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Robust Unknown Input Observer based Fast Adaptive Fault Estimation:

Application to Unicycle Robot

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Abstract—This work studies the problem of fault estimation using a fast adaptive fault diagnosis observer. The estimator bloc considered for this purpose is an Unknown Input Observer (UIO) which is subsequently used for a robust fault detection scheme and also as an adaptive detection design for an additive actuator fault. Stability of the adaptive estimation is provided by a Lyapunov function ending with solving the Linear Matrix Inequalities (LMI). Due to technological advances in the field of electronic devices, the family of robots is of particular interest thanks to their enhanced mobility capabilities. That's why a numerical example on a linear model describing a unicycle robot is used to illustrate the theoretical results.

***Index Terms*— Fault Estimation, adaptive observer, robust unknown input observer, stability of adaptive estimation, robustness, Lyapunov function, Linear Matrix Inequalities (LMI) and Unicycle robot model.**

INTRODUCTION

In the last several years, considerable attention has been focused on the emerging field of robotics. Therefore, many successful robotic manipulator designs have been introduced thanks to their good terrain adaptability. Many researchers are proposed different ways of control robot design, classified types and ensure performance of robots [1].

A large effort has been devoted by the scientific community especially to the field of mobile robot systems. In particular wheeled robots will be expected to provide many convenient and user friendly transport solutions for both people and objects [2]. The importance of the wheeled mobile robots has long been recognized by the robotics research community, as shown by the numerous robotic competitions and research projects run worldwide in the last decades in the RoboCup federation site, (2008).

The class of unicycle type (mobile) robots, i.e. robots having some forward speed but zero instantaneous lateral motion, is frequently selected for designing and modeling robots. For example many of the robotic competition teams of the last decade selected those robots due to their simplicity and good maneuverability, allowing for example to follow complex trajectories [3]. At the same time research was conducted on controllability, feedback linearization and -stabilization [4].

However, the right behavior and high performance of robots can be threatened. So, it must be safe against all possible accidents or external and internal failures. In order to avoid this problem, the reliability can be achieved by fault tolerant control (FTC) [5] which relies on early detection of faults using fault detection and isolation (FDI) block [6]. Several researches focused on this procedure (FDI) which consists in detecting and isolating faults in a physical system by monitoring its inputs and outputs [7], [8] and [9]. A typical system for fault detection and isolation is made of three parts [10]: fault detection indicates that there's a mistake in the operating system, i.e., the occurrence of a fault and the time of the fault occurrence [11]; secondly, fault isolation determines the location and the type of the fault and finally, fault identification determines the size of the fault. Diverse FDI methods have been reported in the literature such as: generating redundancy in the case of physical redundancy between sensors [12] or parity space formulation [13], [14], [15] and [16]. Other approaches based on a Kalman filter have been treated [17]. After FDI bloc, Fault tolerant control (FTC) systems are needed in order to maintain the performance objectives, or if that turns out to be impossible, to assign achievable objectives so as to avoid catastrophic failures [18], [19]. In general, fault tolerance can be achieved in two ways [20]: Passive FTC deals with a presumed set of system component failures based on the actuator redundancy at the controller design stage. The resulting controller usually has a fixed structure and parameters. However, the main inconvenient of a passive FTCS is that as the number of potential failures and the degree of system redundancy increase. So, controller design could become very complex, and the performance of the resulting controller could become significantly conservative. Moreover, if an unanticipated failure occurs, passive FTC cannot ensure system stability and cannot reach again the nominal performance of the system. Controllers switching underlines the fact that many faulty system representations had to be identified so as to synthesize off-line pre-computed and stabilized controllers. Then, an active FTCS is characterized by an on-line FDI process and a control reconfiguration mechanism [21]. According to the FDI module, a control reconfiguration mechanism is designed in order to take into account the possibility of fault occurrence [22]. Advanced and sophisticated controllers have been developed with fault accommodation and tolerance capabilities, in order to meet pre-fault reliability and performance requirements as proposed by [23] for model matching approaches or by [24] to track a trajectory, but also with degraded ones as suggested by [25].

