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3계 슬라이딩 모드 관측기 기반 로봇 고장 진단

Third Order Sliding Mode Observer based Robust Fault Diagnosis for Robot Manipulators

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Abstract: This paper investigates an algorithm for robust fault diagnosis in robot manipulators. The TOSM (Third Order Sliding Mode observer) provides both theoretically exact observation and unknown fault identification without filtration. The EOI (Equivalent Output Injections) of the TOSM observers can be used as residuals for the problem of fault diagnosis and to identify the unknown faults. The obtained fault information can be used for fault detection, isolation as well as fault accommodation to the self-correcting failure system. The computer simulation results for a PUMA 560 robot are shown to verify the effectiveness of the proposed strategy.

Keywords: fault detection, fault diagnosis, sliding mode observer, nonlinear model

I. INTRODUCTION

Various approaches to fault diagnosis in nonlinear systems as well as robot manipulators have been proposed recently. The observer based on normal measurable variables have been approached [1,2]. By using neural network learning, robust fault detection scheme for nonlinear system [3], and for robot manipulators [4,5] have been developed. The basic idea of these methods is to design the robust fault diagnosis by using the model based method, and to use neural network (NN) to approximate the faults involved in the observer design. In [6], a neural-fuzzy model is used to obtain the model based of the unknown dynamic system. One of the best advantages of robust fault diagnoses is that they are not only able to detect the occurrence of a fault, but also can be provided the fault information which is useful for compensating the affect of the faults in the dynamic systems.

Due to important feature of the sliding mode in the system uncertainties such as handling disturbances and modeling uncertainties through the concepts of sliding surface design and equivalent control, SM techniques have been studied for observer states by many researchers [7,8]. However, in SM applications, chattering is the major drawback in the practical realization. To avoid chattering, different approaches have been proposed [9-11]. The most widely used in practical applications to eliminate the chattering are using higher order sliding mode [12,13]. Especially, second order sliding mode [14], for instance, sub-optimal algorithm [15], super-twisting algorithm have been proposed for states observer [16,17]. However, in the second order sliding mode approach, the unknown input is constructed from the discontinuous term which provides the undesired chattering. Hence, to reduce the chattering, the filtration is required in these designs to obtain the unknown input. On the other hand, the filtration provides the delay and error that reduce the fault estimation performance. To avoid filtration which is required of second order sliding mode, the third order sliding mode observer is investigated [18,19]. In [20], the third-order sliding mode observer is designed to estimate the velocities and external perturbation. The obtained estimation of an external perturbation is used to design the controller to compensate the effect of external perturbation in the system.

This paper extends earlier results of our previous work [19], the third-order sliding mode based robust fault diagnosis scheme is designed. The fault information is constructed directly from the equivalent output injection (EOI) of SM without filtration. The obtained fault estimation is used for fault detection, isolation as well as fault accommodation. To verify the effectiveness of the third order sliding mode to fault diagnosis, the simulation is performed on PUMA 560 robot. The remainder of this paper is organized as follows: in section II, the robot dynamics and faults are investigated and problems are given. In section III, the fault diagnosis scheme is designed. The simulation results for a PUMA 560 robot is described in section IV. Section V includes some conclusions.

II. PROBLEM FORMULATION

Let consider a robot dynamics is described by

$$\ddot{q} = M^{-1}(q)[\tau - V_m(q,\dot{q})\dot{q} - G(q)] + \gamma(t-T_f)\phi(q,\dot{q},\tau) \quad (1)$$

where $q \in \Re^n$ is the state vector, τ is the torque produced by actuators, $M(q) \in \Re^{n\times n}$ is the initial matrix, $V_m(q,\dot{q}) \in \Re^n$ is the Coriolis and centripetal force, and $G(q) \in \Re^n$ is the vector of gravity terms, the term $\phi(q,\dot{q},\tau)$ is a vector represents the faults which is composed of actuator faults and/or component faults in robot manipulator, $\gamma(t-T_f) \in \Re^n$ represents the time profile of the faults, and T_f is the time of occurrence of the faults.

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We let the fault time profile $\gamma(\cdot)$ be a diagonal matrix of the form

$$\gamma(t-T_f)=diag\{\gamma_1(t-T_f),\gamma_2(t-T_f),...,\gamma_n(t-T_f)\} \quad (2)$$

where γ_i is a function of fault that represents the fault affecting the *ith* state equation.

The faults with time profiles modeled are given

$$\gamma_i(t-T_f)=\begin{cases}0 & if\ t<T_f\\ 1-e^{-\varphi_i(t-T_f)} & if\ t\geq T_f\end{cases} \quad (3)$$

where $\varphi_i > 0$ represents the unknown fault evolution rate. Small values of φ_i represent incipient faults, while large values of φ_i characterize abrupt fault.

