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Performance based fault diagnosis

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Performance based Fault Diagnosis

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Abstract

Different aspects of fault detection and fault isolation in closed-loop systems are considered. It is shown that using the standard setup known from feedback control, it is possible to formulate fault diagnosis problems based on a performance index in this general standard setup. It is also shown that feedback controllers can be applied directly as residual generators in some cases.

1 Introduction

Fault diagnosis is in general considered from an open-loop point of view, in spite of that the residual generators are, in many cases placed in closed loop feedback systems. Further, it has been shown in [14], that there is a complete separation in the nominal case. It is possible to separate the design of the feedback controller and the residual generator complete in this case. In the uncertain case, this will not in general be possible to a separation between the design of the feedback controller and the residual generator, [14].

Using a parameterization of all residual generators, a coprime factorization of the system is applied, which normally involved the use of a feedback controller, see [6]. From this parameterization of all residual generators, it is clear that the feedback controller can also be applied/considered as a residual generator. It will shortly be shown how the feedback controller can directly be applied as a residual generator.

Following the line of considering fault diagnosis from a closed-loop point of view instead of an open-loop point of view, it will be possible to derive fault diagnosis based on other criteria than the standard detection and/or isolation criteria, [1, 3, 7]. In the standard fault diagnosis, the problem has been derived into three different tasks, the fault detection task, the fault isolation task and at last the fault estimation task, see [16]. In all three steps, the residual generators are optimized with respect to detect faults, isolate faults or estimate faults as optimal as possible. It is important to detect and/or isolate faults in a closed-loop system, but it is also very important to know the effect from the faults on the closed-loop system. In other words,

a large fault at some place in the system might not cause any problems with respect to the performance of the system, whereas other minor faults might result in unacceptable performance reduction. Fault diagnosis based on closed-loop performance is equivalent with model validation vs. controller validation, see [2, 13]. In model validation, the model used for controller design is (in)validated, whereas the controller validation is a validation of the performance of the closed-loop system. Again, a controller design based on a model that cannot be validated might still satisfy the performance conditions for the system, [2, 13].

The standard fault diagnosis methods cannot be applied directly for fault diagnosis based on the closed-loop performance. Instead, the performance of the closed-loop needs to be estimated. Using some new results for observer theory, [11], it turns out that it is possible to estimate the effect from faults,in the system, on the external output from the system. This make it possible to detect faults in the system based on a validation of the closed-loop performance. It is clear, that such a fault detection scheme is an indirect method for detection of faults. Such a fault detection scheme can both be used in connection with fault detection and also in connection with fault isolation. However, based on the fact that the detection is done indirectly, the fault isolation task is a little complicated. In this paper, it is shown how it is possible to use the scheme to isolate faults when it is assumed that only a single fault appear at the time.

Two different formulations of the fault detection problem based on the system performance are considered. In the first setup, it is assumed that the input matrices for both disturbance and additive faults are known. In the second case, it is assumed that the disturbance input and fault input matrices are unknown. As a direct consequence of this, there is no distinction between fault inputs and disturbance inputs. In the first case, the design of residual generators turn out to be standard observer design problem, whereas the design in the second case include some restrictions.

2 System Setup

Consider the following system

$$y(s) = G_{yf}(s)f(s) + G_{yd}(s)d(s) + G_{yu}(s)u(s) \quad (2.1)$$

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where $u \in \mathcal{R}^m$ is the control input vector, $d \in \mathcal{R}^q$ is the disturbance input vector and $y \in \mathcal{R}^p$ is the measurement vector. The fault signal vector $f \in \mathcal{R}^k$ is a collection of fault signals f_i, $i = 1, 2, \ldots, k$, into a vector.

Let a stabilizing feedback controller be given by $K_c(s)$.