On the other hand, if the process's models are precise, the problem of fault detection can be solved by observer bloc or residual generated computed from the inputs and the outputs of the process. Among the approaches of fault diagnosis, some researchers are interested by the adaptive fault diagnosis observer approach [26]. This work focus on the unknown input observer (UIO) knowing that observer design for estimating the state of a system subject to unknown inputs has received considerable attention in the past [27] and [28]. However, very little research has been carried out on estimating the unknown inputs. In [29], unknown inputs are estimated by differentiating the output measurement. In [30], the problem of unknown, constant or slowly varying input estimation using a proportional integral observer (PIO) is discussed.

The contribution in this work is to propose a robust unknown input observer (disturbance decoupling) which is also a fast adaptive fault estimator to enhance the rapidity and certainty of fault estimation. It's in fact a following of a previous work developed in [31].

The present paper begins with an introduction detailing the special terms used for this work (robotic field, FDI, FTC, UIO). The outline is organized as follows: Section 1 describes the linear systems with actuator fault and the background of the standard adaptive observer for fault estimation. In section 2, a robust UIO based on FAFE algorithm is proposed. Section 3 is reserved to the simulation results of a unicycle robots model followed by some concluding remarks in the last section.

PROBLEM STATEMENT

This section introduces the preliminaries and background for the work.

Plant description

Consider the Multiple Input-Multiple Output (MIMO) linear system with actuator fault:

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

where $x(t) \in \mathbb{R}^n$ is the state vector, $u(t) \in \mathbb{R}^m$ is the input vector and $y(t) \in \mathbb{R}^p$ is the output vector. A, B and C are known parameter matrices of dimensions $n \times n, n \times m$ and $p \times n$, respectively.

In this work, we will introduce an additive actuator fault $f(t) \in \mathbb{R}^r$ where F_x is a known matrix with dimension $n \times r$ and $d(t) \in \mathbb{R}^q$ is the unknown input (or disturbance) vector where D_x is the known disturbance matrix with dimension $n \times q$. We assume that the pair (A, C) is observable.

Standard Adaptive Fault Estimation Design

The unknown input observer (UIO) is a generalization of the Luenberger observer. His expression adopted in this work is given with a linear transformation as follow:

$$\begin{cases} \dot{z}(t) = Mz(t) + Nu(t) + P_y y(t) + EF_x \hat{f}(t) \\ \quad \hat{x}(t) = z(t) - L_y y(t) \end{cases} \tag{2}$$

Where M, N, P_y, L_y are matrices that will be designed such that the unknown input will be decoupled from other inputs. $z \in \mathbb{R}^{n\times 1}$ is the state of UIO, obtained by the linear transformation $z = Ex$ and $\hat{x}$ is the estimated state vector. The state estimation error is defined by:

$$\begin{aligned} e_x(t) &= \hat{x}(t) - x(t) \\ &= z(t) - L_y y(t) - x(t) \\ &= z(t) - \left(I + L_y C\right)x(t) \end{aligned} \tag{3}$$

Assuming $E = I + L_y C$, so the state estimation error can be written now as:

$$e_x(t) = z(t) - Ex(t) \tag{4}$$

Then the state error dynamic is described as follow:

$$\dot{e}_x(t) = \dot{z}(t) - E\dot{x}(t) \tag{5}$$

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$$= Mz(t) + Nu(t) + P_y y(t) + EF_x\hat{f}(t) - \mathrm{EAx(t)} - \square\mathrm{Bu(t)} - \square F_x f(t) - ED_x(t)d(t)$$

Or

$$z(t) = e_x(t) + Ex(t) \tag{6}$$

So substituting Eq. 6 in Eq. 5 yields

$$\dot{e}_x(t) = Me_x(t) + MEx(t) + Nu(t) + P_y y(t) + EF_x\hat{f}(t) - \mathrm{EAx(t)} - \square\mathrm{Bu(t)} - \square F_x f(t) - ED_x(t)d(t)$$

$$= Me_x(t) + \left(ME - EA + P_y C\right)x(t) + (N - EB)u(t) + EF_x(\hat{f}(t) - f(t)) - ED_x(t)d(t) \tag{7}$$

