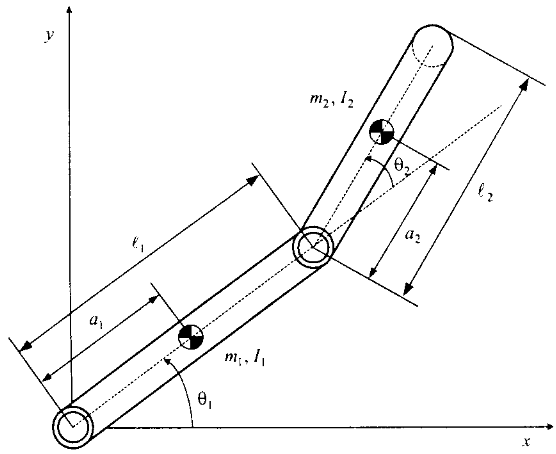

Fig.2 Schematic drawing of two-link D.D arm.

When the momentums of inertia concerning the links are symbolized as I_1, I_2, the terms in the dynamic equation can be obtained by means of the standard Euler-Lagrange dynamic equation as follows:

$$M(\boldsymbol{q})=\begin{bmatrix} J_1+J_2+2rC_2 & J_2+rC_2 \\ J_2+rC_2 & J_2 \end{bmatrix} \tag{3}$$

where

$$J_1=I_1+m_1a_1^{\,2}+m_2\ell_1^{\,2},\quad J_2=I_2+m_2a_2^{\,2},$$
$$r=m_2\ell_1a_2,\quad C_2=\cos q_2,\quad \boldsymbol{q}=[q_1\ \ q_2]^T,$$

and

$$C(\boldsymbol{q},\dot{\boldsymbol{q}})=\begin{bmatrix} -rS_2\dot{q}_2 & -rS_2(\dot{q}_1+\dot{q}_2) \\ rS_2\dot{q}_1 & 0 \end{bmatrix},\ S_2=\sin q_2 . \tag{4}$$

Here, even though the characteristic of friction is very complicated, the approximation of the friction torques is usually assumed by the following form:

$$F(\dot{\boldsymbol{q}})=B\dot{\boldsymbol{q}}+D(\dot{\boldsymbol{q}}) \tag{5}$$

where $B\dot{\boldsymbol{q}}$ and $D(\dot{\boldsymbol{q}})$ represent viscous friction and Coulomb friction, respectively. And also their friction torques are given by

$$B\dot{\boldsymbol{q}}=\begin{bmatrix} b_1\dot{q}_1 \\ b_2\dot{q}_2 \end{bmatrix},\quad D(\dot{\boldsymbol{q}})=\begin{bmatrix} d_1\,\mathrm{sgn}(\dot{q}_1) \\ d_2\,\mathrm{sgn}(\dot{q}_2) \end{bmatrix}. \tag{6}$$

Therefore, the dynamic equation can be described by the linear parameterization form

$$\boldsymbol{\tau}=M(\boldsymbol{q})\ddot{\boldsymbol{q}}+C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}}+B\dot{\boldsymbol{q}}+D(\dot{\boldsymbol{q}})=\Phi(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})\boldsymbol{\sigma} \tag{7}$$

where joint torque is $\boldsymbol{\tau}=[\tau_1\ \ \tau_2]^T$ and the regressor $\Phi(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})$ and the basic parameter $\boldsymbol{\sigma}$ are given by

$$\Phi(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}}) := [\Phi_1\ \ \Phi_2]^T$$
$$=\begin{bmatrix} \ddot{q}_1 & \ddot{q}_1+\ddot{q}_2 & \phi_{13} & \dot{q}_1 & 0 & \mathrm{sgn}(\dot{q}_1) & 0 \\ 0 & \ddot{q}_1+\ddot{q}_2 & \phi_{23} & 0 & \dot{q}_2 & 0 & \mathrm{sgn}(\dot{q}_2) \end{bmatrix} \tag{8}$$

where

$$\phi_{13}=C_2(2\ddot{q}_1+\ddot{q}_2)-S_2(2\dot{q}_1\dot{q}_2+\dot{q}_2^{\,2}),$$
$$\phi_{23}=C_2\ddot{q}_1+S_2\dot{q}_1^{\,2},$$

and

$$\boldsymbol{\sigma}:=[\sigma_1\ \ \sigma_2\ \ \sigma_3\ \ \sigma_4\ \ \sigma_5\ \ \sigma_6\ \ \sigma_7]^T$$
$$=[J_1\ \ J_2\ \ r\ \ b_1\ \ b_2\ \ d_1\ \ d_2]^T . \tag{9}$$

