DESIGN OF OBSERVER-BASED FAULT DETECTION SYSTEMS FOR CONTINUOUS-TIME SYSTEMS FROM FREQUENCY DOMAIN DATA

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Abstract: This paper presents an approach to design observer-based fault detection (FD) systems for continuous linear time-invariant systems directly from frequency domain data. The design doesn't need knowledge of system model. The computation mainly consists in a singular value decomposition (SVD) and a QR decomposition. The proposed approach is finally illustrated by an example.

Keywords: Fault detection; Continuous linear time-invariant systems; Frequency domain data; Subspace methods; Observer-based fault detection

1. INTRODUCTION

With the increasing requirement of modern complex control systems on safety and reliability, fault detection (FD) technique has received much attention since the seventies and achieved considerable theoretical development (Willsky, 1976; Gertler, 1998; Chen and Patton, 1999; Frank *et al.*, 2000; Patton *et al.*, 2000). Applications have been found in automobile industry, process industry, transportation systems, aerospace and aeronautics, etc. The basic idea of model-based FD is to generate analytical redundancy with the help of mathematical model of supervised systems. Observer-based FD is one of the most important kinds of model-based FD approaches (Gertler, 1998; Chen and Patton, 1999; Patton *et al.*, 2000). The central part of an observer-based FD system is an output observer. The fault-indicating signal, usually called residual, is obtained by comparing the measured outputs with their estimations. In the context of both discrete and continuous linear time-invariant (LTI) systems, a number of approaches have been proposed for the design of observer-based FD systems. A standard assumption is that a model of the supervised system is available. If it is not the case, then an identification of the system model is necessary. Inspired by the significant development of subspace identification, in this paper it is shown that for continuous LTI systems, without identifying system model, an observer-based FD system can be directly obtained from frequency domain data.

Since the nineties, subspace identification approaches have been developed (Van Overschee and De Moor, 1996*b*; Favoreel *et al.*, 2000). The advantage of subspace approaches is to directly get a state space model from the process input and output data. The subspace methods don't need to parametrize the model set and to solve nonlinear parametric optimization problems. Thus the computation is straightforward and there is no convergence problem (Van Overschee and De Moor, 1996*b*; Favoreel *et al.*, 2000; Li and Qin, 2001).

In the field of fault detection, Basseville *et al.* (2000) has first applied the subspace identification methods to develop FD algorithms aiming at detect changes in the system eigenstructure. Ding *et al.* (2004) have shown that for discrete LTI systems an observer-based FD system can

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be directly obtained from the system input and output data in the time domain, instead of identifying the model of the system at first. However, it is difficult to transfer this approach directly to continuous LTI systems, because the derivatives of input and output are usually not measurable and can only be approximated by, for instance, the numerical integrator (Li *et al.*, 2003).

Motivated by the frequency domain subspace identification methods (Van Overschee and De Moor, 1996*a*; Mckelvey *et al.*, 1996*a*; Mckelvey *et al.*, 1996*b*; Van Overschee *et al.*, 1997; Yang and Sanada, 2000; Pintelon, 2002; Akcay and Turkay, 2004), this paper shows that the principle developed by Ding *et al.* (2004) can be extended to continuous LTI systems if the frequency domain data instead of the time domain data is used. Indeed, in practice, the frequency domain data are often available at some discrete set of frequencies. Modern sophisticated data analyzers and data acquisition equipment also allow large amounts of time domain data to be compressed into frequency domain data of high quality (Van Overschee and De Moor, 1996*a*; Mckelvey *et al.*, 1996*a*; Mckelvey *et al.*, 1996*b*).

2. PROBLEM FORMULATION

Consider the fault detection problem of continuous LTI systems described by

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t) + E_f f(t)\\ y(t) &= Cx(t) + Du(t) + F_f f(t)\end{aligned} \tag{1}$$

where $x \in \mathbf{R}^n$ denotes the state vector, $u \in \mathbf{R}^{k_u}$ the control input vector, $y \in \mathbf{R}^m$ the measured output vector, and $f \in \mathbf{R}^{k_f}$ the vector of faults to be detected, A, B, C, D, E_f, F_f are constant but **unknown** matrices of compatible dimensions.

