FAULT DIAGNOSIS FOR WATER-HYDRAULIC SERVO CYLINDER SYSTEM WITH KALMAN FILTER

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ABSTRACT

The purpose of this research is to design a system that does not lose controllability even when the sensor fails. The proposed system estimates pressure values in circuit with state filter. If one of the pressure sensors fails, this system can switch the value of pressure sensor to the estimated pressure. The system introduces the Kalman filter to estimate each pressure, because the pressure value is easily affected by noise.

In simulation, water hydraulic drive system performs the position control by the state feedback. A failure of the pressure sensor will be emulated by switching measurement value to a constant. Controller compares the information of the pressure sensor and the estimated value by the Kalman filter. Then controller generates the control input based on estimated value if the pressure sensor was seemed to be failed. The effectiveness was confirmed in simulation.

1. INTRODUCTION

Water hydraulic drive systems using tap water as a working fluid have low environmental load and high cleanliness. Therefore, this system can easily be applied to the field of food processing and pharmaceutical industry [1]. Because of the relatively high bulk modulus, this has advantageous for applications requiring high-speed response. At the same time, in water hydraulic drive system, surge pressure is easily occured, then sensors and other devices in the system are likely to be failed. In particular, the failure of the pressure sensor makes impossible to maintain its control performance. Because, in general, all state variables including pressure will be required for advanced control systems.

In recent years, it is required that failure detection of system is difficult, because the complexity of the mechanical system is developed; for example the steel plant. In particular, the state variables are often assumed to be available in the modern control theory. Since it is usually impossible to install sensors to acquire all state variables, it is necessary to estimate them with some state variable filter. In generally, state estimation by the observer cannot consider the effect of noise. However, when it consider real systems, we should consider noise. The Kalman filter used in this research is able to optimally design a filter, and estimation of state value at online is also possible.

In this research, it is assumed that a pressure sensor installed in water-hydraulic servo cylinder system fails. The controller always compares the information of the pressure sensor and the estimated value by the Kalman filter. If these values deviate than specified value, proposed system detects failure of pressure sensor. Then controller generates control input based on estimated pressure value to maintain the control performance.

2. WATER HYDRAULIC SYSTEM

Fig. 1 shows a water hydraulic circuit of a system used in this research. Failure of pressure sensor in this system means that the P_A or P_B cannot be obtained.

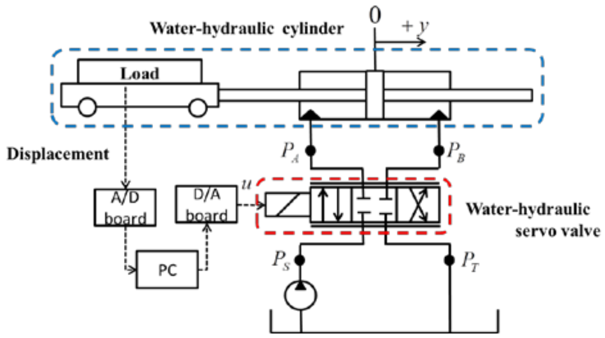


Fig.1 Water-hydraulic servo cylinder system

3. SYSTEM IDENTIFICATION

If system parameters are unknown or difficult to obtain their precise parameters, system identification will be used. This is a method to obtain mathematical model of the system based on the input and output data [2]. Since the denominator polynomial of the transfer function of water hydraulic drive system has a pure integrator, it diverges in the step response. In this research, an output feedback loop was introduced to make the cylinder system act as a servo system. Fig.2 shows an M-sequence signal used for identification. Note that the state variables of the identification model has no physical meaning. Fig.3 shows the results of system identification, and its fitting ratio of model by system identification is 85.67%. Eq.(2) shows the state space model obtained by the system identification.

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{1}$$

where

$$A = \begin{bmatrix} -161.10 & -91.46 & -36.21 \\ 128 & 0 & 0 \\ 0 & 64 & 0 \end{bmatrix}, B = \begin{bmatrix} 8 \\ 0 \\ 0 \end{bmatrix} \tag{2}$$
$$C = \begin{bmatrix} 0.41 & 3.13 & 3.99 \end{bmatrix}$$

