DESIGN METHODS FOR ROBUST FAULT DIAGNOSIS

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Contents

Summary

This is a study of robust observer-based methods of fault detection and isolation. After introducing some basic definitions, the problem of model-based detection and isolation is introduced. This is followed by a summary of the basic ideas behind the use of observers in generating diagnostic residual signals.

The robustness issues are then defined and ideas for improving the robustness properties are outlined. This provides an opportunity to give some of the fundamental ideas behind unknown input observer, eigenstructure assignment and H_∞ optimization approach for

enhancing robustness. An important focus is on the use of disturbance de-coupling principles to achieve robustness in fault diagnosis.

1. Introduction

There are many model-based approaches to fault detection and isolation (FDI) in automated processes. The most common model-based approach makes use of observers to generate diagnostic signals-so called residuals. In the FDI framework, faults are detected by using suitable statistical testing methods such as simply comparing the residual with a (fixed or variable) threshold.

A number of residuals can be designed, each having a special sensitivity to individual faults occurring in different locations in the system. The subsequent analysis of each residual, once a fault is detected, then leads to fault isolation. Therefore, the essential issue in model-based FDI is the design and generation of residuals which facilitate the prompt detection of faults. Well designed residuals should not lead to false detection alarms or missed fault alarms when a diagnostic testing is performed.

The concept of 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. This is, of course, not possible in practice, as an accurate and complete mathematical description of a process is never available. Sometimes, the mathematical structure of the dynamic system is not fully known.

For other applications, the parameters of the system may not be fully known, or may only be known over a limited range of the plant's operation. There is therefore always a "model-reality mismatch" between the plant dynamics and the model used for FDI. As the complexity of a dynamical system increases, the harder becomes the task of modeling the system and its disturbances. One can speak of an "uncertain" system, for which there is an uncertainty of knowledge of the system's structure, its parameters and the affects of disturbances. There are therefore robustness problems in FDI with respect to modeling errors and disturbances.

The goal of robust FDI is to discriminate between the fault effects and the effects of uncertain signals and perturbations, which cause false or missed alarms. The robustness problem in FDI is thus defined as the maximization of the detectability of faults, together with the minimization of the effect of modeling errors and disturbances on the FDI procedure. The ultimate goal of robustness is to provide rapid and reliable detection and isolation of system faults when the plant under control is disturbed, and when the mathematical model upon which the diagnosis is based cannot faithfully reproduce the full operation of the plant.

The aim of this chapter is to present design principles and methods which achieve robustness in FDI, based on the use of observers or filters. Section 2 describes the essential properties of model-based fault diagnosis and residual generation, whilst Section 3 introduces the basic principles of the observer-based approach to FDI. In Section 4 the need for robustness in FDI is outlined in some detail. Section 5 presents the unknown input observer method for robust FDI design. A more complete treatment of this subject would include the use of robust techniques in designing so-called parity equations as also the use of stochastic methods for FDI and designs based on non-linear modelling strategies. The bibliography will help the reader widen the scope of this chapter, using the literature to search for other studies of robust design methods for FDI.

2. Model-based Methods for FDI

2.1. System Model

The state space model of the system with faults is given by:

$$\left.\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + R_1 f(t) \\ y(t) &= Cx(t) + Du(t) + R_2 f(t) \end{aligned}\right\} \tag{1}$$

in the time-domain. The frequency-domain model is:

$$y(s) = G_u(s)u(s) + G_f(s)f(s), \tag{2}$$

where $x(t) \in \mathbb{R}^n$ is the state vector, $u(t) \in \mathbb{R}^r$ is the input vector and $y(t) \in \mathbb{R}^m$ is the output vector. The vector $f(t) \in \mathbb{R}^g$ represents faults, with each element $f_i(t)(i = 1, \cdots, g)$ corresponding to a specific fault. The matrices R_1 and R_2 are known as "fault entry matrices", and represent the effect of faults on the system. *A, B, C* and *D* are system model matrices.

2.2. Residual Generators

The core element of model-based FDI is the generation of residuals. To provide useful information for FDI, the residual $r(t)(\in \mathbb{R}^p)$ should be:

$$r(t) \neq 0 \quad \text{iff} \quad f(t) \neq 0 \tag{3}$$

A fault can be detected by comparing the residual evaluation function $J(r(t))$ with a threshold function $T(t)$ according to the test given below:

$$\left.\begin{aligned} J(r(t)) &\leq T(t) \quad \text{for} \quad f(t) = 0 \\ J(r(t)) &> T(t) \quad \text{for} \quad f(t) \neq 0 \end{aligned}\right\} \tag{4}$$

If the threshold is exceeded by the residual evaluation function, a fault is likely. There are many ways of defining $J(r(t))$ and $T(t)$. For example, $J(r(t))$ can be chosen as the residual vector norm and a positive constant can be used as $T(t)$. Note that this testing is normally performed after the initial transient response has settled down.