Let's define the following errors according to the state $x(t)$, the output $y(t)$and the fault $f(t)$, respectively:

$$e_x(t) = \hat{x}(t) - x(t) \tag{8}$$

$$e_y(t) = \hat{y}(t) - y(t) \tag{9}$$

$$e_f(t) = \hat{f}(t) - f(t) \tag{10}$$

If M is Hurwitz matrix and the following relationships are true:

$$ME + P_y C = EA \tag{11}$$

$$N = EB \tag{12}$$

$$ED_x = 0 \tag{13}$$

Then, the Eq. 7 becomes

$$\dot{e}_x(t) = Me_x(t) + EF_x e_f(t) \tag{14}$$

- Theorem 1

If there exist symmetric positive definite matrices $P, Q\epsilon\mathbb{R}^{n\times n}$, $M\epsilon\mathbb{R}^{n\times n}$, and a matrix $F\epsilon\mathbb{R}^{r\times p}$ which check up the following conditions:

$$P^T M + M^T P = -Q \tag{15}$$

$${F_x}^T P = FC \tag{16}$$

Then the adaptive fault estimation algorithm:

$$\dot{\hat{f}}(t) = -\psi F e_y(t) \tag{17}$$

insure the convergence of the error state and the error fault, i.e.,$\lim_{t\to\infty} e_x(t) = 0$, $\lim_{t\to\infty} e_f(t) = 0$

Note $\psi \in \mathbb{R}^{r\times r}$ is the learning rate matrix.

Due to Eq. 17, we can obtain the actuator fault estimation given by Eq. 18

$$\hat{f}(t) = -\psi F \int_{t_f}^{t} e_y(\tau)d\tau \tag{18}$$

In fact, this expression of fault estimator includes only the integral term. However, this fault representation is suitable only for constant faults. Therefore, it should improve this common adaptive fault estimation design to include the time varying fault dynamic.

UNKNOWN INPUT ADAPTIVE OBSERVER BASED FAFE DESIGN

Description of FAFE Algorithm

To implement this algorithm with successful result, it must follow this assumption and lemma which is given also to verify the linear matrix inequality LMI.

- Assumption: $rank(CD_x) = q$
- Lemma[32]:

Given a scalar $\mu \succ 0$ and a symmetric positive definite matrix P which justify the following inequality:

$$2x^T y \le \frac{1}{\mu}x^T Px + \mu y^T P^{-1} y \tag{19}$$

In the previous theorem, there's no field to consider a time varying fault. So, with $\dot{f}(t) \neq 0$ a novel FAFE algorithm is proposed to ameliorate performances of time varying actuator fault estimation: rapidity, stability and accuracy.

- Theorem 2

Under Assumption and conditions Eq. 11, Eq. 12 and Eq. 13 verified , given scalars $\sigma, \mu, \lambda > 0$, if there exist symmetric positive definite matrices $P \in \mathbb{R}^{n\times n}$, $G \in \mathbb{R}^{r\times r}$ and matrices $M\epsilon\mathbb{R}^{n\times n}$, $F\epsilon\mathbb{R}^{r\times p}$ such that Eq. 16 and the following condition hold,

$$\begin{pmatrix} M^T P + PM & 2PEF_x \\ -2\frac{1}{\sigma}{F_x}^T PM - 2{F_x}^T P & -2\frac{1}{\sigma}{F_x}^T PEF_x + \frac{1}{\sigma\mu}G \end{pmatrix} < 0 \tag{20}$$

then the FAFE algorithm

$$\dot{\hat{f}}(t) = -\psi F(\dot{e}_y(t) + \sigma e_y(t)) \tag{21}$$

can realize $e_x(t)$ and $e_f(t)$ uniformly ultimately bounded.

