SENSOR FAULT DETECTION IN DC SERVO SYSTEM USING UNKNOWN INPUT OBSERVER WITH STRUCTURED RESIDUAL GENERATION

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Abstract:

This paper deals with the sensor fault diagnosis in a DC servo system using Unknown Input Observer (UIO) by residual analysis approach. The basic principle of UIO is to decouple disturbances from the state estimation error. A single full order Unknown input observer is designed to detect sensor faults in the presence of unknown inputs (disturbances). The basic idea behind the use of observers for fault detection is to form residuals from the difference between the actual system outputs and the estimated outputs using an observer. Once a fault occurs, the residuals are expected to react by becoming greater than a prespecified threshold. When the system under consideration is subject to unknown disturbances or unknown inputs, their effect has to be decoupled from the residuals to avoid false alarms. By conducting proper residual analysis, a fault in the system can be identified. Simulations are carried out to verify the effectiveness of the proposed framework for sensor fault detection and estimation.

Keywords: Unknown Input Observer, Disturbance Decoupling, Fault detection, DC servo system

I. Introduction

Modern control systems are becoming more and more complex, sophisticated with increasingly demanding performance goals. These systems must be highly reliable and secure. The complexity and sophistication of the new generation of aircrafts, automobiles, satellites, chemical plants and manufacturing lines, along with growing demands for higher performance, efficiency, reliability and safety, is being met by more automated control and monitoring systems. An effective way to assure their reliability and security is to swiftly detect and isolate their sensor and actuator failures, as well as failures in the systems components. The development of fault detection and diagnosis tools to help the correction of abnormal behavior during operating processes or off-line is a very active research area in automation and controls.

In the last two decades, fault detection and identification for linear and nonlinear systems have received a great deal of attention. The work has been summarized in [1] and [2]. With respect to the methodologies, the most frequently used methods in the process fault detection are based on system estimation, for example, system identification and observer-based approaches. Traditionally, the FDI issues for a nonlinear dynamic system entail linearizing the model at an operating point, and then applying well-known FDI methods for linear systems to generate a residual, which is compared with a threshold function to determine whether a fault has occurred or not. Model-based fault detection and isolation (FDI) techniques use mathematical models of the monitored process and extract features from measured signals, to generate a fault indicating signal which is called a residual.

Among model based analytical redundancy approaches, observer-based schemes have been successfully adopted in a variety of application fields. The Extended Kalman filter (EKF) is one of the most popular model-based techniques used for fault detection and diagnosis in chemical processes [3-6]. Although successful applications of this tool have been reported in the literature for fault detection and diagnosis in chemical processes, the EKF contains several flaws that may seriously affect its performance. Therefore, practical applications of EKF are still very limited. Some of EKF's inconvenience can be overwhelmed using the unscented Kalman filter (UKF) [7]. However, model-based FDI is built upon a number of idealized assumptions, one of which is that the mathematical model used is a faithful replica of the plant dynamics. There are, of course, disturbances and model uncertainties unavoidable for any practical system. Therefore, it is essential in the design of any fault diagnosis system to take these effects into

consideration, so that fault diagnosis can be done reliably and robustly. The goal of a robust FDI is to discriminate between the fault effects and the effects of uncertain signals and perturbations. Indeed, one of the known successful robust fault diagnosis approaches is the use of the disturbance decoupling principle [5], in which the residual is designed to be insensitive to unknown disturbances, whilst sensitive to faults. For this purpose, Frank and Ding developed the unknown input fault detection observer for linear systems which can be designed by use of the Kronecker canonical form [8]. The objective of this paper is to design a robust sensor fault detection and isolation scheme for a DC servo system. An unknown input observer is designed for a linearized model of DC servo system. The ability and performance of the UIO is investigated for abrupt fault detection and isolation in nonlinear process.

The rest of this paper is organized as follows: In Section II the modeling of DC Servo Motor is given in detail. The design procedure of UIO is explained in section III. The fault detection and isolation method is briefed in section IV. Section V deals with the simulation results and discussion on fault detection. Conclusions are given in section VI.

