

2 Overview of FD and FTC Technology

This chapter reviews the FD and FTC technology for both LTI and nonlinear systems, respectively. First, the configurations of observer-based FD and FTC systems for LTI processes are examined, which motivate the investigations on nonlinear FD and FTC configurations in this thesis. Then, a brief description for different types of nonlinear systems is presented. It is followed by the state-of-the-art and the basic methodologies of fault detection and isolation (FDI) and FTC techniques for nonlinear systems.

2.1 FD and FTC Configuration for LTI Systems

Let the minimal state space representation of LTI systems be

$$\mathbf{G} : \begin{cases} \dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \\ \mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u} \end{cases} \quad (2.1)$$

where $\mathbf{x} \in \mathcal{R}^{k_x}$, $\mathbf{u} \in \mathcal{R}^{k_u}$ and $\mathbf{y} \in \mathcal{R}^{k_y}$ represent the state, measured input and output vectors; $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D}$ are system matrices of appropriate dimensions. The corresponding transfer function for system (2.1) is

$$\mathbf{G}(s) = \mathbf{C}(s\mathbf{I} - \mathbf{A})^{-1}\mathbf{B} + \mathbf{D}. \quad (2.2)$$

In linear FD framework [30], it is generally assumed that the influence of disturbances and faults is modelled by extending (2.1) to

$$\mathbf{G}_{\mathbf{w},\mathbf{d}} : \begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{E}_{\mathbf{w}}\mathbf{w}(t) + \mathbf{E}_{\mathbf{d}}\mathbf{d}(t) \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) + \mathbf{F}_{\mathbf{w}}\mathbf{w}(t) + \mathbf{F}_{\mathbf{d}}\mathbf{d}(t) \end{cases} \quad (2.3)$$

where $\mathbf{w} \in \mathcal{R}^{k_w}$ and $\mathbf{d} \in \mathcal{R}^{k_d}$ represents the fault to be detected and unknown disturbance vector, respectively; and $\mathbf{E}_w, \mathbf{E}_d, \mathbf{F}_w$ and $\mathbf{F}_d$ are known matrices of appropriate dimensions.

Next, the coprime factorization techniques for linear systems are considered, which play an essential role in formulating the FD and FTC configurations for LTI systems.

2.1.1 Coprime Factorization Techniques

The following definitions are necessary to introduce linear coprime factorization techniques.

Definition 2.1. (*Right-coprime factorization (RCF)* [169]) A factorization $\mathbf{G}(s) = \mathbf{N}(s)\mathbf{M}^{-1}(s)$ is said to be an RCF of $\mathbf{G}(s)$ if (i) $\mathbf{N}(s) \in \mathcal{RH}_\infty$ and $\mathbf{M}(s) \in \mathcal{RH}_\infty$ and (ii) there exists $\mathbf{Y}(s) \in \mathcal{RH}_\infty$ and $\mathbf{X}(s) \in \mathcal{RH}_\infty$ such that

$$\mathbf{Y}(s)\mathbf{M}(s) + \mathbf{X}(s)\mathbf{N}(s) = \mathbf{I}. \quad (2.4)$$

Definition 2.2. (*Left-coprime factorization (LCF)* [169]) A factorization $\mathbf{G}(s) = \hat{\mathbf{M}}^{-1}(s)\hat{\mathbf{N}}(s)$ is said to be an LCF of $\mathbf{G}(s)$ if (i) $\hat{\mathbf{N}}(s) \in \mathcal{RH}_\infty$ and $\hat{\mathbf{M}}(s) \in \mathcal{RH}_\infty$ and (ii) there exists $\hat{\mathbf{Y}}(s) \in \mathcal{RH}_\infty$ and $\hat{\mathbf{X}}(s) \in \mathcal{RH}_\infty$ such that

$$\hat{\mathbf{N}}(s)\hat{\mathbf{X}}(s) + \hat{\mathbf{M}}(s)\hat{\mathbf{Y}}(s) = \mathbf{I}. \quad (2.5)$$