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- Proof

Consider the following Lyapunov function

$$V(t) = e_x{}^T(t)Pe_x(t) + \frac{1}{\sigma}e_f{}^T(t)\psi^{-1}e_f(t) \tag{22}$$

Its derivative with respect to time is

$$\dot{V}(t) = \dot{e_x}^T(t)Pe_x(t) + e_x{}^T(t)P\dot{e_x}(t) + 2\frac{1}{\sigma}e_f{}^T(t)\psi^{-1}\dot{e_f}(t) \tag{23}$$

$$= (Me_x(t) + EF_x e_f(t))^T Pe_x(t) + e_x{}^T(t)P\left(Me_x(t) + EF_x e_f(t)\right) + 2\frac{1}{\sigma}e_f{}^T(t)\psi^{-1}(\dot{\hat{f}}(t) - \dot{f}(t))$$

$$= e_x{}^T(t)M^TPe_x(t) + e_f{}^T(t)F_x{}^TE^TPe_x(t) + e_x{}^T(t)PMe_x(t) + e_x{}^T(t)P?e_f(t) - 2\frac{1}{\sigma}e_f{}^T(t)F\left(\dot{e}_y(t) + \sigma e_y(t)\right) - 2\frac{1}{\sigma}e_f{}^T(t)\psi^{-1}\dot{f}(t)$$

With Eq. 16, we can deduce $-2\frac{1}{\sigma}e_f{}^T(t)FC(\dot{e}_x(t) + \sigma e x t$ is equal to $-21\sigma efTt FxTPext + \sigma e x t$

Substituting Eq. 14 into Eq. 23 yields:

$$\dot{V}(t) = e_x{}^T(t)M^TPe_x(t) + e_f{}^T(t)F_x{}^TE^TPe_x(t) + e_x{}^T(t)PMe_x(t) + e_x{}^T(t)P?e_f(t) - 2\frac{1}{\sigma}e_f{}^T(t)F_x{}^TP(\dot{e}_x(t) + \sigma e_x(t)) - 2\frac{1}{\sigma}e_f{}^T(t)\psi^{-1}\dot{f}(t)$$

$$\dot{V}(t) = e_x{}^T(t)(M^TP + PM)e_x(t) + 2e_x{}^T(t)P?F_x e_f(t) - 2e_f{}^T(t)F_x{}^TP\left(\frac{1}{\sigma}M + I\right)e_x(t) - 2\frac{1}{\sigma}e_f{}^T(t)F_x{}^TPEF_x e_f(t) - 2\frac{1}{\sigma}e_f{}^T(t)\psi^{-1}\dot{f}(t) \tag{24}$$

From Lemma 1, we can acquire that

$$\frac{1}{\sigma}e_f{}^T(t)\psi^{-1}\dot{f}(t) \le \frac{1}{\sigma\mu}e_f{}^T(t)Ge_f(t) + \frac{\mu}{\sigma}\psi^{-1}G^{-1}\psi^{-1}\dot{f}(t)$$

$$\le \frac{1}{\sigma\mu}e_f{}^T(t)Ge_f(t) + \frac{\mu}{\sigma}f_1{}^2\lambda_{\max}\psi^{-1}G^{-1}\psi^{-1} \tag{25}$$

Substituting Eq. 25 into Eq. 24, we obtain hereafter

$$\dot{V}(t) \le \xi^T(t)\Xi\xi(t) + \delta \tag{26}$$

where

$$\Xi = \begin{bmatrix} M^TP + PM & 2PEF_x \\ -2\frac{1}{\sigma}F_x{}^TPM - 2F_x{}^TP & -2\frac{1}{\sigma}F_x{}^TPEF_x + \frac{1}{\sigma\mu}G \end{bmatrix} \tag{27}$$

and

$$\xi(t) = \begin{pmatrix} e_x(t) \\ e_f(t) \end{pmatrix}, \delta = \frac{\mu}{\sigma}f_1{}^2\lambda_{\max}\psi^{-1}G^{-1}\psi^{-1}$$

It follows that $\dot{V}(t) < 0$ which means that $\left(e_x(t), e_f(t)\right)$ converges to a small set according to Lyapunov stability theory. Therefore, estimation errors of the fault and the state are uniformly bounded. Where, the thorem2 are demonstrated. It's easy to show now from Eq. 21 the fault estimate's expression

$$\hat{f}(t) = -\psi F(e_y(t) + \sigma\int_{t_f}^{t} e_y(\tau)\,d\tau) \tag{28}$$

- Remark

Solving conditions in Theorem 2 needs the LMI toolbox in MATLAB. So, it is easy to solve Eq. 20.