II. Modeling of DC Servo Motor

A DC motor, second order system with multipe input and multiple outputs, is considered as a plant for testing different fault detection and isolation methods using UIO. The model is designed according to the parameter values of armature resistance, armacture inductance, magnetic flux , voltage drop factor, inertia constant and viscous friction.

The inputs to the system are the armature voltage $U_A(t)$ and the load torque $M_L(t)$.In simulation the armature voltage is given as a step function while the load torque is given a fixed value of 0.1.The measured output signals are the armature current $I_A(t)$ and the speed of the motor $\omega(t)$. The model of the DC motor is shown in Figure 1. The values of parameters [9] are listed given by,
Armature Resistance $(Ra) = 1.52\ \Omega$
Armature Inductance $(La) = 6.82*10^{-3}\ \Omega\ s$
Magnetic Flux $(\psi) = 0.33\ V\ s$
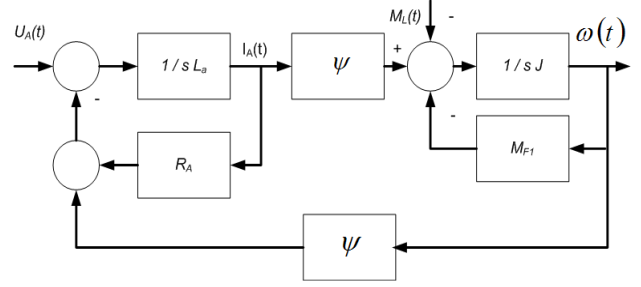Inertia constant $(J) = 0.0192\ kg\ m^2$
Viscous Friction $(M_{Fl}) = 0.36*10^{-3}\ N\ ms$

Figure 1 Signal flow diagram of the DC Motor

The armature current $I_A(t)$ and armature speed $\omega(t)$ are represented as,
$$L_a \dot{I}_A(t) = -R_a I_A(t) - \psi\omega(t) - U_A(t)$$
$$J\dot{\omega}(t) = \psi I_A(t) - M_{Fl}\omega(t) - M_L(t) \qquad (1)$$

The general continuous state space form with faults or disturbance is represented as

$$\dot{x}(t) = Fx(t) + Gu(t) + L_l f_l(t) \qquad (2)$$

$$y(t) = Cx(t) + Du(t) + M_m f_m(t) \qquad (3)$$

Where $x(t) \in R^n$ is a state vector, $u(t) \in R^m$ represents control input vector, $y(t) \in R^p$ is a measurement output vector, F, G, C and D are known constant matrices. The continuous time system in (2) and (3) can be discretised using 0.1 second sampling time to obtain the discrete time model as represented in eqn. (4)

$$x(k+1) = Ax(k) + Bu(k) + Lf_l(k)$$
$$y(k) = Cx(k) + Du(k) + Mf_m(k) \qquad (4)$$
Where
$A = e^{FT}$, T is sampling time
$B = T*A*G, C = C, D = D, L = T*F*L_l$ and $M = M_m$

The state space model of the DC motor is obtained by considering the loop current (I_A) and speed (ω) as state variables, and terminal voltage (U_A) as input and the (unknown) load M_L as disturbance. The resultant state space model is obtained as in (5) and (6).

$$\begin{bmatrix} \dot{I}_A(t) \\ \dot{\omega}(t) \end{bmatrix} = \begin{bmatrix} -R_a/L_a & -\psi/L_a \\ \psi/J & -M_{F1}/J \end{bmatrix} \begin{bmatrix} I_A(t) \\ \omega(t) \end{bmatrix} +$$
$$\begin{bmatrix} \frac{1}{L_A} \\ 0 \end{bmatrix} \begin{bmatrix} U_A(t) \\ M_L(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{-1}{J} \end{bmatrix} M_L \qquad (5)$$

$$\begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} = \begin{bmatrix} I_A(t) \\ \omega(t) \end{bmatrix} =$$
$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} I_A(t) \\ \omega(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \end{bmatrix} \begin{bmatrix} U_A(t) \\ M_L(t) \end{bmatrix} \qquad (6)$$