It is assumed that the feedback controller satisfies some closed-loop performance specifications. Now, let a coprime factorization of the system $G_{yu}(s)$ in (2.1) and the stabilizing controller $K_c(s)$ be given by:

$$G_{yu} = N_u M^{-1} = \tilde{M}^{-1} \tilde{N}_u, \quad N_u, M, \tilde{N}_u, \tilde{M} \in \mathcal{RH}_\infty$$

$$K_c = UV^{-1} = \tilde{V}^{-1}\tilde{U}, \quad U, V, \tilde{U}, \tilde{V} \in \mathcal{RH}_\infty$$

$$(2.2)$$

where the eight matrices in (2.2) must satisfy the double Bezout equation given by, see [15, 17]:

$$\begin{pmatrix} I & 0 \\ 0 & I \end{pmatrix} = \begin{pmatrix} \tilde{V} & -\tilde{U} \\ -\tilde{N}_u & \tilde{M} \end{pmatrix} \begin{pmatrix} M & U \\ N_u & V \end{pmatrix}$$

$$= \begin{pmatrix} M & U \\ N_u & V \end{pmatrix} \begin{pmatrix} \tilde{V} & -\tilde{U} \\ -\tilde{N}_u & \tilde{M} \end{pmatrix}$$

$$(2.3)$$

It is possible to rewrite the system in (2.1) using the coprime factorization of $G_{yu}(s)$. The system in (2.1) take then the following form:

$$y(s) = \tilde{M}^{-1}(s)(\tilde{N}_f(s)f(s) + \tilde{N}_d(s)d(s) + \tilde{N}_u(s)u(s))$$

$$(2.4)$$

Let the residual signal/vector r be given by

$$r = Hy = \Psi(f, d) \tag{2.5}$$

In general, we might have to take H to be a nonlinear bounded-input, bounded-output stable operator, which makes Ψ also a nonlinear operator. In the case that H is a linear operator, there exist transfer matrices G_{rf} and G_{rd} such that

$$r = G_{rf}f + G_{rd}d$$

A parameterization of all generators for a given system can be given in terms of a stable transfer matrix $Q(s) \in \mathcal{RH}_\infty$. The residual vector r is given by [6]:

$$r = Q(s)(\tilde{M}(s)y(s) - \tilde{N}_u u(s))$$

$$= Q(s)(\tilde{N}_f(s)f(s) + \tilde{N}_d(s)d(s))$$

$$(2.6)$$

The matrix $Q(s)$ is the free matrix to be designed, such that the specified performance conditions for the residual generator is satisfied. Note that $Q(s) = I$ is allowed, which result in a residual generator that is only based on the feedback controller (or the observer in the case of an observer based controller).

3 Definitions and Problem Formulation

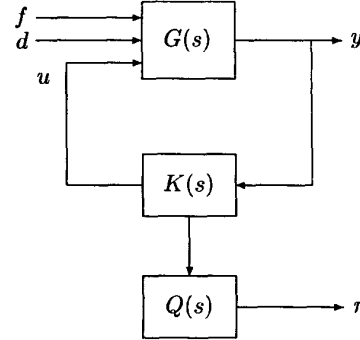A block diagram of the closed-loop system including a residual generator is shown in Figure 1.

Figure 1: Feedback control system including a residual generator

$G(s)$ and $K(s)$ in Figure 1 are given by

$$G(s) = [G_{yu}(s) \; G_{yd}(s) \; G_{yf}(s)]$$

$$K(s) = \begin{bmatrix} K_c(s) \\ \tilde{M}(s) - \tilde{N}_u(s)K_c(s) \end{bmatrix}$$

$$= \begin{bmatrix} UV^{-1} \\ V^{-1} \end{bmatrix} = \begin{bmatrix} U \\ I \end{bmatrix} V^{-1}$$

The standard setup known from robust control, see e.g. [17], will be applied in connection with the design of residual generators. The standard setup is shown in Figure 2.
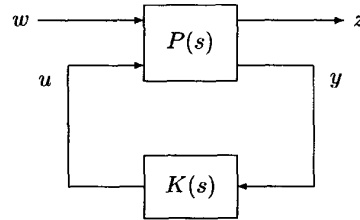
Figure 2: The standard setup for feedback control

In Figure 2, P is the generalized plant, w is an external input, z is the external output to be controlled, i.e. minimize the effect from w on z, y and u are the measurement and the control signal, respectively.

The standard setup has been applied in connection with formulation of design problems for residual generators before, see e.g. [3, 4, 10]. However, it is in general

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difficult to formulate design problems for residual generators in the standard setup. The reason is that the external output z is in general not well defined. Only in the fault estimation case, the external output z is well defined.