But, there are some difficulties in solving Eq. 16 and Eq. 20 simultaneously to extract P, F and G. So, it must transform Eq. 16 into the following optimization problem [12]:

Minimize η subject to Eq. 20 and

$$\begin{bmatrix} \eta I & F_x{}^TP - FC \\ (F_x{}^TP - FC)^T & \eta I \end{bmatrix} > 0 \tag{29}$$

APPLICATION TO UNICYCLE ROBOT

Unicycle Robot model

A linearized dynamic model of a unicycle robot in nominal case [33], [34], is given as state space formulation as

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{30}$$

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where $x(t) = \begin{pmatrix} \vartheta \\ \omega \\ \varphi \\ \dot{\varphi} \end{pmatrix}$ is the state vector, $u(t) = \begin{pmatrix} \tau_L \\ \tau_R \end{pmatrix}$ is the input vector and $(A, B, C)$are the system matrices with appropriate dimensions.

$$A = \begin{pmatrix} 0 & 0 & 2.16 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 72.49 & 0 \end{pmatrix}, C = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$B^T = \begin{pmatrix} -1.64 & -1.64 & 0.000 & 0 \\ 0.029 & -0.029 & -24.15 & -24.15 \end{pmatrix},$$

Faulty case

To develop our work, an actuator fault will occur in the input channel and an unknown disturbance will be taken. So, the robot model is written in faulty case as follow:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + F_x f(t) + D_x d(t) \\ y(t) = C_1 x(t) \end{cases} \tag{31}$$

where

$$F_x = \begin{pmatrix} 1 & 0 \\ 0.5 & 0 \\ 2 & 0 \\ 1 & 0 \end{pmatrix}, D_x = \begin{pmatrix} 0.05 & 0 \\ 0.2 & 0.3 \\ 2 & 0 \\ 0 & 1 \end{pmatrix}, C_1 = C$$

It is assumed that the pair (A, C_1) is observable and verifying that $rank(C_1 D_x) = q = 2$

Thus, our proposed design is applicable.

Numerical results

Solving the parameters of unknown input observer by satisfying the conditions Eq. 11, Eq. 12 and Eq. 13, we obtain

$$L_y = -D_x(C_1 D_x)^+ = \begin{pmatrix} -0.0006 & -0.0023 & -0.0248 & 0.0007 \\ -0.0023 & -0.0909 & -0.0909 & -0.2727 \\ -0.0248 & -0.0909 & -0.9903 & 0.0273 \\ 0.0007 & -0.2727 & 0.0273 & -0.9182 \end{pmatrix}$$

where $(X)^+$ is the pseudo inverse matrix of X.

$$E = eye(4) + L_y \mathrm{C}_1$$

$$E = \begin{pmatrix} 0.9994 & -0.0023 & -0.0248 & 0.0007 \\ -0.0023 & 0.9091 & -0.0909 & -0.2727 \\ -0.0248 & -0.0909 & 0.0097 & 0.0273 \\ 0.0007 & -0.2727 & 0.0273 & 0.0818 \end{pmatrix}$$

$$N = EB = \begin{pmatrix} -1.6855 & -1.6854 \\ 6.6166 & 6.5638 \\ -0.6195 & -0.6142 \\ -1.9850 & -1.9691 \end{pmatrix}$$

Assuming $M = \begin{pmatrix} -1.7 & 0 & 0 & 0 \\ 0 & -2 & 0 & 0 \\ 0 & 0 & -1.1 & 1 \\ 0 & 0 & 0 & -1.8 \end{pmatrix}$