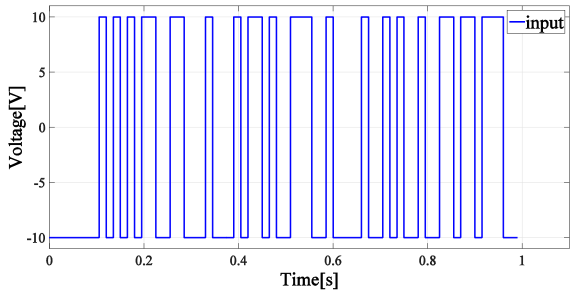


Fig.2 M-sequence signal of identification input

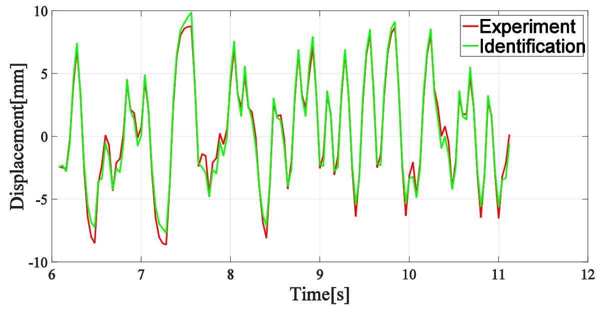


Fig.3 Agreement of system identification result

4. STABILIZATION STATE FEEDBACK CONTROLLER DESIGN

Consider the state feedback controller to stabilize the system Eq.(1). Here, $A \in R^{n\times n}$, $B \in R^{n\times 1}$, $C \in R^{1\times n}$. Control input Eq.(3) using the state feedback gain $K \in R^{1\times n}$ is given by.

$$u(t) = Kx(t) + y_{ref}(t) \tag{3}$$

Therefore, differential Equation of state is

$$\dot{x}(t) = (A + BK)x(t) + By_{ref}(t) \tag{4}$$

Fig.4 shows block diagram of Eq.(1) applied Eq.(3).

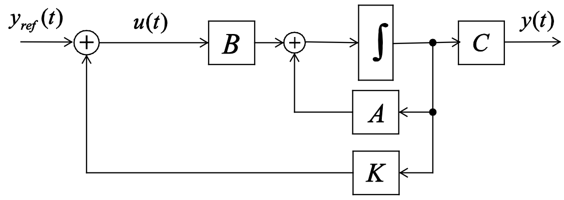


Fig.4 State estimation algorithm of Kalman filter

5. KALMAN FILTER

Kalman filter consists of two basic theories; the least-squares estimation method and the maximum likelihood estimation method. Therefore, optimal Kalman filter design for system with observation noise and system noise, it is possible to apply to estimate the state variable. Consider system Eq.(5) in discreat time.

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + v(k) \\ y(k) = Cx(k) + w(k) \end{cases} \tag{5}$$

For Eq.(5), the state estimation by the Kalman filter is given by the following Equations [3].

$$\hat{x}^-(k) = A\hat{x}(k-1) + Bu(k-1) \tag{6}$$
$$P^-(k) = AP(k-1)A^T + \sigma_v{}^2 BB^T \tag{7}$$
$$g(k) = \frac{P^-(k)C}{C^T P^-(k)C + \sigma_w{}^2} \tag{8}$$
$$\hat{x}(k) = \hat{x}^-(k) + g(k)(y(k) - C^T \hat{x}^-(k)) \tag{9}$$
$$P(k) = (I - g(k)C^T)P^-(k) \tag{10}$$

Fig.5 shows its block diagram.

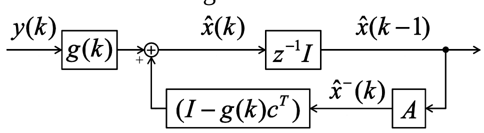


Fig.5 Block diagram of Kalman filter

Eq.(9) is a linear predictor for $\hat{x}^-$ and y in the same structure to the least squares estimation, and is updated with the latest measurement value in the same as the maximum likelihood estimation.

6. SIMULATION RESULTS

In this section, the failure diagnosis performance of proposed controller for water hydraulic cylinder system is examined. For a given a sensor failure, controller should maintain its position control performance.

In simulation, the water hydraulic system with noise in Eq.(11) is considered;

$$\begin{cases} \dot{x}(t) = Ax(t) + B(u(t) + v(t)) \\ y(t) = Cx(t) + w(t) \end{cases} \tag{11}$$

where A, B and C are given by Eq.(2). Mean of system noise $v(t)$ and measurement noise $w(t)$ are set to 0. Dispersions of system noise $v(t)$ and measurement noise $w(t)$ are given by $\sigma_v^2 = 1.0$, $\sigma_w^2 = 4.0$, respectively. For all simulations, the reference position is set to y_{ref} = 10[mm].

6.1 CONVENTIONAL STATE FEEDBACK CONTROLLER

As a first step, the conventional state feedback control is designed ignoring both system measurement noise. Feedback gain K is designed as follows;

$$K = [16.39 \quad 11.17 \quad 1.51]$$

Fig.6 shows the step response of simulation result with v = w = 0 in Eq.(11) and these effectiveness for position control can be confirmed.