It is well-known that given an LTI system in the form of (Chen and Patton, 1999; Frank *et al.*, 2000; Patton *et al.*, 2000)

$$\begin{aligned}qx &= Ax + Bu + E_f f\\ y &= Cx + Du + F_f f\end{aligned} \tag{2}$$

where q denotes either the derivative operation for continuous-time signals or the difference operation for discrete-time signals, the dynamic system

$$\begin{aligned}qz &= Gz + Ju + Ly\\ r &= wz + pu + vy\end{aligned} \tag{3}$$

can be used to generate a residual signal r, i.e. $\forall u$, $\lim_{k\to\infty} r(k) = 0$ if $f = 0$ and r deviates from zero as long as $f \neq 0$, if G is stable and there exists a matrix T so that equations

$$\begin{aligned}TA - GT &= LC, \quad vC + wT = 0\\ TB - LD &= J, \quad\ \ p + vD = 0\end{aligned} \tag{4}$$

are satisfied.

In the following, a lemma is introduced which motivates the work in this paper (Ding *et al.*, 1998; Ding *et al.*, 2004).

Lemma Assume that matrices $A \in \mathbf{R}^{n\times n}, B \in \mathbf{R}^{n\times k_u}, C \in \mathbf{R}^{m\times n}, D \in \mathbf{R}^{m\times k_u}$. If vectors

$$v_s = \begin{bmatrix} v_{s,0} & v_{s,1} & \cdots & v_{s,s}\end{bmatrix}, \quad v_{s,i} \in \mathbf{R}^{1\times m} \tag{5}$$

and

$$v_s H_s = \begin{bmatrix} \rho_0 & \rho_1 & \cdots & \rho_s\end{bmatrix}, \quad \rho_i \in \mathbf{R}^{1\times k_u} \tag{6}$$

are known, where

$$H_s = \begin{bmatrix} D & 0 & \cdots & 0\\ CB & D & \ddots & \vdots\\ \vdots & \ddots & \ddots & 0\\ CA^{s-1}B & \cdots & CB & D\end{bmatrix}$$

and v_s satisfies

$$v_s \begin{bmatrix} C\\ CA\\ \vdots\\ CA^s\end{bmatrix} = 0, \tag{7}$$

then there exists a matrix

$$T = \begin{bmatrix} v_{s,1} & \cdots & v_{s,s-1} & v_{s,s}\\ v_{s,2} & \cdots & v_{s,s} & 0\\ \vdots & & & \vdots\\ v_{s,s} & 0 & \cdots & 0\end{bmatrix}\begin{bmatrix} C\\ CA\\ \vdots\\ CA^{s-1}\end{bmatrix}$$

so that G, J, L, w, p, v defined by

$$\begin{aligned}G &= \begin{bmatrix} 0 & \cdots & 0 & g_1\\ 1 & \cdots & 0 & g_2\\ \vdots & & & \vdots\\ 0 & \cdots & 1 & g_s\end{bmatrix}\\ J &= \begin{bmatrix} \rho_0\\ \rho_1\\ \vdots\\ \rho_{s-1}\end{bmatrix} + \begin{bmatrix} g_1\\ g_2\\ \vdots\\ g_s\end{bmatrix}\rho_s\\ L &= -\begin{bmatrix} v_{s,0}\\ v_{s,1}\\ \vdots\\ v_{s,s-1}\end{bmatrix} - \begin{bmatrix} g_1\\ g_2\\ \vdots\\ g_s\end{bmatrix} v_{s,s}\\ w &= \begin{bmatrix} 0 & \cdots & 0 & -1\end{bmatrix}\\ p &= -\rho_s\\ v &= v_{s,s}\end{aligned} \tag{8}$$

with $g_1, g_2, \cdots, g_s$ being free selectable constants satisfy equations (4).