III. Unknown Input Observer

Consider a continuous linear time invariant steady space model of the system

$$\dot{x}(t) = Ax(t) + Bu(t) + Ed(t)$$
$$y(t) = Cx(t) \tag{7}$$

$x \in R^{nx1}$ represents the state vector, u represents input vector, y represents sensor output, A represents system coefficient matrix, B represents input coefficient matrix, C represents output coefficient matrix, $d \in R^{qx1}$ represents the unknown input vector, and $E \in R^{nxq}$ represents the unknown input distribution matrix.

The structure of the UIO is described as [10],

$$\dot{z}(t) = Fx(t) + TBu(t) + Ky(t)$$
$$\hat{x}(t) = z(t) + Hy(t) \tag{8}$$

$\hat{x} \in R^{nx1}$ represents the estimated state vector and $T \in R^{nxn}$, $K \in R^{nxn}$ and $H \in R^{nxn}$ are matrices satisfying requirements.

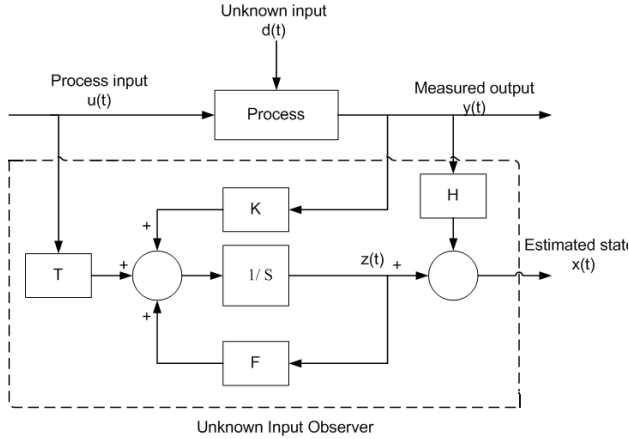The block diagram of Unknown Input Observer is shown in Figure 2.

Figure 2. Block diagram of UIO

The error vector is given by

$$e(t) = x(t) - \hat{x}(t) \tag{9}$$

The state estimation error is governed by the following equation:

$$e(t) = x(t) - \hat{x}(t) = x(t) - z(t) - Hy(t)$$
$$= x(t) - z(t) - HCx(t)$$
$$= (I - HC)x(t) - z(t) \tag{10}$$

Using eqn. (10), derivative of the vector is obtained

$$\dot{e}(t) = (A - HCA - K_1C)e(t)$$
$$+ (A - HCA - K_1C)z(t)$$
$$+ (A - HCA - K_1C)Hy(t) + (I - HC)Bu(t)$$
$$+ (I - HC)Ed(t) - Fz(t) - TBu(t) -$$
$$K_2y(t)$$
$$= (A - HCA - K_1C)e(t)$$
$$+ [F - (A - HCA - K_1C)]z(t)$$
$$- [K_2 - (A - HCA - K_1C)]Hy(t)$$
$$- [T - (I - HC)]Bu(t) - (I - HC)Ed(t) \tag{11}$$

The following relations hold true
$$(HC - I)E = 0 \tag{12}$$
$$T = (I - HC) \tag{13}$$
$$F = A - HCA - K_1C \quad K_2 \tag{14}$$
$$K_2 = FH \tag{15}$$
$$K = K_1 + K_2 \tag{16}$$

Derivative of the error vector (11) will be $\dot{e}(t) = Fe(t)$ and then the solution of the error vector is $e(t) = e^{Ft}e(0)$. If F is chosen as a Hurwitz matrix, the solution of the error equation goes to zero asymptotically. So, $\hat{x}$ converges to x. Note that in equation (14), the matrix K_1 (that stabilizes matrix F) is not unique. This design freedom can be used to generate a directional residual for fault isolation.