The residual is generated based on the information provided by the system input and output signals using a residual generator:

$$r(s) = H_u(s)u(s) + H_y(s)y(s) \tag{5}$$

Here, $H_u(s)$ and $H_y(s)$ are transfer matrices which are realizable using stable linear systems. To satisfy the condition (3), these two transfer matrices should be governed by:

$$H_u(s) + H_y(s)G_u(s) = 0 \tag{6}$$

Eq. (5) can be considered as a general form of representation of all residual generators. The design of the residual generator amounts quite simply to the choice of the transfer matrices $H_u(s)$ and $H_y(s)$ which satisfies Eq. (6). Residual generation can be carried out either in continuous or discrete-time format. In the case of a non-linear process, model linearization around an operating point should be considered, although non-linear models can also be used for residual generation.

2.3. Fault Detectability

When faults occur in the monitored system, the response of the residual is:

$$r(s) = H_y(s)G_f(s)f(s) = G_{rf}(s)f(s) \tag{7}$$

where $G_{rf}(s) = H_y(s)G_f(s)$ represents the relation between the residual and faults. To detect the i_{th} fault f_i using the residual $r(s)$, the $i-$th column $\left[G_{rf}(s)\right]_i$ of the transfer matrix $G_{rf}(s)$ should be non-zero:

$$\left[G_{rf}(s)\right]_i \neq 0 \tag{8}$$

If this condition holds true, the i_{th} fault f_i is detectable in the residual r. This is defined as the fault detectability condition of the residual r to the fault f_i.

3. Observer-based Residual Generation

There are many approaches for residual generation. The most common one uses the state observer. The basic idea is to estimate the outputs of the system from the measurements (or a subset of measurements) by using either Luenberger observer (s) in a deterministic setting or Kalman filter (s) in a stochastic setting. Then, the (weighted) output estimation error (or innovations in the stochastic case), is used as a residual. For FDI purposes, only the output estimation is required. The estimation of the state vector is unnecessary.

The "functional observer" is really what is used in FDI. A residual generator based on a generalized Luenberger is given by:

$$\left.\begin{aligned}\dot{z}(t)&=Fz(t)+Ky(t)+Ju(t)\\ r(t)&=L_1z(t)+L_2y(t)+L_3u(t)\end{aligned}\right\}\tag{9}$$

and the matrices in this equation should satisfy:

$$\left.\begin{aligned}&F \text{ has stable eigenvalues}\\ &TA - FT = KC\\ &J = TB - KD\\ &L_1T + L_2C = 0\\ &L_3 + L_2D = 0\end{aligned}\right\},\tag{10}$$

where T is a state transformation matrix to be designed. When the residual generator Eq. (9) is applied to the system Eq. (1), the residual is:

$$\left.\begin{aligned}\dot{e}(t)&=Fe(t)-TR_1f(t)+KR_2f(t)\\ r(t)&=L_1e(t)+L_2R_2f(t)\end{aligned}\right\},\tag{11}$$

where $e(t)=z(t)-Tx(t)$. It can be seen that the residual depends solely and totally on faults. The simplest method in observer-based residual generation is to use a full-order observer, with $T = I$.

4. The Need for Robustness in FDI

Clearly, model-based FDI makes use of a mathematical system model. The closer the model represents the system, the better will be the reliability and performance in FDI. However, modeling errors and disturbances are inevitable, and hence there is a need to develop robust FDI algorithms. A robust FDI system is sensitive only to faults, even in the presence of a model-reality mismatch. To achieve robustness in FDI, the residual should be insensitive to uncertainty, while sensitive to faults, and therefore robust. A system with uncertainty can be described by:

$$\left.\begin{aligned}\dot{x}(t)&=(A+\Delta A)x(t)+(B+\Delta B)u(t)+E_1d(t)+R_1f(t)\\ y(t)&=(C+\Delta C)x(t)+(D+\Delta D)u(t)+E_2d(t)+R_2f(t)\end{aligned}\right\}\tag{12}$$

Here $d(t)\in\mathbb{R}^q$ is an unknown input (disturbance) vector with known distribution matrices E_1 and E_2. $\Delta A, \Delta B, \Delta C, \text{and } \Delta D$ represent modeling errors caused by parameter errors or variations. The system input-output description is then:

$$y(s)=\left(G_u(s)+\Delta G_u(s)\right)u(s)+G_d(s)d(s)+G_f(s)f(s)\tag{13}$$

By substituting the system output *y(s)* into the residual generator Eq. (5), the residual is:

$$r(s) = H_y(s)G_f(s)f(s) + H_y(s)\Delta G_u(s)u(s) + H_y(s)G_d(s)d(s), \tag{14}$$

Both faults and modeling uncertainty (disturbances and modeling errors) affect the residual. The essence of robust FDI is to discriminate between them.