Given RCF and LCF of $\mathbf{G}(s)$, as well as $\mathbf{X}(s), \mathbf{Y}(s), \hat{\mathbf{X}}(s), \hat{\mathbf{Y}}(s)$, it is known from [169] that the generalized double Bezout identity holds

$$\begin{aligned} & \begin{bmatrix} \mathbf{Y}(s) & \mathbf{X}(s) \\ -\hat{\mathbf{N}}(s) & \hat{\mathbf{M}}(s) \end{bmatrix} \begin{bmatrix} \mathbf{M}(s) & -\hat{\mathbf{X}}(s) \\ \mathbf{N}(s) & \hat{\mathbf{Y}}(s) \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{M}(s) & \hat{\mathbf{X}}(s) \\ -\mathbf{N}(s) & \hat{\mathbf{Y}}(s) \end{bmatrix} \begin{bmatrix} \mathbf{Y}(s) & -\mathbf{X}(s) \\ \hat{\mathbf{N}}(s) & \mathbf{M}(s) \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}. \end{aligned} \quad (2.6)$$

Assuming that system (2.1) is controllable and observable, the transfer functions in (2.6) can be constructed as follows

$$\begin{aligned} \mathbf{M}(s) &= \mathbf{F}(s\mathbf{I} - \mathbf{A} - \mathbf{BF})^{-1}\mathbf{B} + \mathbf{I} \\ \mathbf{N}(s) &= (\mathbf{C} + \mathbf{DF})(s\mathbf{I} - \mathbf{A} - \mathbf{BF})^{-1}\mathbf{B} + \mathbf{D} \end{aligned}$$

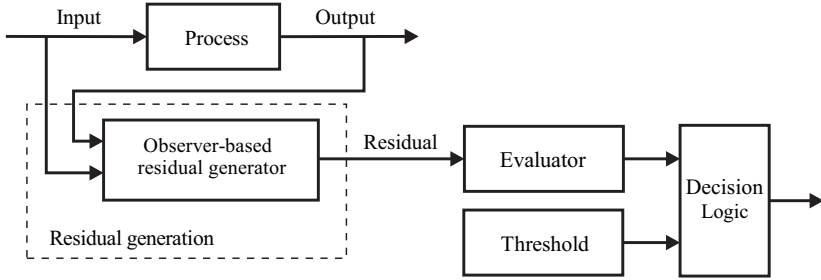


Figure 2.1: Observer-based fault detection configuration

$$\begin{aligned}
 \mathbf{Y}(s) &= \mathbf{F}(s\mathbf{I} - \mathbf{A} - \mathbf{BF})^{-1}\mathbf{L} \\
 \mathbf{X}(s) &= (\mathbf{C} + \mathbf{DF})(s\mathbf{I} - \mathbf{A} - \mathbf{BF})^{-1}\mathbf{L} + \mathbf{I} \\
 \hat{\mathbf{X}}(s) &= -\mathbf{F}(s\mathbf{I} - \mathbf{A} + \mathbf{LC})^{-1}(\mathbf{B} - \mathbf{LD}) + \mathbf{I} \\
 \hat{\mathbf{Y}}(s) &= \mathbf{F}(s\mathbf{I} - \mathbf{A} + \mathbf{LC})^{-1}\mathbf{L} \\
 \hat{\mathbf{N}}(s) &= \mathbf{C}(s\mathbf{I} - \mathbf{A} + \mathbf{LC})^{-1}(\mathbf{B} - \mathbf{LD}) + \mathbf{D} \\
 \hat{\mathbf{M}}(s) &= -\mathbf{C}(s\mathbf{I} - \mathbf{A} + \mathbf{LC})^{-1}\mathbf{L} + \mathbf{I}
 \end{aligned} \tag{2.7}$$

where $\mathbf{F}$, $\mathbf{L}$ are matrices of appropriate dimensions that ensure the stability of $\mathbf{A} + \mathbf{BF}$ and $\mathbf{A} - \mathbf{LC}$. Details can be found in [169].

2.1.2 The Configuration of Observer-based FD Systems

Fig. 2.1 shows the architecture of a standard observer-based FD system, which consists of an observer-based residual generator, a residual evaluator and a decision block with an embedded threshold [30].

Observer-based Residual Generator

To achieve a successful fault detection, residual generators play an key role in generating the residual signal that is sensitive to fault variables.