The objective of this paper is to design a robust fault diagnosis scheme that allows the use of equivalent output injection of sliding mode for detecting and isolating any faults $\phi(q,\dot{q},\tau)$ in robotic systems.

III. FAULT DIAGNOSIS OBSERVER

In this section, the fault diagnosis scheme is designed based on the second order sliding mode and third order sliding mode observers.

With $x_1=q\in\Re^n$ and $x_2=\dot{q}\in\Re^n$, the robot dynamics as expressed in eq. (1) can be written in state space form as

$$\begin{aligned}\dot{x}_1&=x_2\\ \dot{x}_2&=f(x_1,x_2,\tau)+\gamma(t-T_f)\phi(q,\dot{q},\tau)\end{aligned} \quad (4)$$

where $f(x_1,x_2,\tau)=M^{-1}(q)[\tau-V_m(q,\dot{q})\dot{q}-G(q)]$.

Based on eq. (4), the second order sliding mode observer is designed as

$$\begin{aligned}\dot{\hat{x}}_1&=\hat{x}_2+\alpha_1|x_1-\hat{x}_1|^{1/2}sign(x_1-\hat{x}_1)\\ \dot{\hat{x}}_2&=f(x_1,x_2,u)+\alpha_2 sign(x_1-\hat{x}_1)\end{aligned} \quad (5)$$

where α_i is the sliding gains.

Substituting eq. (4) into eq. (5), the estimation error is obtained:

$$\begin{aligned}\dot{\tilde{x}}_1&=\tilde{x}_2-\alpha_1|x_1-\hat{x}_1|^{1/2}sign(x_1-\hat{x}_1)\\ \dot{\tilde{x}}_2&=d(x_1,\hat{x}_2,\tilde{x}_2)+\phi(q,\dot{q},t)-\alpha_2 sign(x_1-\hat{x}_1)\end{aligned} \quad (6)$$

where $\tilde{x}=x-\hat{x}$ and $d(x_1,\hat{x}_2,\tilde{x}_2)=f(x_1,x_2,\tau)-f(x_1,\hat{x}_2,\tau)$.

To guarantee the stability and finite time convergence of the observer scheme, the sliding gains should be chosen as:

$$\begin{aligned}&\alpha_1>\phi^+\\ &\alpha_2>3\phi^++2\frac{\phi^{+^2}}{\alpha_1^2}\end{aligned} \quad (7)$$

Where ϕ^+ is the upper bound of the fault: $\phi(q,\dot{q},\tau)<\phi^+$.

After convergence of the differentiator, the observer states in eq. (5) ($\hat{x}_1$, $\hat{x}_2$) converges to the true states in eq. (4) (x_1, x_2). The second term in eq. (6) can be written as

$$z_{eq}=\alpha_2 sign(x_1-\hat{x}_1)=\phi(q,\dot{q},t) \quad (8)$$

From the eq. (8), the fault function is estimated by $z_{eq}=\alpha_2 sign(x_1-\hat{x}_1)$, which is the discontinuous function so that to reconstruct the unknown input from the discontinuous term, a low-pass filter is needed. However, using the low-pass filter provides the time delay and error that decreases the performance of the systems. To overcome this drawback, the third order sliding mode observer is proposed as

$$\begin{aligned}\dot{\hat{x}}_1&=\hat{x}_2+\alpha_2|x_1-\hat{x}_1|^{2/3}sign(x_1-\hat{x}_1)\\ \dot{\hat{x}}_2&=f(x_1,\hat{x}_2,\tau)+\alpha_1|\dot{\hat{x}}_1-\hat{x}_2|^{1/2}sign(\dot{\hat{x}}_1-\hat{x}_2)+\hat{z}\\ \dot{\hat{z}}&=\alpha_0 sign(\dot{\hat{x}}_1-\hat{x}_2)\end{aligned} \quad (9)$$

where α_i is the sliding mode gain to be designed.