Note that matrices G, J, L, w, p, v in (8) are entirely determined by the components of vectors

v_s, v_sH_s and free parameters $g_1, \cdots, g_s$. The lemma indicates that once vectors v_s and v_sH_s are known with v_s satisfying (7) and free parameters $g_1, \cdots, g_s$ are chosen, then parameters G, J, L, w, p, v satisfying equations (4) can be directly computed without knowledge of A, B, C, D (and T). Since G is in the canonical form, it is easy to get $g_1, \cdots, g_s$ which ensure the stability of matrix G (Kailath, 1980).

The lemma is proven and initially used by Ding *et al.* (2004) to design a discrete observer-based FD system in the form of (3) for discrete LTI systems directly from process input and output data in the time domain. This paper shows that a continuous observer-based FD system (3) can be obtained for continuous LTI systems by using the frequency domain data.

The problem to be solved in this paper is formulated as: Given **frequency domain samples** $G(j\omega_1), G(j\omega_2), \cdots, G(j\omega_N)$ of system (1) in normal operations, determine an observer-based FD system.

3. DESIGN APPROACH

In this section, an approach is presented which leads to an observer-based FD system from the frequency domain data.

3.1 *Basic idea*

The frequency domain dynamics of system (1) in normal operations ($f = 0$) is governed by

$$\begin{aligned} j\omega X(j\omega) &= AX(j\omega) + BU(j\omega) \\ Y(j\omega) &= CX(j\omega) + DU(j\omega) \end{aligned} \qquad (9)$$

where j is the imaginary unit. From (9), it yields

$$\begin{aligned} j\omega Y(j\omega) &= CAX(j\omega) + CBU(j\omega) + j\omega DU(j\omega) \\ (j\omega)^2 Y(j\omega) &= CA^2X(j\omega) + CABU(j\omega) \\ &\quad + CBj\omega U(j\omega) + (j\omega)^2 DU(j\omega) \\ &\ \ \vdots \end{aligned}$$

which can be summarized in the matrix form as

$$\begin{bmatrix} Y(j\omega) \\ j\omega Y(j\omega) \\ \vdots \\ (j\omega)^s Y(j\omega) \end{bmatrix} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} X(j\omega) + \begin{bmatrix} D & 0 & \cdots & 0 \\ CB & D & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ CA^{s-1}B & \cdots & CB & D \end{bmatrix} \begin{bmatrix} U(j\omega) \\ j\omega U(j\omega) \\ \vdots \\ (j\omega)^s U(j\omega) \end{bmatrix}$$

where s is an integer.

Denote by $G(j\omega)$ the frequency response of system (1) to the control input. It is evident that $Y(j\omega) = G(j\omega)$ when $U(j\omega) = I$ (identity matrix of dimension $k_u \times k_u$). Given frequency response $G(j\omega)$ at different frequencies $\omega_1, \omega_2, \cdots, \omega_N$, the following relation

$$G_N = H_o X_N + H_s I_N \qquad (10)$$

holds, where

$$\begin{aligned} G_N &= \begin{bmatrix} G(j\omega_1) & \cdots & G(j\omega_N) \\ j\omega_1 G(j\omega_1) & & j\omega_N G(j\omega_N) \\ \vdots & & \vdots \\ (j\omega_1)^s G(j\omega_1) & \cdots & (j\omega_N)^s G(j\omega_N) \end{bmatrix} \\ X_N &= \begin{bmatrix} X(j\omega_1) & \cdots & X(j\omega_N) \end{bmatrix} \\ I_N &= \begin{bmatrix} I & \cdots & I \\ j\omega_1 I & & j\omega_N I \\ \vdots & & \vdots \\ (j\omega_1)^s I & \cdots & (j\omega_N)^s I \end{bmatrix} \\ H_o &= \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} \\ H_s &= \begin{bmatrix} D & 0 & \cdots & 0 \\ CB & D & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ CA^{s-1}B & \cdots & CB & D \end{bmatrix} \end{aligned} \qquad (11)$$

Let

$$\begin{aligned} \bar{G}_N &= \begin{bmatrix} \mathrm{Re}(G_N) & \mathrm{Im}(G_N) \end{bmatrix} \\ \bar{X}_N &= \begin{bmatrix} \mathrm{Re}(X_N) & \mathrm{Im}(X_N) \end{bmatrix} \\ \bar{I}_N &= \begin{bmatrix} \mathrm{Re}(I_N) & \mathrm{Im}(I_N) \end{bmatrix} \end{aligned} \qquad (12)$$

Since H_o, H_s are real matrices, there is

$$\bar{G}_N = H_o \bar{X}_N + H_s \bar{I}_N \qquad (13)$$

In the next, we show that based on (13) a vector v_s satisfying (7) (i.e. in the left null space of H_o) and v_sH_s can be identified. After this is done, an observer-based FD system can be readily constructed for system (1) according to the lemma.