3. MANIPULATOR IDENTIFICATION

If the physical parameters concerning all links are known, the dynamic equation of manipulator can be uniquely decided from them. Identifying all physical parameters is a sufficient condition for decision of dynamic equation. Since the link length of arm is known, the set of physical parameters are given by

$$\mathbf{p}=\{I_1,I_2,m_1,m_2,a_1,a_2,b_1,b_2,d_1,d_2\}\in R^{10} . \tag{10}$$

On the other hand, deciding uniquely all physical parameters from (7) is impossible. The parameters which can be identified from the dynamic equation are only such basic parameters as (9). Therefore, the basic parameter is defined as the set of a necessary and sufficient parameter for dynamic equation.

Here, in order to apply to the update law of a scalar type, the linear parameterization (7) of vector type is appropriately separated to following scalar form

$$\tau_i=\varphi_i^{\,T}\theta_i \quad (i=1,2) \tag{11}$$

where the vector $\varphi_i \in R^{k_i}$ $(k_i < p)$ is selected from the i^{th} row vector in the regressor and the parameter vector $\theta_i \in R^{k_i}$ is properly picked up from the basic parameter $\boldsymbol{\sigma}$. The estimate model is also defined as

$$y_i(t)=\varphi_i^{\,T}(t)\,\hat{\theta}_i(t) \quad (i=1,2) \tag{12}$$

where the vector $\hat{\theta}_i(t)\in R^{k_i}$ is the estimated value and $y_i(t)$ is the output of the estimate model. The condition of the recursive estimation is completed in every sampling interval by filling the motion data

$$\{\ q_i(t),\ \dot{q}_i(t),\ \ddot{q}_i(t),\ \tau_i(t)\ \} \quad (i=1,2) . \tag{13}$$

When the signal to noise (S/N) ratio of the dynamical system is a good condition, the least-squares estimation has few bias with respect to the estimated value. Consequently, the recursive identification based on least-squares method is summarized by the following formulation:

Recursive least-squares algorithm:

$$\hat{\theta}_i(t)=\hat{\theta}_i(t-1)+\frac{P_i(t-1)\varphi_i(t)}{\lambda_i(t)+\varphi_i^{\,T}(t)P_i(t-1)\varphi_i(t)}\varepsilon_i(t) ,$$

$$P_i(t)=\frac{1}{\lambda_i(t)}\left\{P_i(t-1)-\frac{P_i(t-1)\varphi_i(t)\varphi_i^{\,T}(t)P_i(t-1)}{\lambda_i(t)+\varphi_i^{\,T}(t)P_i(t-1)\varphi_i(t)}\right\} ,$$

$$\varepsilon_i(t)=\tau_i(t)-\Phi_i^{\,T}(t)\,\hat{\sigma}(t-1) ,$$

$$\lambda_i(t)=(1-\mu_i)\lambda_i(t-1)+\mu_i ,\quad (i=1,2) \tag{14}$$

where weighting sequences $\lambda_i(t)$ is usually chosen within $0.98<\lambda_i(t)\le 1$ and μ_i is the constant for adjusting the forgetting factor.