Theorem 1: Necessary and sufficient conditions for the observer (8) to be a UIO for defined system in (7) are,

(i) *rank* (CE) = *rank* (E)
(ii) (C,A_1) is a detectable pair,
Where $A_1 = A - E [(CE)^T CE]^{-1}(CE)^T CA$.
A flow chart of UIO design procedure is shown in Figure 3.

Inputs
A,B,E,C,F

rank(CE)=rank(E) — N

Y

$H = E((CE)^T(CE)^{-1}(CE)^T)$
$T = I-HC$
$A_1 = TA$

Pair(C,A1) observable — Y → UIO exist
Compute K_1 by pole placement

N

Construct p to perform observable canonical decomposition on (C, A_1)

Pair (C,A_1) detectable — N → UIO does not exit

Y

Select n_1 desirable eigenvalues and then assign them to $A_{11}-K^1{}_pC^T$

$K_1 = P^{-1}K_p$
$= P^{-1}[(K^1p)^T (K^2p)^T]$
$F = A_1.K_1C$
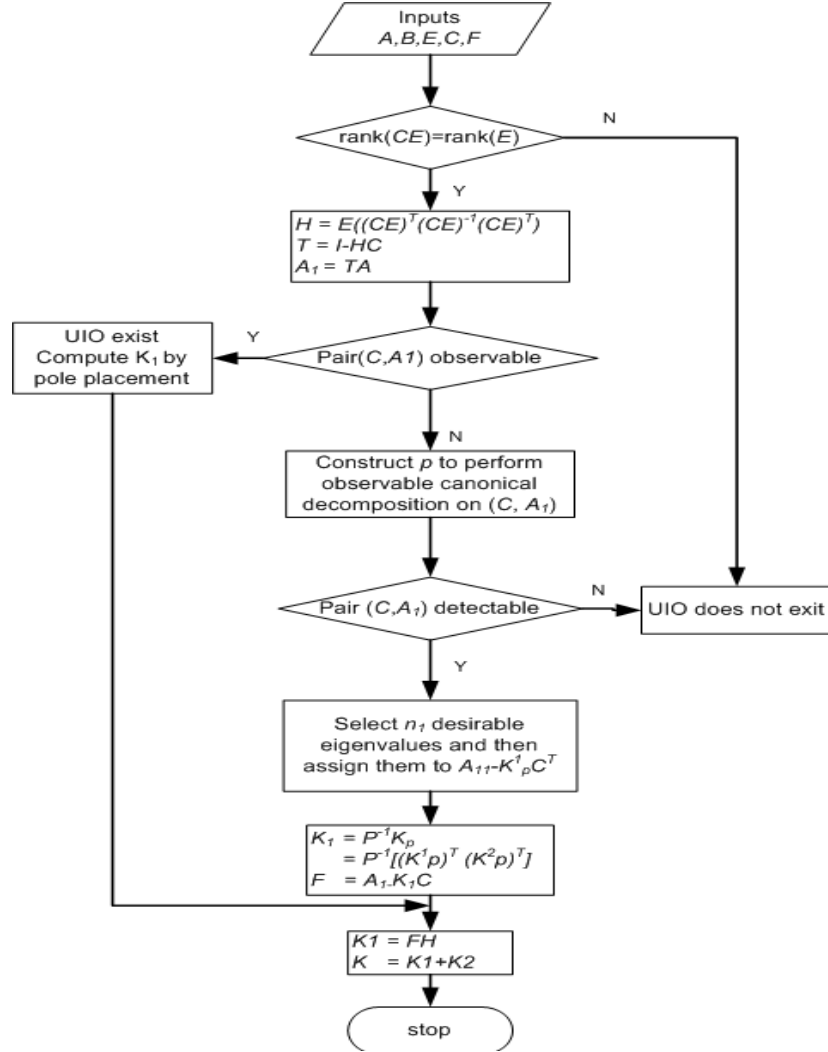
$K1 = FH$
$K = K1+K2$