Equation (13) can be re-written as

$$\begin{bmatrix} \bar{G}_N \\ \bar{I}_N \end{bmatrix} = \begin{bmatrix} H_o & H_s \\ O & I \end{bmatrix} \begin{bmatrix} \bar{X}_N \\ \bar{I}_N \end{bmatrix}$$

Because matrix $\begin{bmatrix} \bar{X}_N \\ \bar{I}_N \end{bmatrix}$ is of full row rank, $\begin{bmatrix} \bar{G}_N \\ \bar{I}_N \end{bmatrix}$ and $\begin{bmatrix} H_o & H_s \\ O & I \end{bmatrix}$ have the same left null space. Assume that there is the following singular value decomposition (SVD)

$$\begin{bmatrix} \bar{G}_N \\ \bar{I}_N \end{bmatrix} = U \begin{bmatrix} S & O \\ O & O \end{bmatrix} V' \qquad (14)$$

with orthogonal matrices

$$U = \begin{bmatrix} U_1 & U_2 \end{bmatrix}, \; V = \begin{bmatrix} V_1 & V_2 \end{bmatrix}$$

then U_2' builds the basis of the left null space of $\begin{bmatrix} \bar{G}_N \\ \bar{I}_N \end{bmatrix}$ and also that of $\begin{bmatrix} H_o & H_s \\ O & I \end{bmatrix}$.

Partition U_2' as

$$U_2' = \begin{bmatrix} U_{\Sigma 1} & U_{\Sigma 2} \end{bmatrix}$$

Because

$$\begin{aligned} & U_2' \begin{bmatrix} H_o & H_s \\ O & I \end{bmatrix} \\ & = \begin{bmatrix} U_{\Sigma 1} & U_{\Sigma 2} \end{bmatrix} \begin{bmatrix} H_o & H_s \\ O & I \end{bmatrix} = 0 \end{aligned}$$

there is

$$\begin{aligned} U_{\Sigma 1} H_o &= 0, \\ U_{\Sigma 1} H_s &= -U_{\Sigma 2} \end{aligned} \tag{15}$$

So one vector v_s satisfying (7) and the corresponding vector $v_s H_s$ can be chosen as

$$\begin{aligned} v_s &= \alpha U_{\Sigma 1} \\ v_s H_s &= -\alpha U_{\Sigma 2} \end{aligned} \tag{16}$$

where α is any nonzero row vector of compatible dimensions.

3.2 *Order selection*

It can be seen that the order of the resulting observer is equal to s. The smaller s is, the less the online computation efforts the FD system needs. On the other side, to identify v_s and $v_s H_s$, usually s is selected much higher than the system order to ensure that H_o is not of full row rank and there exists $U_{\Sigma 1}$ satisfying $U_{\Sigma 1} H_o = 0$.

Note that if vector α is selected in such a way that v_s has the following structure

$$v_s = \begin{bmatrix} v_{s,0} & \cdots & v_{s,\nu} & 0 & \cdots & 0 \end{bmatrix} \tag{17}$$

where $\nu < s$, then

$$v_s H_s = \begin{bmatrix} \rho_0 & \cdots & \rho_\nu & 0 & \cdots & 0 \end{bmatrix} \tag{18}$$

and the order of the observer can be reduced to ν, since

$$v_s \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} = \begin{bmatrix} v_{s,0} & v_{s,1} & \cdots & v_{s,\nu} \end{bmatrix} \begin{bmatrix} C \\ CA \\ \vdots \\ CA^\nu \end{bmatrix} = 0$$