3.1 Fault Estimation

First, let's consider the fault estimation problem as a standard problem. Following the line of the filtering problem formulated as a standard problem in [17], the residual vector r should then be an estimate $\hat{f}$ of the fault vector, i.e.

$$r = \hat{f}$$

The external input and output vectors in Figure 2 are then given by

$$w = \begin{bmatrix} f \\ d \end{bmatrix}, \ f = \begin{bmatrix} f_1 \\ \vdots \\ f_k \end{bmatrix}, \ d = \begin{bmatrix} d_1 \\ \vdots \\ d_q \end{bmatrix}$$
$$z = f - r = f - \hat{f}$$

Using the coprime description of the residual generator in (2.6) gives the following generalized plant P for the standard setup in Figure 2:

$$P = \begin{bmatrix} [I_{k \times k} \ 0] & -I \\ [\tilde{N}_f \ \tilde{N}_d] & 0 \end{bmatrix}$$

A number of exact and almost exact fault estimation problems has been considered in [8]. Solvability conditions are also given in [8]. These conditions are quite restrictive. Instead of requiring exact or almost exact fault estimation, optimal fault estimation has been considered in [9]. Here, a number of designing residual generators that reject the disturbance exact or almost exact and optimize the estimate of the fault vector, has been considered. The solvability conditions are much weaker than the solvability conditions obtaining exact or almost exact fault detection. Further, a weighting matrix has also been included in the optimal fault estimation problems. This can also make the solvability conditions less restrictive.

3.2 Output Fault Detection

Instead of focusing on the faults directly in connection with fault detection, fault isolation or fault estimation, the focus can be on the effect from the faults on the performance output of the system.

Let's consider the standard setup in Figure 2, where z is the external output, specifying the signals to be controlled. Let the external input vector w be given by the fault f and the disturbance d. It is assumed that the feedback controller is designed with respect to the

performance specification on the transfer function matrix from d to z. This means that in normal operation, i.e. in the fault free case with $f = 0$, the disturbance d influence on the output z is acceptable.

Note that in this section, it is assumed that the external output z applied with output fault estimation is the same as the external output applied in connection with the performance description of the closed loop system. However, another output vector than z can be selected in connection with the output fault detection. The results presented are independent of the choice of the output vector.

Now, let the external output z be separated into two vectors given by

$$z = z_d + z_f \tag{3.1}$$

where z_d is the external output with respect to the disturbance input d and z_f is the external output with respect to the fault input f, respectively. The closed-loop transfer function from the external input w (or d and f) to the external output z can then be written as

$$z_d = T_{zd}(s)d$$
$$z_f = T_{zf}(s)f$$

where T_{zd} and T_{zf} are the two closed loop transfer functions.

In general, it will not be possible to measure z, neither z_d or z_f. Therefor, the output z_f needs to be estimated for obtaining the effect from fault signals on the external output z. The design problem is then to design the residual generator such that

$$r = \hat{z}_f$$

Using this residual vector, the output estimation error z_e is then given by:

$$\begin{aligned} z_e &= z_f - \hat{z}_f \\ &= T_{zf}f - Hy \\ &= (T_{zf} - HT_{yf})f - HT_{yd}d \end{aligned} \tag{3.2}$$

where T_{yf} and T_{yd} are the closed loop transfer functions from f and d to the measurement output y, respectively. Using the residual vector in (2.6) with $Q = I$, the estimation error z_e then takes the following form:

$$z_e = (T_{zf} - HT_{rf})f - HT_{rd}d \tag{3.3}$$

where T_{rf} and T_{rd} are the closed loop transfer functions from f and d to the residual signal r given by (2.6) with $Q = I$, respectively.

Using the standard setup, P in Figure 2 with $w = \begin{pmatrix} f \\ d \end{pmatrix}$ then takes the following form:

$$P = \begin{pmatrix} \begin{pmatrix} T_{zf} & 0 \end{pmatrix} & -I \\ \begin{pmatrix} T_{rf} & T_{rd} \end{pmatrix} & 0 \end{pmatrix}$$

Based on the standard setup, it is possible to formulate a number of output fault estimation problems. In next section, these results will be used in connection with fault detection and fault isolation.