3.1 The regressor for identifying D.D arm

There are some ways for separating the regressor vector in the case of identifying basic parameters of D.D arm. It is necessary to choose so that a separated system does not mutually have an influence upon the apriori error $\varepsilon_i(t)$ of (14). The pairs of identification model with respect to regressor and estimate vector filling such condition are given by

$$\begin{cases} \varphi_1^T(t) = [\ddot{q}_1(t) \quad \dot{q}_1(t) \quad \mathrm{sgn}(\dot{q}_1(t))] \\ \hat{\theta}_1^T(t) = [\hat{\sigma}_1(t) \quad \hat{\sigma}_4(t) \quad \hat{\sigma}_6] \\ \varphi_2^T(t) = [\ddot{q}_1(t) + \ddot{q}_2(t) \quad \phi_{23}(t) \quad \dot{q}_2(t) \quad \mathrm{sgn}(\dot{q}_2(t))] \\ \hat{\theta}_2^T(t) = [\hat{\sigma}_2(t) \quad \hat{\sigma}_3(t) \quad \hat{\sigma}_5 \quad \hat{\sigma}_7] \end{cases} \tag{15}$$

and

$$\begin{cases} \varphi_1^T(t) = [\ddot{q}_1(t) \quad \ddot{q}_1(t) + \ddot{q}_2(t) \quad \phi_{13}(t) \quad \dot{q}_1(t) \quad \mathrm{sgn}(\dot{q}_1(t))] \\ \hat{\theta}_1^T(t) = [\hat{\sigma}_1(t) \quad \hat{\sigma}_2(t) \quad \hat{\sigma}_3(t) \quad \hat{\sigma}_4(t) \quad \hat{\sigma}_6(t)] \\ \varphi_2^T(t) = [\dot{q}_2(t) \quad \mathrm{sgn}(\dot{q}_2(t))] \\ \hat{\theta}_2^T(t) = [\hat{\sigma}_5(t) \quad \hat{\sigma}_7(t)]. \end{cases} \tag{16}$$

Although it is verified that both models provide a fine performance through numerical simulation, the pair of identification model (15) is used for demonstrating the experiment in this paper.

4. ACQUISITION OF REGRESSOR

When the system identification has different sensor dynamics, the accuracy of estimation deteriorates. The availability of the filter for compensating the difference of the sensor characteristics was proposed in [4]. However, the proposed method was not fully verified in presence of observation noise. Two methods are described in order to obtain a motion data for filling the regressor of (15). The derivative filter is indispensable for execution of both methods.

M1. Case of having accessible data of both joint torque and joint position.

Fig. 3 shows the first approach in which the link velocity and the link acceleration are calculated by first derivative filter G_1 and second derivative filter G_2, respectively, from position measurements. The joint torque and the joint position are measured through the current detection and the optical encoder, respectively, in every sampling interval. The motion data of the estimated velocity, acceleration, torque, position, etc. are given, respectively, by the following various filters.

$$\begin{cases} \tau_a = G_0\tau, \quad q_a = G_0 q \\ \mathrm{sgn}(\dot{q}_a) = G_0\,\mathrm{sgn}(\dot{q}), \ \dot{q} = \{q(t) - q(t-1)\}/T \\ \dot{q}_a = G_1 q, \quad \ddot{q}_a = G_2 q \end{cases} \tag{17}$$

$$G_0 = \frac{1}{(1+\tau_f s)^3}, \quad G_1 = sG_0, \quad G_2 = s^2 G_0 \tag{18}$$

M2. Case of having accessible data concerning joint torque, joint position and joint velocity.

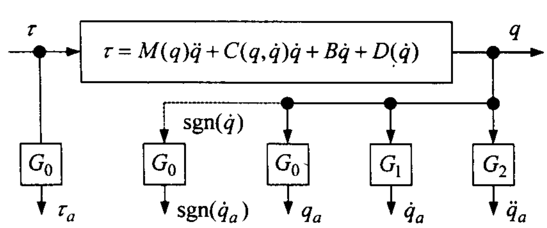

Fig. 3 Compensation of sensor dynamics by M1.

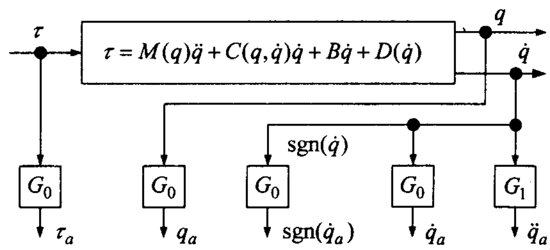

Fig. 4 Compensation of sensor dynamics by M2.