According to the lemma, the observer-based FD system can be constructed based on $\bar{v}_s$ and $\bar{v}_s H_s$ defined by

$$\begin{aligned} \bar{v}_s &= \begin{bmatrix} v_{s,0} & v_{s,1} & \cdots & v_{s,\nu} \end{bmatrix} \\ \bar{v}_s H_s &= \begin{bmatrix} \rho_0 & \cdots & \rho_\nu \end{bmatrix} \end{aligned} \tag{19}$$

One of the ways to find such a vector α is by the QR factorisation. Let $U_{\Sigma 1}$ be factorised as

$$U_{\Sigma 1} = U_Q U_R \tag{20}$$

with U_Q unitary and the right upper triangular block of U_R being zero. If α is setted as the first row of U_Q', then $\alpha U_{\Sigma 1}$ will be the first row of U_R and thus has the most zero elements due to the relation $U_R = U_Q' U_{\Sigma 1}$.

3.3 *Algorithm*

In summary, an observer-based FD system in the form of

$$\begin{aligned} \dot{z}(t) &= Gz(t) + Ju(t) + Ly(t) \\ r(t) &= wz(t) + pu(t) + vy(t) \end{aligned} \tag{21}$$

can be designed for continuous LTI system (1), whose model is unknown, based on frequency response samples $G(j\omega_1)$, $G(j\omega_2), \cdots, G(j\omega_N)$ in normal operations as below:

- Set the value of s.
- Build matrices $\bar{G}_N, \bar{I}_N$ by (11) and (12).
- Do the SVD of $\begin{bmatrix} \bar{G}_N \\ \bar{I}_N \end{bmatrix}$ as (14) to get matrix U_2.
- Partition U_2' as $\begin{bmatrix} U_{\Sigma 1} & U_{\Sigma 2} \end{bmatrix}$.
- Do the QR factorization as (20) and set α to the first row of U_Q'.
- Compute vectors $v_s, v_s H_s$ by (16).
- Choose $g_1, g_2, \cdots, g_s$ so that all eigenvalues of G are on the left complex plane.
- Compute G, J, L, w, p, v according to (8).

The numerical property of the algorithm can be further improved by applying the w-operator approach like (Yang and Sanada, 2000).

4. EXAMPLE

To illustrate the algorithm, consider an example of a 3rd-order system, whose model is unknown. 200 samples of the frequency response of the system are collected with the frequency $\omega_1, \omega_2, \cdots, \omega_N$, $N = 200$, varying from 0.05 to 10 rad/s equidistantly (as shown in Fig.1-2). The model used for generating the frequency response data is indeed

$$\begin{aligned} \dot{x} &= \begin{bmatrix} 0 & 0.5 & 1 \\ -1 & -1 & 0.25 \\ 1 & 0.25 & -2 \end{bmatrix} x + \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} u + \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \end{bmatrix} f \\ y &= \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} x + \begin{bmatrix} 1 & 1.5 \end{bmatrix} u + \begin{bmatrix} 0 & 1 \end{bmatrix} f \end{aligned} \tag{22}$$

Set $s = 9$. To apply the proposed algorithm, first build matrices $\bar{G}_N \in \mathbf{R}^{10 \times 800}$, $\bar{I}_N \in \mathbf{R}^{20 \times 800}$

as (11). Do the SVD of $\begin{bmatrix} \bar{G}_N \\ \bar{I}_N \end{bmatrix}$ and get matrix $U_2 \in \mathbf{R}^{30\times 7}$. Partition U_2' into $U_{\Sigma 1} \in \mathbf{R}^{7\times 10}$, $U_{\Sigma 2} \in \mathbf{R}^{7\times 20}$. Doing the QR factorization $U_{\Sigma 1} = U_Q U_R$ yields