Definition 2.3. (Observer-based residual generator [30]) An observer-based residual generator for (2.3) is a system

$$\mathbf{r}(s) = \mathbf{K}(s) \begin{bmatrix} \mathbf{u}(s) \\ \mathbf{y}(s) \end{bmatrix} \tag{2.8}$$

such that (i) for any input $\mathbf{u}$,

$$\lim_{t \rightarrow \infty} \mathbf{r}(t) = \mathbf{0}, \quad \text{if } \mathbf{w} = \mathbf{0}, \mathbf{d} = \mathbf{0} \quad (2.9)$$

(ii) for some fault in the system, $\mathbf{r}(t) \neq \mathbf{0}$.

It is worth noting that LCF $\mathbf{G}(s) = \hat{\mathbf{M}}^{-1}(s)\hat{\mathbf{N}}(s)$ implies a residual generator for (2.3) as

$$\mathbf{r}(s) = \hat{\mathbf{M}}(s)\mathbf{y}(s) - \hat{\mathbf{N}}(s)\mathbf{u}(s) = \begin{bmatrix} -\hat{\mathbf{N}}(s) & \hat{\mathbf{M}}(s) \end{bmatrix} \begin{bmatrix} \mathbf{u}(s) \\ \mathbf{y}(s) \end{bmatrix}. \quad (2.10)$$

Together with (2.7), the state space representation of (2.10) is given by

$$\begin{aligned} \dot{\hat{\mathbf{x}}}(t) &= \mathbf{A}\hat{\mathbf{x}}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{L}\mathbf{r}(t) \\ \hat{\mathbf{y}}(t) &= \mathbf{C}\hat{\mathbf{x}}(t) + \mathbf{D}\mathbf{u}(t) \\ \mathbf{r}(t) &= \mathbf{y}(t) - \hat{\mathbf{y}}(t) \end{aligned} \quad (2.11)$$

where $\hat{\mathbf{x}}(t)$ and $\hat{\mathbf{y}}(t)$ represent the estimation of the state and output vectors. $\mathbf{L}$ is the observer gain which is to be designed such that (2.11) is stable and residual signal $\mathbf{r}(t)$ satisfies

$$\forall \mathbf{u}(t), \mathbf{x}(0), \lim_{t \rightarrow \infty} \mathbf{r}(t) = \mathbf{0}. \quad (2.12)$$

It is noted that (2.11) is the most widely used residual generator, which is also called fault detection filter (FDF).

To gain a deeper insight into residual generation, the parametrization form of LTI residual generators is introduced in [30].

Theorem 2.1. *Given an LTI system described by (2.3) and let $\mathbf{G}(s) = \hat{\mathbf{M}}^{-1}(s)\hat{\mathbf{N}}(s)$ be the left coprime factorization of $\mathbf{G}(s)$, then any LTI residual generator can be parameterized by*

$$\mathbf{r}(s) = \mathbf{R}_f(s) \left(\hat{\mathbf{M}}(s)\mathbf{y}(s) - \hat{\mathbf{N}}(s)\mathbf{u}(s) \right) \quad (2.13)$$

where $\mathbf{R}_f(s) \in \mathcal{RH}_\infty$ is also called post-filter.

The proof can be found in [35].

The parameterization of residual generators plays an important role in linking residual generation and evaluation, as well as their optimization in the linear observer-based FD framework [32].

Residual Evaluation

Residual evaluation is a procedure for processing residual signal aiming at extracting information of the fault signal. There are two major strategies for the purpose of residual evaluation. Statistic testing is one of them, which is well established in the framework of statistical methods [11]. The other one is the so-called norm-based residual evaluation [43]. In fact, the norm-based residual evaluation is an extended form of the limit monitoring strategy widely used in practice, where a norm of the residual signal, typically either

- $\mathcal{L}_2$ -norm

$$J_2(\mathbf{r}) = \|\mathbf{r}(t)\|_2 = \left(\int_0^\infty \mathbf{r}^T(t)\mathbf{r}(t)dt \right)^{1/2} \quad (2.14)$$

or

- $\mathcal{L}_\infty$ -norm

$$J_\infty(\mathbf{r}) = \|\mathbf{r}(t)\|_\infty = \sup_t (\mathbf{r}^T(t)\mathbf{r}(t))^{1/2} \quad (2.15)$$

is adopted.