stop

Figure 3. Flow chart of UIO Design procedure

IV. Fault Detection and Isolation

The core of the model-based fault diagnosis scheme is a process model running parallel to the process [11]. Today, it would be quite natural for anyone equipped with knowledge of the advanced control theory to replace the process model by an observer, in order to, for instance, increase the robustness against the model uncertainties, disturbances and deliver an optimal estimate of the process output. In order to detect and isolate faults in a system we need to look for some fault symptoms. The most common fault symptom that is used for fault detection and isolation is residual. The common procedure for fault detection and isolation using residuals is made of two main steps: residual generation, and residual evaluation.

Residual Generation

Residual generation is the core element of an observer based fault detection system. The residuals are generated using the difference between the real and the estimated output of the system. This difference is usually computed using the norm of the output estimation error vector. UIO approach for fault detection makes use of the disturbance decoupling principle, in which the residual is computed assuming the decoupling of the effects of faults on different inputs. For the purpose of fault isolation, it is also assumed that the effect of a fault is decoupled from the effects of other faults. A well designed residual signal is defined such that it is equal or near zero in the fault free case and is clear from zero when the system is faulty.

$r(t) = 0 \quad or \quad (r(t) \approx 0) \qquad Faulty\ free\ case$
$r(t) \neq 0 \qquad\qquad\qquad\qquad Faulty\ Case$

Residual Evaluation

The residual is examined in terms of the likelihood of a fault, and a logical decision-making process is then applied aiming at to decide if the fault has occurred and avoid wrong decisions, such as false alarm and fault ignored [12]. The final decision is made after a simple comparison between a threshold T(t) (it can be adaptive or constant) and the residual evaluation function J(r(t)). This decision is shown by a binary variable S_r. This binary variable is set to 1 if the value of the residual evaluation function J(r(t)) exceeds the threshold T(t) value, otherwise it is set to 0.

$$J(r(t) \leq T(t) \ then \ \ S_r = 0 \ \ \ (Fault \ free \ case)$$
$$J(r(t) > T(t) \ then \ \ \ S_r = 0 \ \ \ (Faulty \ case)$$

V. Simulation Results of the FDI methods applied to DC servo system:

In this section, the simulation results of the generalized unknown input observer scheme applied to a DC servo system is demonstrated. Linear model of the system, which is obtained by linearizing the system around stable equilibrium point is considered for the design procedures. The system matrices are,

$$A = \begin{bmatrix} -222.87 & -48.39 \\ 17.19 & -.012 \end{bmatrix} \qquad B = \begin{bmatrix} 146.63 \\ -52.08 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}$$

The design procedure is started by verifying the first condition rank (E)=rank(CE)=I. Then the matrices H,T and A1 are computed as,

$$H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad T = \begin{bmatrix} 0.331 & -0.551 \\ -0.222 & 0 \end{bmatrix}$$

$$A1 = \begin{bmatrix} -0.343 & -0.437 \\ 0.003 & 0.034 \end{bmatrix}$$

The observability matrix of (C,A1) is a full rank matrix thus it satisfies the condition (ii) of theorem 1. Therefore the UIO can be designed using the following values of F and K.

$$F = \begin{bmatrix} -0.048 & -0.055 \\ 0.154 & -0.765 \end{bmatrix} \qquad K = \begin{bmatrix} -0.035 & -0.472 \\ -0.222 & 0.111 \end{bmatrix}$$

Figure 4 shows the estimated and actual values of first state variable. The UIO is able to estimate the state variable accurately even in the presence of load disturbance. Result of single sensor fault is shown in Figure 5. A sudden rise of the second state variable (abrupt fault) at 600 msec produces a residual greater

than the threshold value. The observer is able to reject the unknown disturbance in the form of load disturbance which is represented as M_L in the state equation. When the system is in normal working condition the generated residual is equal to zero or near zero implies the fault free case and in case of sensor fault the residual generated is greater than the prespecified value which clearly indicates the malfunction in the sensor.