$$U_Q = \begin{bmatrix} 0.0008 & 0.0019 & 0.0017 & 0.0011 & 0.0064 & 0.1753 & -0.9845 \\ -0.0014 & -0.0036 & -0.0030 & -0.0063 & -0.0385 & -0.9837 & -0.1755 \\ 0.0199 & 0.0052 & 0.0030 & -0.0952 & -0.9945 & 0.0394 & 0.0005 \\ 0.3188 & 0.7049 & 0.6232 & -0.1121 & 0.0225 & -0.0055 & 0.0017 \\ 0.0731 & -0.0902 & -0.1153 & -0.9819 & 0.0948 & 0.0032 & -0.0002 \\ 0.9339 & -0.3292 & -0.0857 & 0.1104 & 0.0061 & -0.0008 & -0.0000 \\ 0.1434 & 0.6217 & -0.7688 & 0.0438 & -0.0004 & -0.0004 & -0.0001 \end{bmatrix}$$

$$U_R = \begin{bmatrix} 0.0107 & 0.1234 & 0.2576 & 0.0859 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.0088 & 0.0877 & 0.0522 & -0.2630 & -0.1112 & 0 & 0 & 0 & 0 & 0 \\ 0.0063 & 0.0588 & 0.0089 & -0.1030 & 0.2567 & 0.1221 & 0 & 0 & 0 & 0 \\ -0.0042 & -0.0380 & 0.0018 & 0.0462 & -0.1183 & 0.2524 & 0.1267 & 0 & 0 & 0 \\ 0.0027 & 0.0238 & -0.0036 & -0.0221 & 0.0589 & -0.1231 & 0.2503 & 0.1284 & 0 & 0 \\ 0.0016 & 0.0144 & -0.0031 & -0.0110 & 0.0304 & -0.0631 & 0.1246 & -0.2494 & -0.1291 & 0 \\ 0.0010 & 0.0086 & -0.0022 & -0.0056 & 0.0161 & -0.0332 & 0.0645 & -0.1250 & 0.2490 & 0.1293 \end{bmatrix}$$

Select α as the first row of U_Q', namely,

$$\alpha = \begin{bmatrix} 0.0008 \ -0.0014 \ 0.0199 \ 0.3188 \\ 0.0731 \ 0.9339 \ 0.1434 \end{bmatrix}$$

As a result,

$$\bar{v}_s = \begin{bmatrix} 0.0107 \ 0.1234 \ 0.2576 \ 0.0859 \end{bmatrix} \in \mathbf{R}^{1\times 4}$$
$$\bar{v}_s H_s = \begin{bmatrix} 0.0483 \ 0.0429 \ 0.5098 \ 0.4642 \ 0.4293 \\ 0.4723 \ 0.0859 \ 0.1288 \end{bmatrix} \in \mathbf{R}^{1\times 8}$$

It is seen that $\nu = 3$. By choosing $g_1 = -1$, $g_2 = -3$, $g_3 = -3$, an observer-based FD system of 3rd order is obtained as

$$\dot{z}(t) = \begin{bmatrix} 0 & 0 & -1 \\ 1 & 0 & -3 \\ 0 & 1 & -3 \end{bmatrix} z(t) + \begin{bmatrix} 0.0751 \\ 0.1342 \\ 0.0000 \end{bmatrix} y(t) + \begin{bmatrix} -0.0376 & -0.0859 \\ 0.2522 & 0.0778 \\ 0.1717 & 0.0859 \end{bmatrix} u(t)$$
$$r(t) = \begin{bmatrix} 0 & 0 & -1 \end{bmatrix} z(t) + 0.0859 y(t) + \begin{bmatrix} -0.0859 & -0.1288 \end{bmatrix} u(t)$$