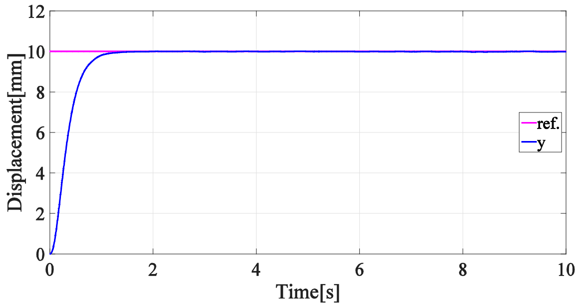
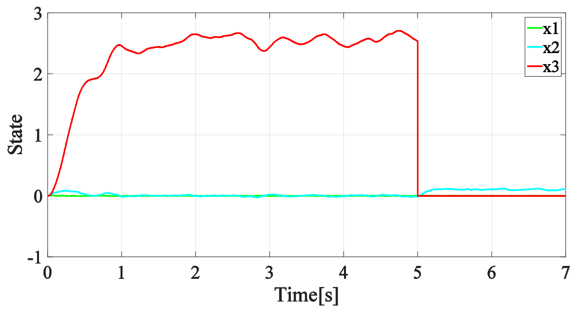
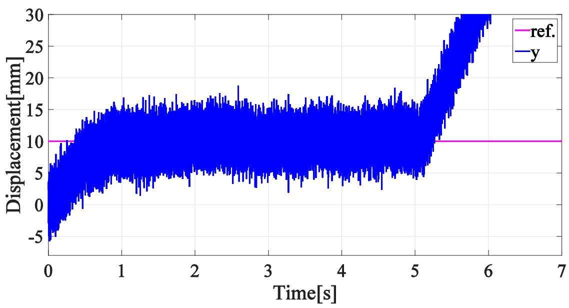


Fig.6 Step response with state feedback for noise free system

Then, the sensor failure as well as system noise/ measurement noise are considered. Sensor failure will be emulated by switching the measurement value to 0 at 5 [s].



(a) State variables



(b) Step response

Fig.7 Step response for pressure sensor failure

Fig.7 shows state variables and step response of simulation result. From the Figure, system response diverged to large value and the feedback controller couldn't work well because some state variable have no information on the system.

6.2 FEEDBACK CONTROLLER WITH STATE ESTIMATION BY KALMAN FILTER

Fig.8 to Fig.10 show the estimated state variables with designed Kalman filter in Eqs.(6)-(10). These Figures show that filtered values give estimated values corresponding state variables. Table 1 shows error of mean square of x. It found that the state estimation with high accuracy were achieved from the results in Table 1.

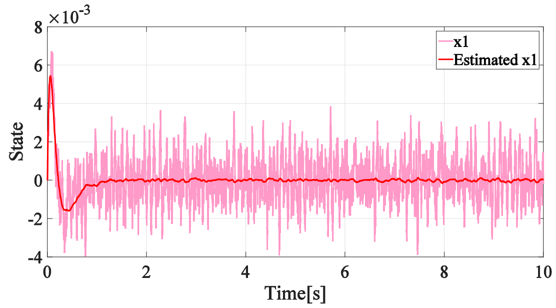


Fig.8 state **x**1when pressure sensor is failure and state estimation by Kalman filter

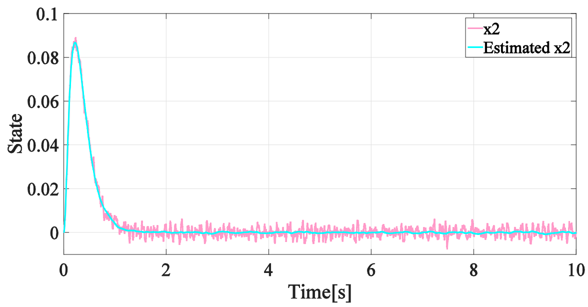


Fig.9 state **x**2 when pressure sensor is failure and state estimation by Kalman filter

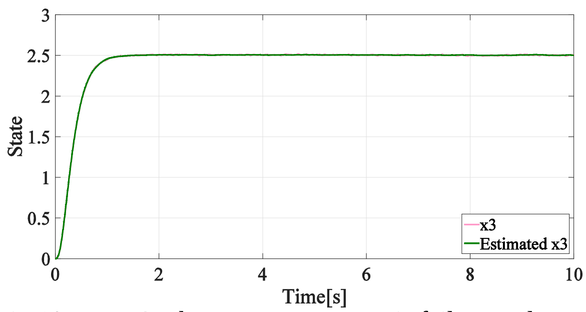


Fig.10 state **x**3 when pressure sensor is failure and state estimation by Kalman filter