Threshold Setting and Decision Logic

Generally speaking, the threshold is set as the possible maximum influence of $\mathbf{x}(0) = \mathbf{x}_0$ and the (bounded) unknown input vector $\mathbf{d}(t)$ on the fault-free residual vector $\mathbf{r}(t)$. Let

$$J_{\text{th},2} = \sup_{\mathbf{x}_0, \mathbf{d}, \mathbf{f}=\mathbf{0}} J_2(\mathbf{r}) \quad (2.16)$$

$$J_{\text{th},\infty} = \sup_{\mathbf{x}_0, \mathbf{d}, \mathbf{f}=\mathbf{0}} J_\infty(\mathbf{r}) \quad (2.17)$$

be the associated thresholds for evaluation functions (2.14) and (2.15). Thus, the following detection logic

$$\begin{cases} J_2(\mathbf{r}) > J_{\text{th},2} \implies \text{faulty} \\ J_2(\mathbf{r}) \leq J_{\text{th},2} \implies \text{fault-free} \end{cases} \quad (2.18)$$

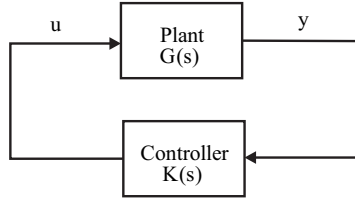


Figure 2.2: Standard feedback control loop

or

$$\begin{cases} J_{\infty}(\mathbf{r}) > J_{\text{th},\infty} \implies \text{faulty} \\ J_{\infty}(\mathbf{r}) \leq J_{\text{th},\infty} \implies \text{fault-free} \end{cases} \quad (2.19)$$

together with residual generator, gives an $\mathcal{L}_2$ or $\mathcal{L}_{\infty}$ observer-based FD system, respectively.

2.1.3 The Configuration of Observer-based FTC

For this purpose, the stabilizing controllers for LTI systems are characterized in terms of observer-based residual generators.

Observer-based Controller Parametrization Forms

Consider the standard feedback control loop shown in Fig. 2.2, where $\mathbf{G}(s)$ is an LTI system with state space representation (2.1). It is well-known that the Youla-Kucera parametrization

$$\begin{aligned} \mathbf{K}(s) &= (\mathbf{Y}(s) - \mathbf{M}(s)\mathbf{Q}_c(s))(\mathbf{X}(s) - \mathbf{N}(s)\mathbf{Q}_c(s))^{-1} \\ &= \left(\hat{\mathbf{X}}(s) - \mathbf{Q}_c(s)\hat{\mathbf{N}}(s) \right)^{-1} \left(\hat{\mathbf{Y}}(s) - \mathbf{Q}_c(s)\hat{\mathbf{M}}(s) \right), \quad \mathbf{Q}_c(s) \in \mathcal{RH}_{\infty} \end{aligned} \quad (2.20)$$

gives all the stabilizing controllers for the plant $\mathbf{G}(s)$ [169]. In [34], an observer-based realization of Youla-Kucera parametrization has been investigated.

Theorem 2.2. *Given the feedback control loop shown in Fig. 2.2 with plant $\mathbf{G}(s)$ being factorized by $\mathbf{G}(s) = \hat{\mathbf{M}}^{-1}(s)\hat{\mathbf{N}}(s) = \mathbf{N}(s)\mathbf{M}^{-1}(s)$, then any stabilizing controller for $\mathbf{G}(s)$ can be parameterized by*

$$\begin{aligned}\mathbf{u}(s) &= \mathbf{F}\hat{\mathbf{x}}(s) + \mathbf{R}(s)(\mathbf{y}(s) - \hat{\mathbf{y}}(s)) \\ \mathbf{R}(s) &= -\mathbf{Q}_c(s) \in \mathcal{RH}_\infty.\end{aligned}\tag{2.21}$$