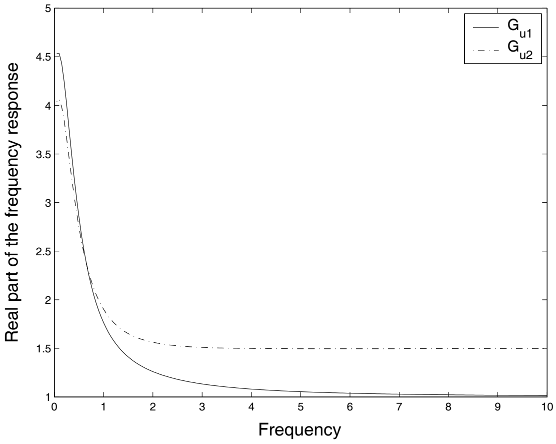

Fig. 1. Real part of the frequency domain data

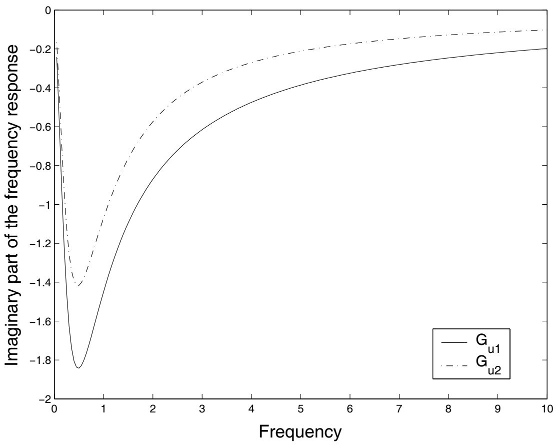

Fig. 2. Imaginary part of the frequency domain data

In the simulation, it is assumed that the control inputs are, respectively, a step signal (step time at $0s$) of amplitude 1 and a sine function $\sin t$. Two kinds of faults have been simulated. In the first case, consider a component fault $f = \begin{bmatrix} f_1(t) & 0 \end{bmatrix}'$, where $f_1(t)$ is a step signal (step time at $50s$) of amplitude 1. The residual signal is shown in Fig. 3. In the second case, consider a sensor fault $f = \begin{bmatrix} 0 & f_2(t) \end{bmatrix}'$, where $f_2(t)$ is a step signal (step time at $50s$) of amplitude 1. The residual signal is shown in Fig. 4. It is seen that in both cases the residual keeps to be 0 in the fault-free case and deviates from 0 after the fault happens, which enables a quick detection of the fault.

5. CONCLUSION

This paper proposes a model-free design approach of observer-based FD systems for continuous linear time-invariant systems. First, two vectors v_s and $v_s H_s$ are identified from the frequency domain data. Then, an observer-based FD system is readily constructed. The proposed approach is applicable to data with arbitrary frequency spacing. The design procedure is illustrated by a numerical

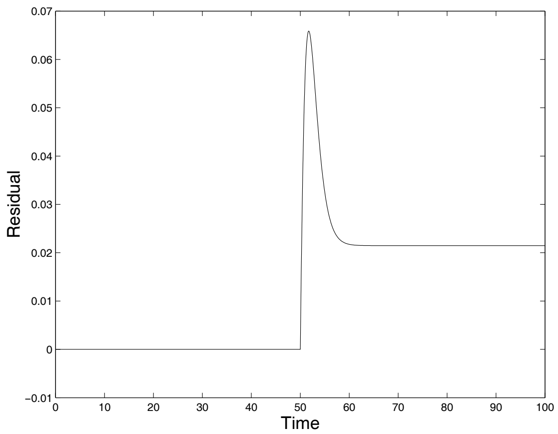

Fig. 3. The residual signal in the component fault case

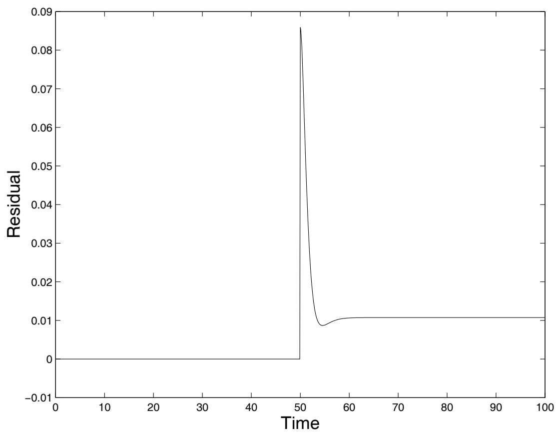

Fig. 4. The residual signal in the sensor fault case

example. An extension of the proposed approach to cope with noise-corrupted frequency domain data is an important topic of the future research. For the aim of fault isolation, it is also necessary to extend the approach to handle systems with deterministic disturbances. Study in this respect is being carried out.

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