From the eqs. (4) and (9), the state estimation error in the presence of the fault ($t\geq T_f$) is defined

$$\begin{aligned}\dot{\tilde{x}}_1&=\tilde{x}_2-\alpha_2|x_1-\hat{x}_1|^{2/3}sign(x_1-\hat{x}_1)\\ \dot{\tilde{x}}_2&=d(x_1,\hat{x}_2,\tilde{x}_2)+\phi(q,\dot{q},t)-\alpha_1|\dot{\hat{x}}_1-\hat{x}_2|^{1/2}sign(\dot{\hat{x}}_1-\hat{x}_2)-\hat{z}\\ \dot{\tilde{z}}&=\alpha_0 sign(\dot{\hat{x}}_1-\hat{x}_2)\end{aligned} \quad (10)$$

After convergence of the differentiator the estimation states ($\hat{x}_1$, $\hat{x}_2$) converges to the true states (x_1,x_2), the second term of the eq. (10) can be written as:

$$\dot{\tilde{x}}_2=\phi(q,\dot{q},t)-\alpha_1|\dot{\hat{x}}_1-\hat{x}_2|^{1/2}sign(\dot{\hat{x}}_1-\hat{x}_2)-\hat{z}\equiv 0 \quad (11)$$

when the differentiator converges to zero, the second term of the eq. (11) ($\alpha_1|\dot{\hat{x}}_1-\hat{x}_2|^{1/2}sign(\dot{\hat{x}}_1-\hat{x}_2)$) converges to zero. Then, from the eq. (11), the fault function can be reconstructed as

$$\hat{z}=\phi(q,\dot{q},t) \quad (12)$$

From eqs. (11) and (12), $\hat{z}$ is a continuous function so that the fault can be obtained directly from the equivalent of the sliding mode without filtration.

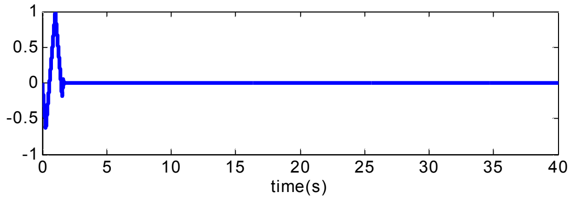
The obtained fault information can be used for fault detection and isolation as well as fault accommodation to self-correct the effect of fault in robot system.

IV. SIMULATION RESULTS

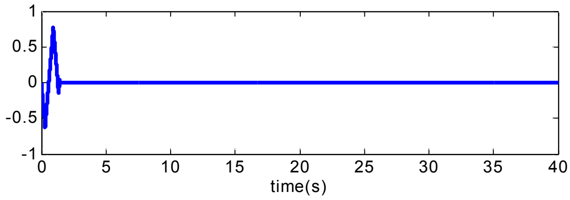
In order to verify the effectiveness of the proposed strategy, its overall procedure is simulated for a PUMA560 robot where the first three joints are used. PUMA robot is well known industrial robot that has been widely used in industrial application and robotic research. Its explicit dynamic model and its parameter values are given in Ref. [20]. The sliding gains are selected as $\alpha_0=1.1L$, $\alpha_1=1.5L$ and $\alpha_2=1.9L$ where we select $L=3$.

First, in normal operation, the robot is controlled to track the desired trajectory. The three equivalent output injection of third order sliding mode keep stay around zero. It is shown in Fig. 1 where there is no presence of fault.

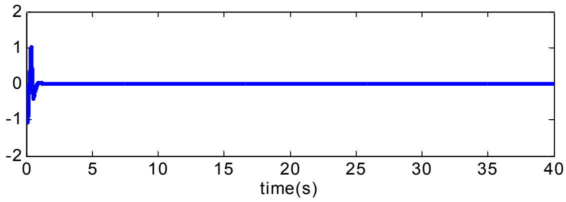
To verify the performance of the third order sliding mode in terms of fault detection and isolation, we supply some intentional faults to the system. In first case, we consider a fault



(a) EOI at Joint 1.



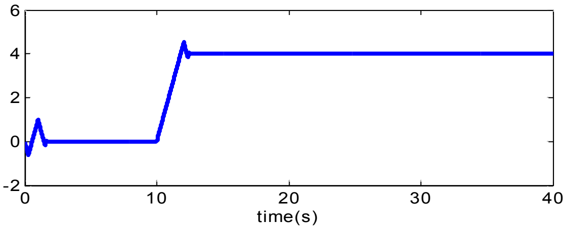
(b) EOI at Joint 2.



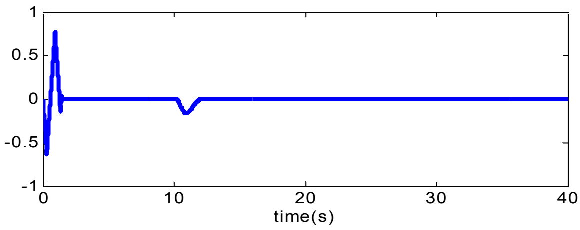
(c) EOI at Joint 3.