It is possible to formulate the following fundamental output fault estimation problems (for a definition of fundamental FDI problems, see [12]):

- The $\mathcal{H}_2$ optimal output fault estimation problem subject to exact disturbance decoupling

- The $\mathcal{H}_2$ suboptimal output fault estimation problem subject to exact disturbance decoupling

- The $\mathcal{H}_\infty$ suboptimal output fault estimation problem subject to exact disturbance decoupling

- The $\mathcal{H}_2$ suboptimal output fault estimation problem subject to almost disturbance decoupling

- The $\mathcal{H}_\infty$ suboptimal output fault estimation problem subject to almost disturbance decoupling

Due to the fact that all these problems can be considered as special cases of the general input decoupled observer problem considered in [11], a precise problem formulation is not given here. Further, the solvability conditions for these five fundamental output fault estimation problems can also be found in [11], together with methods for designing observers that satisfy the solvability conditions.

3.3 Output Fault Detection of Unknown Faults

Let's consider the case when the input directions for d and f are unknown, i.e. $\tilde{N}_d$ and $\tilde{N}_f$ in (2.4) are unknown. In this case, there is no need to distinguish between disturbance d and faults f, Therefor only the fault input f will be included in the rest of this section. Based on this, the residual vector r in (2.6) then takes the following form:

$$
\begin{aligned}
r &= Q(s)(\tilde{M}(s)y(s) - \tilde{N}_u u(s)) \\
&= Q(s)\tilde{r}
\end{aligned}
\tag{3.4}
$$

where $\tilde{r}$ can be measured.

The estimation error z_e given by (3.2) then takes the following form:

$$
z_e = (T_{zr} - H)\tilde{r}
\tag{3.5}
$$

From (3.5), it is quite clear that the optimal residual generator is given by

$$
H = T_{zr}
$$

However, it is important to note that it is a requirement that the closed-loop transfer function from f to z need to be written as

$$
T_{zf} = T_{zr}T_{rf}
$$

i.e. the external output z need to be a linear function of the measurement output y. If this condition is not satisfied, the output estimation error given by (3.5) cannot be derived. This is a strong condition that will not in general be satisfied. To overcome this problem, some modifications need to be done. There are two obviously ways to modify the fault output detection problem.

One way to overcome the problem is to select another external output vector z, such that z become a linear function of the measurement vector y. This will in general be a a good alternative. As an alternative to this, an input model (i.e. a model of T_{rf}) for the faults can be applied. To make such an input model as general as possible, the input matrix in the state space realization of G_{yf} can be selected as the identity matrix. Then it is again possible to apply the standard methods for the design of the residual generator H.

It should be pointed out, that the fault output detection problem for unknown input, considered in this section, is equivalent with performance/controller validation of closed loop systems, see e.g. [2].

4 Output Fault Diagnosis

The output fault estimation problems considered in Section 3 will now be applied in connection with fault detection and fault isolation.

An important element in detection and isolating faults is the decision task. The decision task involved a threshold Γ_{th} selected such that:

- If $\|r\| < \Gamma_{th}$ then either no faults has occurred or the norm of the fault is below a certain level, i.e. $\|f\| < \gamma_f$.

- If $\|r\| \geq \Gamma_{th}$ then one or more faults has occurred. Moreover, if $\|f\| > \gamma_f$, then $\|r\| > \Gamma_{th}$.

The selection of the threshold level Γ_{th} is optimal if the residual vector satisfies the above conditions. However, in practice it will not in general be possible to select the threshold level such that the above conditions are satisfied. The selection of the threshold will be a trade-off between maximizing detecting faults above a certain level γ_f and minimize the detecting faults below the selected level γ_f. In general it will not be possible to select the threshold such that all faults above a certain level are detected and all faults below the level

are not detected. In this case, it will not be possible to remove false alarms and missing detection/isolation exactly by the selection of the threshold. False alarms are when non-existing faults or faults below γ_f are detected. Missing detection are the cases where faults with magnitude above γ_f are not detected, [7]. However, in the cases where exact, almost exact or optimal fault diagnosis can be obtained, it is possible to select the threshold level optimal, i.e. such that the above two conditions are satisfied. Due to the fact that the disturbance is exact or almost exact rejected from the residual vector, the threshold level can be selected to zero or almost zero.