Fig. 4 shows the second approach in which the link acceleration is calculated by the derivation filter from velocity measurements. The velocity is generally available from conversion of the frequency to the voltage with respect to the encoder pulse signal. The motion data of the estimated acceleration, torque, position, velocity, etc. are given, respectively, by reducing the order of filters in M1 method as follows.

$$\begin{cases} \tau_a = G_0\tau, \ q_a = G_0 q, \ \mathrm{sgn}(\dot{q}_a) = G_0\,\mathrm{sgn}(\dot{q}) \\ \dot{q}_a = G_0\dot{q}, \ \ddot{q}_a = G_1\dot{q} \end{cases} \tag{19}$$

$$G_0 = \frac{1}{(1+\tau_f s)^2}, \qquad G_1 = sG_0, \tag{20}$$

The operation of these filters is also calculated by discrete form using the bilinear transformation

$$s = \frac{2}{T}\left(\frac{z-1}{z+1}\right) \tag{21}$$

where T is the sampling period.

5. SIMULATION OF SYSTEM

Both approaches of M1 and M2 are compared with respect to the performance of D.D arm identification. The identification in the case of M1 method is first described. Table1 is the basic parameter of D.D arm model used commonly in both simulations. Table2 shows the condition of simulation. Furthermore, Table3 is the results of M1 estimation with changing the time constant τ_f of each filter. The identification in the case of M2 method is secondly described. The velocity noise shown in Table4 is appended to the simulation condition of Table.2. Likewise, Table5 is the results of M2 estimation with changing the time constant τ_f of each filter.

Table1 Basic parameters of D.D manipulator.

J_1 [kgm^2]	J_2 [kgm^2]	r [kgm^2]	b_1 [Nms]	b_2 [Nms]	d_1 [Nm]	d_2 [Nm]
0.429	0.071	0.162	5.236	1.116	3.208	0.743

Table2 Condition for identification of D.D robot.

torque to first joint	$\tau_1 = 12.5\sin 2k\pi T$	[Nm]
torque to second joint	$\tau_2 = 3.75\sin 2k\pi T$	[Nm]
observation noise to Link1 position	$\sigma_{q1}^2 = 1\times10^{-8}$	[rad]
observation noise to Link2 position	$\sigma_{q2}^2 = 1\times10^{-7}$	[rad]
sampling period	$T = 0.001$	[sec]
data numbers for identification	$k = 10000$	

Table3 Results of M1 identification.

τ_f	Estimation error [%]						
	$\hat{J}_1$	$\hat{J}_2$	$\hat{r}$	$\hat{b}_1$	$\hat{b}_2$	$\hat{d}_1$	$\hat{d}_2$
0.002	55.8	70.5	34.0	17.8	3.1	23.5	1.9
0.004	21.7	23.3	17.9	15.9	17.1	24.1	37.8
0.006	5.1	3.4	4.8	16.4	16.7	24.3	37.7
0.008	18.4	14.4	16.5	15.8	15.7	22.6	36.2
0.01	23.8	18.0	20.3	15.0	15.1	21.0	35.4
0.02	28.2	19.7	21.8	12.4	13.6	16.6	32.2

Table4 Appended condition for M2 identification.

observation noise to Link1 velocity	$\sigma_{\dot{q}1}^2 = 5\times10^{-5}$ [rad/sec]
observation noise to Link2 velocity	$\sigma_{\dot{q}2}^2 = 1\times10^{-4}$ [rad/sec]

Table5 Results of M2 identification.

τ_f	Estimation error [%]						
	$\hat{J}_1$	$\hat{J}_2$	$\hat{r}$	$\hat{b}_1$	$\hat{b}_2$	$\hat{d}_1$	$\hat{d}_2$
0.002	20.2	21.5	29.1	1.5	5.0	0.8	9.4
0.004	12.1	14.2	16.3	0.6	2.4	0.5	5.0
0.006	9.3	12.1	13.2	0.3	1.7	0.9	3.6
0.008	8.4	11.0	11.7	0.1	1.3	1.3	3.0
0.01	7.9	10.4	10.9	0.1	1.1	1.7	2.4
0.02	7.2	8.3	8.5	1.6	0.4	3.8	1.2