Then, choosing $\mu = 1, \sigma = 1, \lambda = 1$ and solving our linear matrices inequalities in Eq. 20 and Eq. 29, we obtain these results subsequently:

$$P = 1.0e + 007 \times \begin{pmatrix} 1.3398 & -0.1015 & -0.6311 & -0.2442 \\ -0.1015 & 1.5613 & -0.1244 & -0.0869 \\ -0.6311 & -0.1244 & 2.8093 & -0.1790 \\ -0.2442 & -0.0869 & -0.1790 & 1.6083 \end{pmatrix},$$

$$F = 1.0e + 007 \times \begin{pmatrix} -0.2173 & 0.3435 & 4.7463 & 0.9625 \\ 0 & 0 & 0 & 0 \end{pmatrix},$$

$$G = 1.0e + 007 \times \begin{pmatrix} -5.3913 & 0 \\ 0 & -4.4126 \end{pmatrix}.$$

With a sampling time $T = -1s$, the system is subjected to some boots:

The initial reference value $r(t) = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$, the initial state $x(t) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$, the reference input $u(t) = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$,

Compiling the FAFE design, we can obtain the simulation results shown in the following section.

Simulation results

Nominal case:

The simulation result illustrated in Fig. 1 and Fig. 2 shows clearly that the system's response converges to the setpoint in nominal conditions in absence of fault or any unknown input disturbance.

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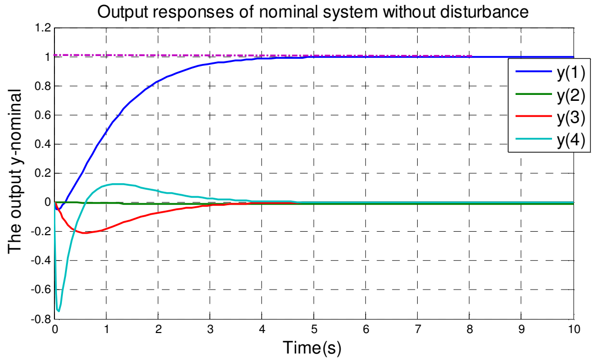

Figure 1. Output responses of nominal system

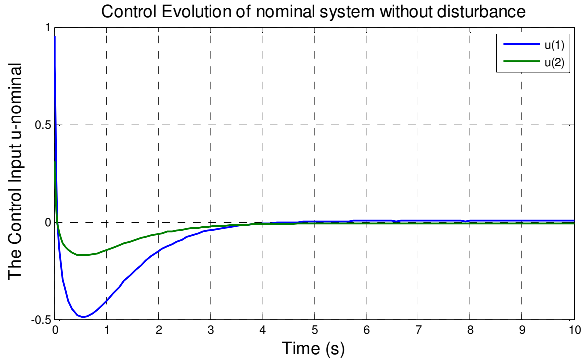

Figure 2. Signal Control in nominal case

In Fig. 3 and Fig. 4 we remark some oscillations in the trajectory followed and control signal because of input disturbance shown in Fig. 5.