Table 1 **x** of error of mean square

	Error of mean square
$E[(x_1 - \hat{x}_1)^T (x_1 - \hat{x}_1)]$	2.62×10^{-9}
$E[(x_2 - \hat{x}_2)^T (x_2 - \hat{x}_2)]$	7.05×10^{-8}
$E[(x_3 - \hat{x}_3)^T (x_3 - \hat{x}_3)]$	4.94×10^{-6}

6.3 SWITCHING STATE FEEDBACK SYSTEM USING A STATE ESTIMATION VALUE BY THE KALMAN FILTER

Consider the case that both the noise and the pressure sensor failure exist. Controller switches the state value by Kalman filter and state value from pressure sensor when pressure sensor failure has been detected with threshold of 1 between two values. Fig.11 shows error of x_3 of true value and estimated value. Fig.12 shows a switching the state estimation value by Kalman filter and state value from 5[s]. Fig.13 shows enlarged view of Fig.11. Table 2 shows y of error of mean square.

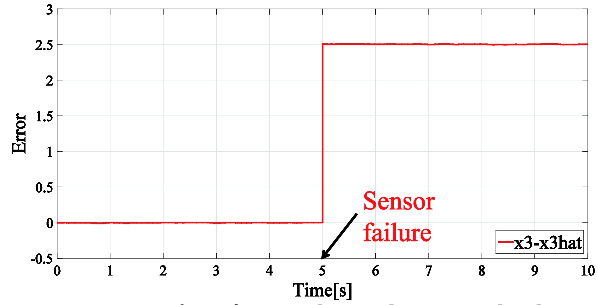


Fig.11 Error of x_3 of true value and estimated value

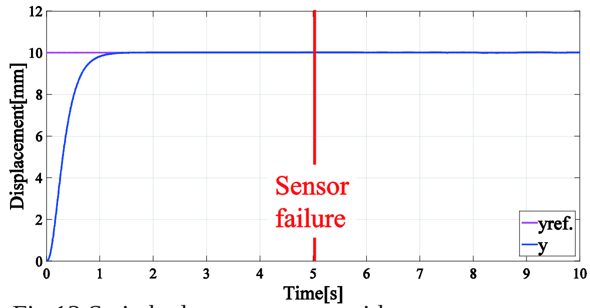


Fig.12 Switched step response with pressure sensor failure and state estimation by Kalman filter

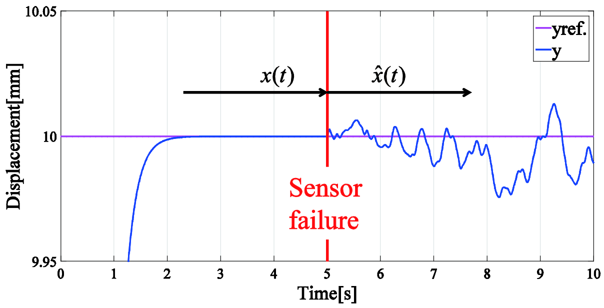


Fig.13 Enlarged view of Fig.11

Table 2 y of error of mean square

	$E[(y-\hat{y})^T(y-\hat{y})]$
error of mean square	4.84×10^{-5}

We can confirm that to employ state value by Kalman filter is effectiveness from this result.

7. CONCLUSION

Proposed system in this paper switches the state value from pressure sensor to the estimation value with Kalman filter when the noise is mixed and the pressure sensor is failure. The proposed controller generates the control input with estimated value. In numerical simulation, it is shown that state estimation by Kalman filter is effective.

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[2]Adachi, S. Basics of system identification, Tokyo Electric and Publication Administration, pp. 78-93, 2009.
[3] Adachi, S. Fundamentals of Kalman filter, Tokyo Electric and Publication Administration, pp. 96-133, 2012.

NOMENCLATURE

v : system noise

σ_v^2 : dispersion of system noise

w : observation noise

σ_v^2 : dispersion of measurement noise

$\hat{x}^-$: priori state estimation

P^- : priori Covariance matrix

g : Kalman gain

$\hat{x}$: posteriori state estimation

P : posteriori Covariance matrix

Shohei Tsuruda received the B.E. degrees in machinery and control systems from Shibaura institute of technology, 2014. He is a graduate school student in master course of system Engineering and Science, SIT. His Current interests include the fault diagnosis by Kalman filter.

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