Proof. Recall that all proper controllers achieving internal stability for plant $\mathbf{G}(s)$ can be written as

$$\mathbf{K}(s) = \left(\hat{\mathbf{X}}(s) - \mathbf{Q}_c(s)\hat{\mathbf{N}}(s) \right)^{-1} \left(\hat{\mathbf{Y}}(s) - \mathbf{Q}_c(s)\hat{\mathbf{M}}(s) \right) \tag{2.22}$$

which leads to

$$\begin{aligned}\left(\hat{\mathbf{X}}(s) - \mathbf{Q}_c(s)\hat{\mathbf{N}}(s) \right) \mathbf{u}(s) &= \left(\hat{\mathbf{Y}}(s) - \mathbf{Q}_c(s)\hat{\mathbf{M}}(s) \right) \mathbf{y}(s) \\ \Rightarrow \hat{\mathbf{X}}(s)\mathbf{u}(s) &= \hat{\mathbf{Y}}(s)\mathbf{y}(s) - \mathbf{Q}_c(s) \left(\hat{\mathbf{M}}(s)\mathbf{y}(s) - \hat{\mathbf{N}}(s)\mathbf{u}(s) \right).\end{aligned}\tag{2.23}$$

Letting

$$\mathbf{A}_L := \mathbf{A} - \mathbf{L}\mathbf{C}, \mathbf{B}_L := \mathbf{B} - \mathbf{L}\mathbf{D} \tag{2.24}$$

it follows from the residual generator (2.11) that

$$\begin{aligned}\hat{\mathbf{x}}(s) &= (s\mathbf{I} - \mathbf{A}_L)^{-1} (\mathbf{B}_L\mathbf{u}(s) + \mathbf{L}\mathbf{y}(s)) \\ \mathbf{r}(s) &= \hat{\mathbf{M}}(s)\mathbf{y}(s) - \hat{\mathbf{N}}(s)\mathbf{u}(s).\end{aligned}\tag{2.25}$$

Furthermore, from

$$\hat{\mathbf{X}}(s) = \mathbf{I} - \mathbf{F}(s\mathbf{I} - \mathbf{A}_L)^{-1}\mathbf{B}_L, \hat{\mathbf{Y}}(s) = \mathbf{F}(s\mathbf{I} - \mathbf{A}_L)^{-1}\mathbf{L} \tag{2.26}$$

we have that

$$\begin{aligned}\mathbf{u}(s) &= \mathbf{F}(s\mathbf{I} - \mathbf{A}_L) (\mathbf{B}_L\mathbf{u}(s) + \mathbf{L}\mathbf{y}(s)) \\ &\quad - \mathbf{Q}_c(s) \left(\hat{\mathbf{M}}(s)\mathbf{y}(s) - \hat{\mathbf{N}}(s)\mathbf{u}(s) \right) \\ &= \mathbf{F}\hat{\mathbf{x}}(s) + \mathbf{R}(s)\mathbf{r}(s)\end{aligned}\tag{2.27}$$

with $\mathbf{R}(s) = -\mathbf{Q}_c(s)$, which completes the proof. $\square$

Moreover, the following theorem is put forward to reveal a new interpretation of the control loop stabilization and the unique role of the residual signal [31, 153, 165].

Theorem 2.3. *Given the feedback control loop (in Fig. 2.2) with a stabilizing controller $\mathbf{u}_o(s)$, then the set of all controllers that stabilize the given plant $\mathbf{G}(s)$ can be parameterized by*

$$\mathbf{u}(s) = \mathbf{u}_0(s) + \mathbf{R}_c(s)\mathbf{r}(s), \quad \mathbf{R}_c(s) \in \mathcal{RH}_\infty \quad (2.28)$$

Proof. Splitting $\mathbf{R}(s)$ into

$$\mathbf{R}(s) = \mathbf{R}_0(s) + \mathbf{R}_c(s), \quad \mathbf{R}_0(s) \in \mathcal{RH}_\infty \quad (2.29)$$

and substituting into (2.21) gives

$$\mathbf{u}(s) = \mathbf{F}\hat{\mathbf{x}}(s) + \mathbf{R}_0(s)\mathbf{r}(s) + \mathbf{R}_c(s)\mathbf{r}(s), \quad \mathbf{R}_c(s) \in \mathcal{RH}_\infty. \quad (2.30)$$

Noting that

$$\mathbf{u}_0(s) = \mathbf{F}\hat{\mathbf{x}}(s) + \mathbf{R}_0(s)\mathbf{r}(s) \quad (2.31)$$

spans the space of stabilizing controllers by varying $\mathbf{R}_0(s)$ over all proper, stable, rational matrices. The set of all controllers for plant $\mathbf{G}(s)$ can be parameterized by (2.28), which completes the proof of the theorem. $\square$

Note that the residual signal delivers the information about the unknown inputs in the system. This fact establishes the relationship between control and diagnostics, and motivates the integration of the residual access into the design of FTC systems.