그림 1. 로봇의 정상 동작 시, 각 관절에서 3계 슬라이딩 모드 관측기로부터 얻어진 EOI($\hat{z}$)

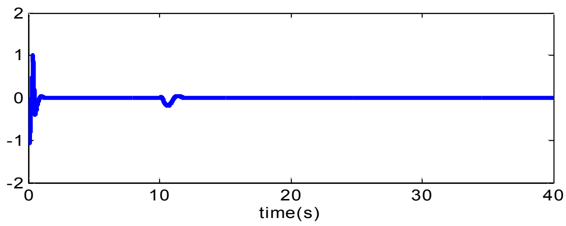
Fig. 1. Equivalent output injections($\hat{z}$) at each joint from the third order sliding mode observer in normal operation of the robot.



(a) EOI at Joint 1.



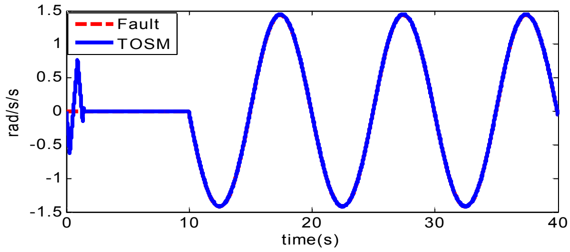
(b) EOI at Joint 2.



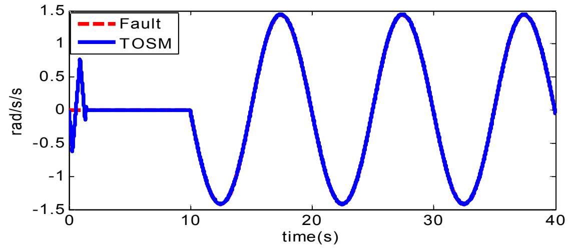
(c) EOI at Joint 3.

그림 2. 고장함수 ϕ_1 이 존재할 때, 각 관절에서 3계 슬라이딩 모드 관측기로부터 얻어진 EOI ($\hat{z}$).

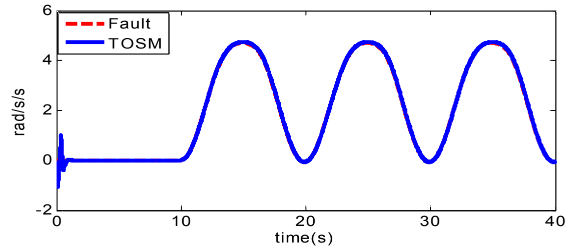
Fig. 2. Equivalent output injections of at each joint from the third order sliding mode observer with a fault of ϕ_1.



(a) The given fault function and its corresponding EOI at joint 1.



(b) The given fault function and its corresponding EOI at joint 2.



(c) The given fault function and its corresponding EOI at joint 3.

그림 3. 고장함수 ϕ_2 이 존재할 때, 각 관절에서 3계 슬라이딩 모드 관측기로부터 얻어진 고장함수 추정값(EOI)과 주어진 고장함수 비교.

Fig. 3. Comparison of the given fault function with its corresponding equivalent output injections at each joint from the third order sliding mode observer with the fault of ϕ_2.

$\phi_1 = [4,\ 0,\ 0]^T$ to occur at $t = 10s$. It means we have a fault only in the first joint. From the results of EOIs in Fig. 2, we can see that the first output of sliding mode remains around zero when $t < 10s$ and jumps to 4 when $t \geq 10s$, while the second and third outputs of sliding mode still remain around zero. It verifies that the fault ϕ_1 is correctly detected and isolated.

To further show the effectiveness of the proposed algorithm, we devise the arbitrary fault which could cover various mathematical functions:

$$\phi_2 = \begin{bmatrix} 2q_1^3 + 2q_3 + 0.5\dot{q}_2 \\ 0.9q_2 + 0.06\dot{q}_2 + 0.9\sin(\dot{q}_3) \\ -1.2q_3 - 1.8\sin(q_1) - 0.9\sin(q_3) \end{bmatrix} \tag{13}$$

This fault is assumed to occur at t = 10s. Fig. 3 shows the time histories of the fault function and the equivalent output injections of the sliding mode observer in each joint. Fig. 2 and Fig. 3 show how well the proposed algorithm works for the fault detection and isolation. In there, the assumed fault functions are very closely identified so that there are both almost no error and almost no time delay.

V. CONCLUSIONS

A robust fault diagnosis algorithm in robotic systems by using a third order sliding mode observer is proposed. The fault information can be obtained directly from the equivalent output injection of the SM observer without filtration for fault detection and isolation. Through the computer simulations for a 3-DOF PUMA 560 robot, the proposed algorithm has the capability to identify the supplied fault functions with both almost no error and almost no time delay. They show effectiveness of the proposed algorithm.