4.1. Robustness to Disturbances

If the residual generator satisfies:

$$H_y(s)G_d(s) = 0, \tag{15}$$

the disturbance will be totally de-coupled from the residual $r(t)$. This is the principle of disturbance de-coupling for robust residual generation (see Section 6).

If the condition (15) cannot be fulfilled, perfect (accurate) de-coupling is not achievable. One can consider an optimal or approximate de-coupling by minimizing the following performance index over a specified frequency range:

$$J = \frac{\left\| H_y(j\omega)G_d(j\omega) \right\|}{\left\| H_y(j\omega)G_f(j\omega) \right\|} \tag{16}$$

The choice of norm in the above equation depends on the design technique used.

4.2. Robustness to Modeling Errors

For modeling errors represented by $\Delta G_u(s)$, the robust problem is more difficult to solve. Two main approaches have been proposed. The passive robust solution in FDI makes use of adaptive threshold at the decision-making stage.

The active robust FDI is based on an attempt to account for uncertainty in residual generation. An active way is to obtain an approximate structure for the uncertainty, i.e., to represent modeling errors, approximately as disturbances:

$$\Delta G_u(s)u(s) \approx G_{d1}(s)d_1(s), \tag{17}$$

where $d_1(s)$ is an unknown vector and $G_{d1}(s)$ is an essential transfer matrix. When this approximate structure is used for designing the disturbance de-coupling residual generator, a suitably robust FDI is achievable. In Section 5, examples are given to illustrate the many various types of modelling uncertainties that can be treated within the unknown input framework.

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Biographical Sketches

Jie Chen received BEng and MSc degrees in Control Systems Engineering from Beijing University of Aeronautics and Astronautics, China, in 1984 and 1987 respectively, and DPhil degree in Electronic Engineering from University of York, UK, in 1995. He joined the Department of Mechanical Engineering of Brunel University as a Lecturer of Aeronautical Engineering in February 1998. Before that, he worked in the University of Hull, UK as a Lecturer of Control Systems Engineering between July 1995 to January 1998. From March 1990 to September 1994, he worked as a Research Associate, in the University of York, UK, while he pursued his DPhil degree. From October 1994 to June 1995, he spent a short period in the University of Strathclyde, UK as Post-Doctoral Research Fellow. He has worked in the field of fault diagnosis and fault-tolerant control for many years and has published over 60 papers in international journals and conference proceedings on the subject. He is a member of IFAC Technical Committee: SAFEPROCESS. He was awarded jointly with R. J. Patton the 1997 IEE Kelvin Premium for a paper published in IEE Proceedings-D. His current research interests are: model-based fault diagnosis and applications to non-linear systems, robust and fault-tolerant control, neuro-fuzzy techniques for control and fault diagnosis.

Ron Patton was born in Peru in 1949 and was educated at Emmanuel Grammar School, Swansea and Sheffield University, graduating with BEng (1972) in Electronic and Electrical Engineering and MEng

(1974), PhD (1980) degrees in Control Systems Engineering. He is Senior Member of the AIAA and IEEE and currently holds Membership of the IEE and is Chartered Engineer in the United Kingdom. Working in the hospital service in medical physics during 1968/1969 Ron was a founder member of the Electronics laboratory at the Royal Free Hospital, London. During 1972/1973 Ron worked as a telecommunications expert at the BBC Research Department, UK. He turned later to control systems and after pursuing PhD studies on non-linear dynamics in biology Ron then worked for GEC Electrical Projects, Rugby and Sheffield City Polytechnic on Kalman filtering in "Dynamic Ship Positioning Control Systems". Ron became lecturer at Sheffield Hallam University in 1978 and moved as lecturer to the then new Electronics Department at York University in 1981 where he focused on fault diagnosis and aerospace control systems, with promotion to Senior Lecturer in 1987. In 1995 he was appointed to his present position of Professor of Control and Intelligent Systems Engineering in the University of Hull. Professor Patton is a well-known expert on the research topics of model-based fault diagnosis, fault-tolerant control and eigenstructure assignment design, having published 7 books covering these subjects and authored more than 270 papers in leading journals and international conferences. With Jie Chen he was recipient of the IEE Kevin Premium award in 1997 for an IEE Proceedings-D paper on Stochastic Approaches to Robust Fault Diagnosis. During 1993/1994 he chaired the IEEE UK & R Ireland Region 8 Chapter on Control Systems and chaired the International Programme Committees for UKACC CONTROL'98 and IFAC SAFEPROCESS'97. He has served on numerous conference committees in control engineering. During 1996 to 2002 Ron served the International Federation of Automatic Control (IFAC) as chairman for the Technical Committee SAFEPROCESS, leading this field into one of the main technical activities of IFAC. He continues to serve as consultant advisor in fault diagnosis and fault-tolerant control for many international organizations.