The selection of the threshold values for the fault detection problems considered in Section 3 can therefor be based on the performance of the residual generator. One obvious way to select the threshold values is to let the threshold value depend on the magnitude of the external output vector z. Again, this can be done i a number of different ways. The most direct way is to let the threshold be a linear function of the maximal norm of the external output z for $f = 0$, i.e. $z = z_d$. Let the maximal norm of z_d be denoted by γ_z. Let γ_z be given by

$$\gamma_z = max\|z_d\|$$

A threshold value is then given by

$$\Gamma_{th} = \alpha \times \gamma_z$$

where α is a positive real scalar parameter selected suitable. Note that z_d will not in general be measurable. Therefor, the maximal norm of the external output vector need to be estimated. Instead of using the residual vector r and the external output vector z in connection with the decision task, we can let the decision task be based on signals instead. For doing this, let $\gamma_{z,i}$ be the maximal value of the $i - th$ external output signal $z_{d,i}$, i.e.

$$\gamma_{z,i} = max|z_{d,i}|$$

Then we have a threshold value for every single residual signal defined by

$$\Gamma_{th,i} = \alpha_i \times \gamma_{z,i}, \ i = 1, \cdots, k$$

where α_i is a positive real scalar parameter selected suitable. Based on this, a fault has appeared in the system if and only if the following inequality is satisfied for at least one i:

$$|r_i| \geq \Gamma_{th,i}$$

Out from this the system is only fault free if and only if

$$|r_i| < \Gamma_{th,i}, \ \forall i \in [1, \cdots, k]$$

Another possibility in connection with fault detection based on output fault estimation is to make fault detection in different levels. Lets consider the signal based fault detection problem where three levels of fault detection are applied. Let the three threshold values be given by

$$\begin{aligned} \Gamma_{th,i,1} &= \alpha_{i,1} \times \gamma_{z,i} \\ \Gamma_{th,i,2} &= \alpha_{i,2} \times \gamma_{z,i} \\ \Gamma_{th,i,3} &= \alpha_{i,3} \times \gamma_{z,i} \end{aligned}$$

with $\alpha_{i,1} < \alpha_{i,3} < \alpha_{i,3}$. We will then say that we have a fault detection of level 1 if a fault is detected by using the lower threshold value $\Gamma_{th,i,1}$, etc. This can be applied to supervise the system in a more detailed way. In the above case, the three fault detection levels can be used in the following way:

- If $\Gamma_{th,i,2} > \|r_i\| \geq \Gamma_{th,i,1}$, a fault is detected at level 1. A minor fault (fault signal with a small amplitude) has appeared in the system. Nothing else is done.

- If $\Gamma_{th,i,3} > \|r_i\| \geq \Gamma_{th,i,2}$, a fault is detected at level 2. A fault has appeared in the system. The performance of the system might not be satisfied now, but the system is still running in a stable way.

- If $\|r_i\| \geq \Gamma_{th,i,3}$, a fault is detected at level 3. A major fault has appeared and the system is closed down or the fault situation need to be handle by e.g. reconfiguration of the system/controller.

Until now, only the fault detection case has been considered in connection with output fault estimation. Out from the concept, it is natural to estimate the effect from the fault/faults in the system on the external output z. However, based on the fact that the residual generators are optimized with respect to estimate the fault effect on the external output, it is possible to apply the setup for fault isolation. This can be done by designing a bank of residual generators where every residual generator is sensitive to all faults apart from one single fault, see the description in e.g. [5]. No further details will be given in this conference paper.

At last in connection with fault isolation based on output fault estimation, it should be pointed out that such a method might not be an optimal way to isolate faults. Instead, methods that are more directly related with fault isolation should be applied, see e.g. [3, 7].

5 Conclusion

A number of optimal output fault estimation problems for continuous-time systems has been considered in this

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paper. It has been shown how the output fault estimation can be applied in connection with fault detection and fault isolation. The fault detection is related to the closed-loop performance of the system. The detection is based on an estimation of reduction of the closed-loop performance caused by faults. It is further shown how it is possible to make fault detection in different levels.

Only the continuous-time case has been considered in this paper. However, the discrete-time case can be handled in the same way.

The results given in this paper is presented without using any weighting matrices in connection with the problem formulations. However, it is without loss of generality to include weighting matrices in the equation for the estimation error in (3.2).

The fault detection approach applied in this paper is related with performance validation of closed-loop feedback systems. In both cases, we want to detect faults or model uncertainties that reduce the performance of the system too much. The advantage in both cases by using the performance of the closed-loop system is that large model uncertainties or large faults that will not reduce the performance are not detected. The level of detection/validation is based directly on the performance specification of the system.

Acknowledgment

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