The three parameters on $\hat{J}_1$, $\hat{J}_2$ and $\hat{r}$ have most minimum errors in case of $\tau_f = 0.006$ in Table3, respectively, but other parameters are different. Both of $\hat{b}_1$ and $\hat{d}_1$ have great bias in all cases. Therefore, it is too difficult to improve the accuracy, even if the filter time constant is adjusted many times. On the other hand, the five parameters of $\hat{J}_1$, $\hat{J}_2$, $\hat{r}$, $\hat{b}_2$ and $\hat{d}_2$ have most minimum errors in case of $\tau_f = 0.02$ in Table5, respectively. Also, both of $\hat{b}_1$ and $\hat{d}_1$ have small error in all cases. Therefore, M2 is superior compared with M1 in the simultaneous estimation. Fig. 5 shows the transition process of estimated parameters in case of $\tau_f = 0.006$ of M2.

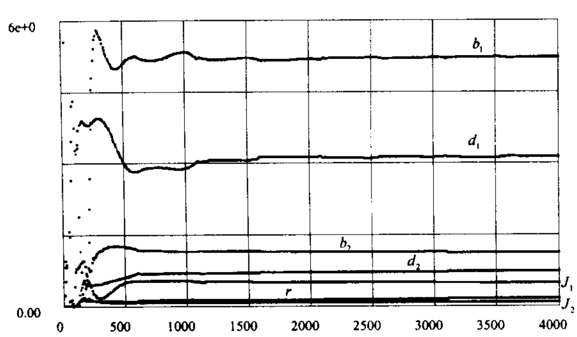

Fig.5 Transition process of estimated parameters.

Table6 Condition for SICE D.D arm identification.

torque to first joint	$\tau_1 = 18.75\sin 2k\pi T$ [Nm]
torque to second joint	$\tau_2 = 5.625\sin 2k\pi T$ [Nm]
sampling period	$T = 0.001$ [sec]

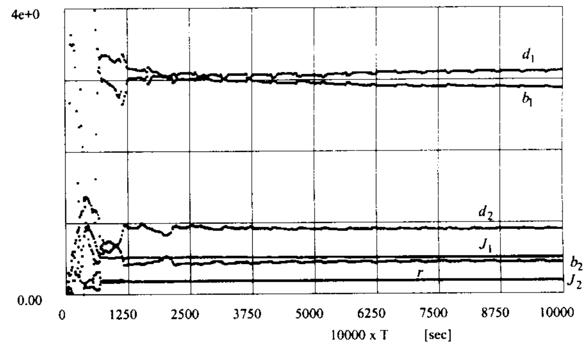

Fig.6 Transition process of estimated parameters.

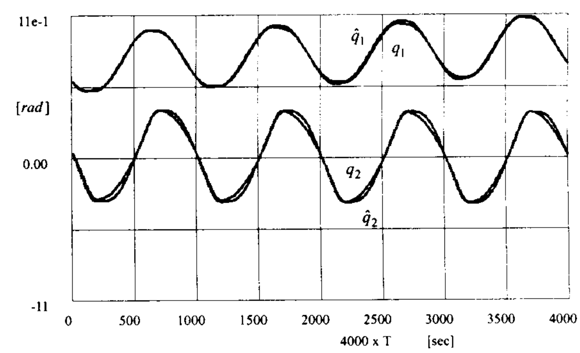

Fig.7 Both responses of D.D arm and model.

6. IDENTIFICATON OF SICE D.D ARM

In this section the experiment result of recursive estimation to SR-402DD using M2 method is shown. Table6 shows the condition for the identification experiment. Also, both payloads of 3[kg] and 1[kg] were used in the experiment. Fig.6 shows the transition process of estimated parameters in the case of 3[kg] and $\tau_f = 0.006$. Fig.7 shows the response of D.D arm and the response of estimated model, respectively. The sufficient performance is assured from experimental results and it is possible to apply to the adaptive control of D.D manipulator.

7. CONCLUSIONS

It was verified through the simulation that the accuracy of simultaneous estimation is improved by the proposed method. Furthermore, the effectivity was confirmed by applying to the SICE D.D robot.

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