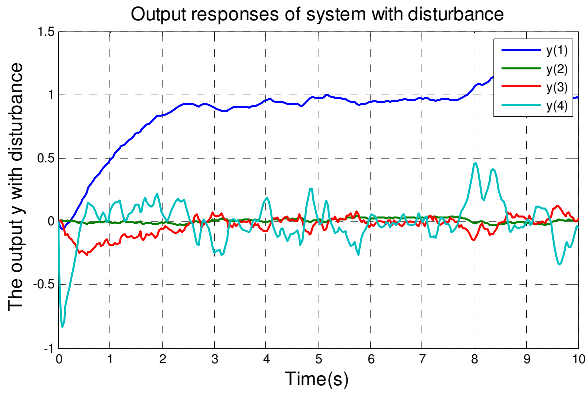

Figure 3. Output responses with unknown input disturbance

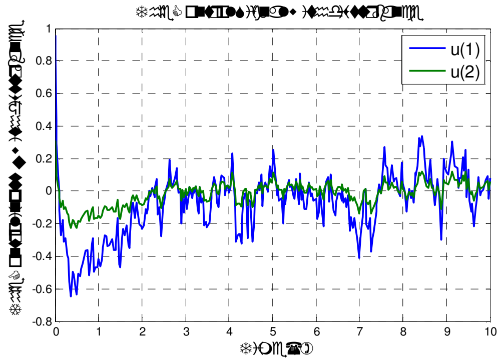

Figure 4. Signal Control with unknown input disturbance

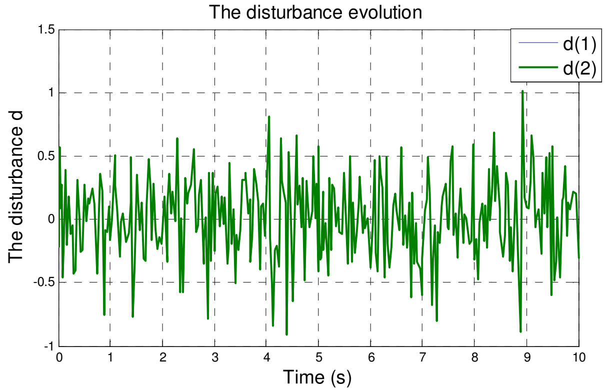

Figure 5. The Disturbance Evolution

Faulty model

Considering a partial actuator failure occurring at time $t_f = 5s$, the faulty-model response is shown in Fig.6 and Fig.7 where the deviation takes a few instants. So, the system's behavior and the control's evolution were changed at that time. In Fig.8 and Fig.9, it's clear that the disturbance vector has a great impact on the system's responses. That's why; we need a robust observer after to decouple the unknown input shown in Fig.5.

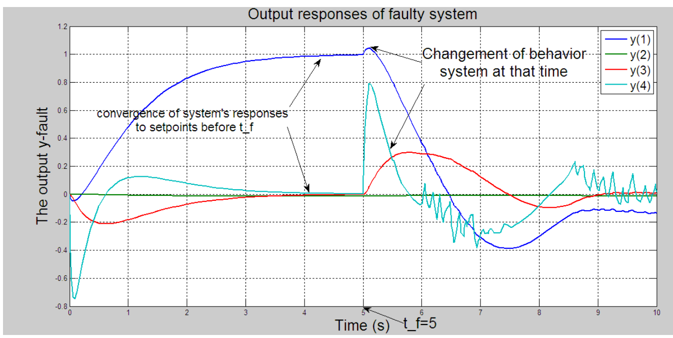

Figure 6. Output responses in faulty case with decoupling the disturbance

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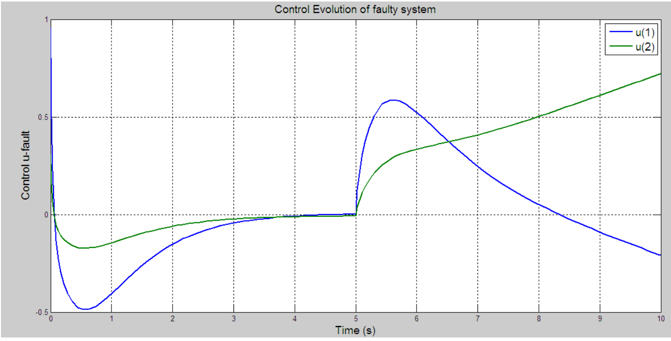