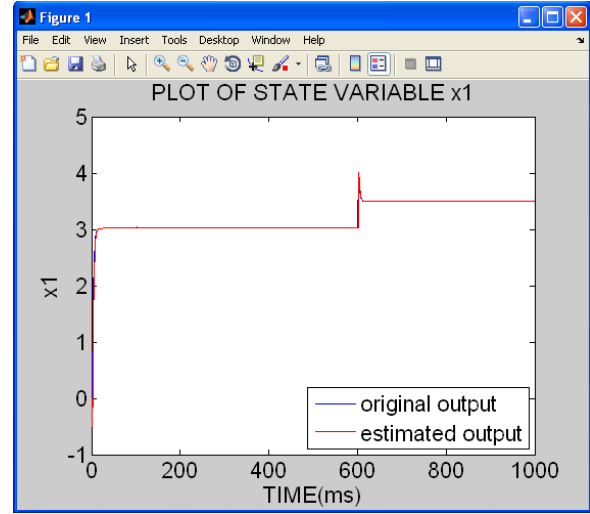### State Estimation of current and speed sensors:

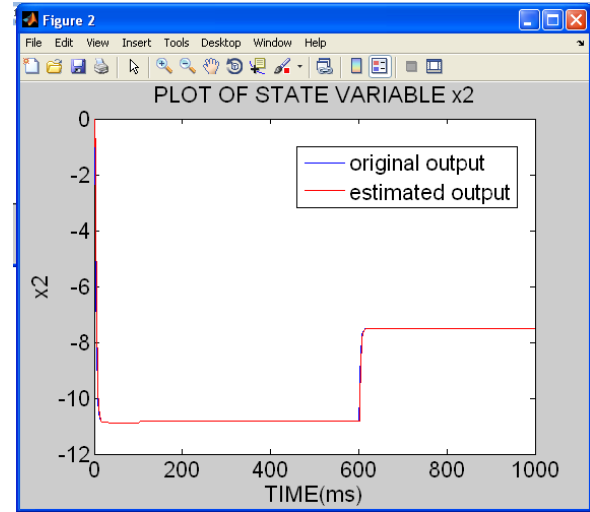Figure 4. Current sensor with abrupt fault at 600 msec

Figure 5. Speed Sensor output

The fault isolation problem is to locate the fault or to determine which sensor has failed. In this work, a structured residual set in which each residual is sensitive to certain fault is designed for fault identification. The generated residual is given in Figure 6.
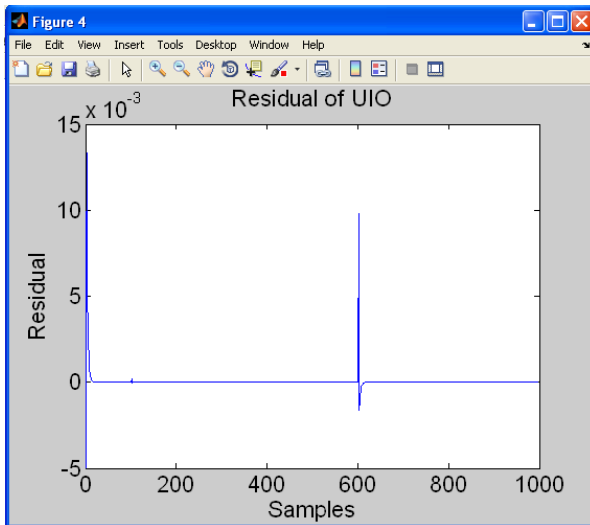
Figure 6. Residual of UIO

VI. CONCLUSION

In this paper, the fault detection and identification for a class of nonlinear system, in the form of DC servo system, is implemented using Unknown Input Observer with structured residual generation method. Single sensor fault present in the system was identified by residual evaluation technique and the ability of the UIO to decouple the disturbance from the fault was also simulated. However, this fault detection and isolation scheme cannot isolate simultaneous faults, and this is the open research area for development of this method.

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