REFERENCES

[1] J. J. Gertler, "Survey of model-based failure detection and isolation in complex plants," *IEEE Control Systems Magazine,* vol. 8, no. 6, pp. 3-11, Dec. 1988.

[2] P. M. Frank and X. Ding, "Survey of robust residual generation and evaluation methods in observer-based fault detection systems," *Journal of Process Control*, vol. 7, no. 6, pp. 403-424, Dec. 1997.

[3] M. M. Polycarpou and Alexander B. Trunov, "Learning approach to nonlinear fault diagnosis: detectability analysis," *IEEE Trans. Automat. Contr*., vol. 45, no. 4, pp. 806-812, Apr. 2000.

[4] A. T. Vemuri and M. M. Polycarpou, "Neural network based robust fault diagnosis in robotic systems," *IEEE Trans. Neural Networks*, vol. 8, pp. 1410-1420, Nov. 1997.

[5] M. Van, H. J. Kang, and Y. S. Ro, "A robust fault detection and isolation scheme for robot manipulators based on neural networks," *Lecture Notes of Computer Science 6838*, pp. 25-32. Springer-Verlag, 2011.

[6] S. Mohsen and M. Mohsen, "A neuro-fuzzy online fault detection and diagnosis algorithm for nonlinear dynamic systems," *International Journal of Control, Automation and Systems*, vol. 9, no. 4, pp. 665-670, Aug. 2011.

[7] V. Utkin, "Variable structure systems with sliding modes," *IEEE Transactions on Automatic Control*, vol. 22, no. 2, pp. 212-222, Apr. 1977.

[8] V. Utkin, *Sliding Modes in Control and Optimizations*, Springer-Verlag, Berlin, Germany, 1992.

[9] Y. Xiong and M. Saif, "Sliding mode observer for nonlinear uncertain systems," *IEEE Transactions on Automatic Control*, vol. 46, no. 12, pp. 2012-2017, Dec. 2001.

[10] K. C. Veluvolu, Y. C. Soh, and W. Cao, "Robust observer with sliding mode estimation for nonlinear uncertain systems," *IET Control Theory & Applications*, vol. 1, no. 5, pp. 1533-1540, Sep. 2007.

[11] C. Edwardsa, S. K. Spurgeonb, and R. J. Patton, "Sliding mode observers for fault detection and isolation," *Automatica*, vol. 36, pp. 541-553, Apr. 2000.

[12] A. Levant, "Sliding order and sliding accuracy in sliding mode control," *Int. J. Control*, vol. 58, no. 6, pp. 1247-1263, 1993.

[13] A. Levant, "Robust exact differentiation via sliding mode technique," *Automatica*, vol. 34, pp. 379-384, Mar. 1998.

[14] G. Bartolini, A. Ferrara, and E. Usai, "Chattering avoidance by second order sliding mode control," *IEEE Transactions on Automatic Control*, vol. 43, no. 2, pp. 241-246, Feb. 1998.

[15] D. Brambilla, L. M. Capisani, A. Ferrara, and P. Pisu, "Fault detection for robot manipulators via second-order sliding modes," *IEEE Transactions on Industrial Electronics*, vol. 55. pp. 3954-3963, 2008.

[16] J. Davila, L. Fridman, and A. Levant, "Second-order sliding-mode observer for mechanical systems," *IEEE Transactions on Automatic Control*, vol. 50, no. 11, pp. 1785-1789, Nov. 2005.

[17] J. Davila, L. Fridman, and A. Poznyak, "Observation and identification of mechanical systems via second order sliding modes," *International Workshop on Variable Structure Systems, VSS'06.*, pp. 232-237, Jun. 2006.

[18] L. Fraguela Cuesta, L. Fridman, and V. V. Alexandrov, "Position stabilization of a stewart platform: high-order sliding mode observers based approach," *50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC)*, pp. 5971-5976, Dec. 2011.

[19] M. Van, H. J. Kang, and Y. S. Suh, "A robust fault diagnosis for robot manipulators using third order sliding mode observer," *Proc. of the 27th ICROS Annual Conference (in Korean)*, pp. 488-489, Seoul, Korea, Apr. 2012.

[20] B. Armstrong, O. Khatib, and J. Burdick, "The explicit dynamic model and inertial parameters of the PUMA 560 arm," *IEEE Conference on Robotics and Automation,* vol. 3, pp. 510-518, Apr. 1986.

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