Figure7. Signal Control in faulty case with decoupling the disturbance

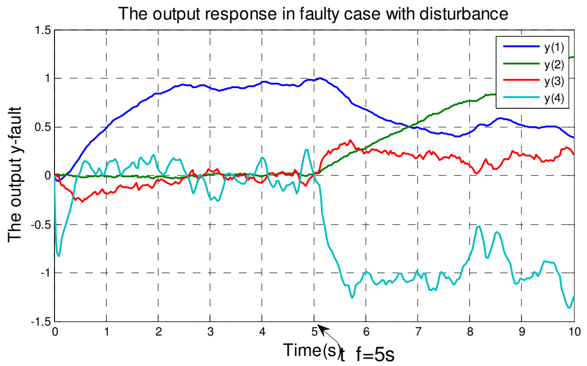

Figure8. Output responses in faulty case with disturbance input

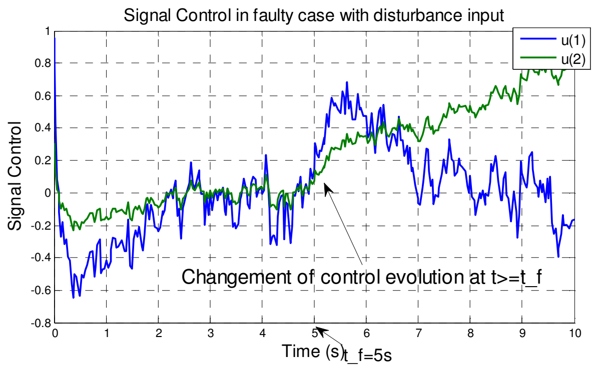

Figure9. Signal Control in faulty case with disturbance input

Fault Estimation

Hereafter, we will highlight the fault estimation obtained thanks to a robust unknown input observer. Firstly, if there is no fault occurred and under the influence of disturbance, the fault estimation is shown in Fig.10. So, it's the order of 10^{-14} near to zero.

Secondly, When introducing a fault vector $f(t) = \begin{bmatrix} {f_1}^T(t) \\ {f_2}^T(t) \end{bmatrix}$, where $f_1(t) = \begin{cases} 0.5 \; if \; t \geq t_f \\ 0 \quad if \; t < t_f \end{cases}$ and $f_2(t) = 0$ (taken in this example $t_f = 5s$), It's easy from Fig.11 to select the peak achieved by the additive actuator fault thanks to the robust estimator used despite of the disturbance vector. Therefore, this estimation is characterized by the strength of fault estimation's response and the clear evolution of fault included.

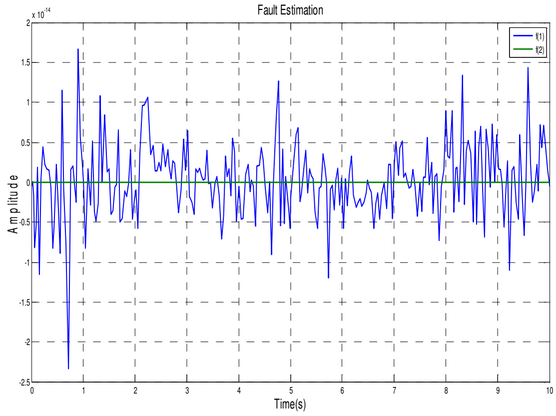

Figure10. Null Fault Estimation

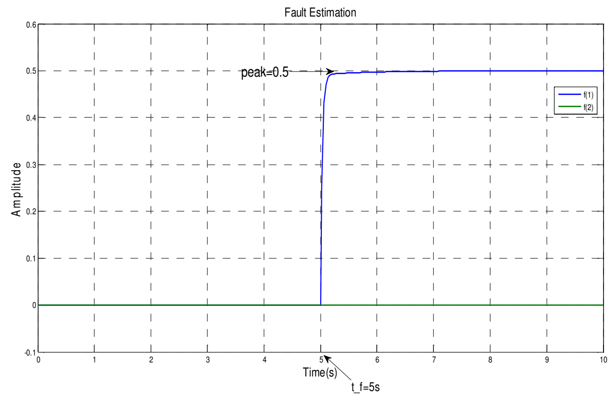

Figure11.Evolution of fault estimation with FAFE algorithm

Conclusion

In this paper an adaptive observer technique for deterministic system has been developed for estimation of actuator fault and to guarantee the strength. In particular it is obvious that the FAFE algorithm can improve performances of fault estimation, including constant and time-varying fault. The application of this scheme to a unicycle robot model shows that actuator fault can be estimated with satisfactory rapidity and accuracy.

Further research work includes two aspects. The first one is that fault accommodation strategy-based fault-tolerant controller will be designed to compensate for these faults using the FAFE algorithm, which can guarantee the stability and reliability of control systems. Since most of industrial systems are uncertain and nonlinear, extension of the proposed method to robust fault diagnosis for uncertain nonlinear systems is another interesting issue.

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