FTC Architecture

Similar to the well-known Youla-Kucera parameterization, Theorem 2.2 and 2.3 also characterize all possible stabilizing controllers for a given plant. The latter term $\mathbf{R}(s)\mathbf{r}(s)$ or $\mathbf{R}_c(s)\mathbf{r}(s)$ denotes the dynamic compensator, and makes no difference on system stability. Thus, it can be employed as a compensatory term to take care of the action caused by disturbing variables or fault variable. Once a stabilizing controller $\mathbf{u}_0(s)$ has been provided, there is a one-to-one correspondence between the parameter matrix $\mathbf{R}(s)$ or $\mathbf{R}_c(s)$ and the controller transfer matrix $\mathbf{K}(s)$.

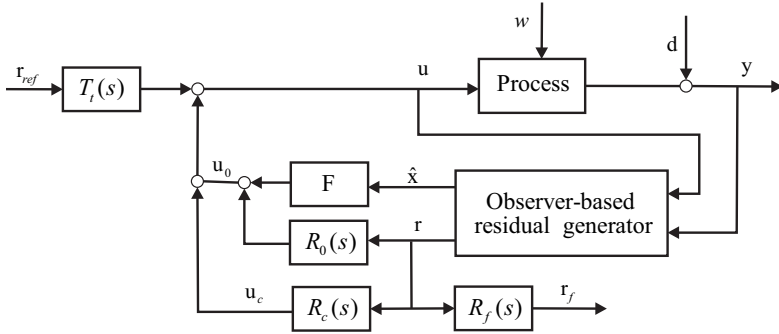


Figure 2.3: The FTC architecture

For FTC purposes, one will be much better off by concentrating on the design of $\mathbf{R}(s)$ or $\mathbf{R}_c(s)$. Also from the viewpoint of practical applications, it would be better to attain performance specifications by only adjusting $\mathbf{R}(s)$ or $\mathbf{R}_c(s)$, instead of redesigning the nominal controller $\mathbf{F}\hat{\mathbf{x}}(s)$ or $\mathbf{u}_0(s)$, which may affect system stability. As a result, together with the parametrization of residual generators (2.13), an observer-based FTC architecture is presented in Fig. 2.3 with

- an observer-based residual generator

$$\begin{aligned}\dot{\hat{\mathbf{x}}}(t) &= \mathbf{A}\hat{\mathbf{x}}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{L}\mathbf{r}(t) \\ \mathbf{r}(t) &= \mathbf{y}(t) - \mathbf{C}\hat{\mathbf{x}}(t) - \mathbf{D}\mathbf{u}(t)\end{aligned}\quad (2.32)$$

- a control law

$$\mathbf{u}(s) = \mathbf{u}_0(s) + \mathbf{R}_c(s)\mathbf{r}(s) + \mathbf{T}_t(s)\mathbf{r}_{\text{ref}} \quad (2.33)$$

- a fault diagnosis algorithm

$$\mathbf{r}_f(s) = \mathbf{R}_f(s)\mathbf{r}(s). \quad (2.34)$$

$\mathbf{r}_{\text{ref}}$ denotes the reference signal and $\mathbf{T}_t(s)$ is designed to achieve the desired tracking performance. It is noted that for $\mathbf{R}_0(s) = \mathbf{0}$, $\mathbf{R}_c(s) = \mathbf{0}$, we have a standard observer-based state feedback control. Moreover, $\mathbf{R}_f(s)$ is a post-filter applied to optimizing the FD performance [30].

2.2 FDI and FTC Schemes for Nonlinear Systems

Due to the great effort in the past two decades, observer-based FDI and FTC technique has established itself as an attractive research area in control engineering and theory. Among the actual research topics in this area, nonlinear observer-based FDI and FTC belong definitely to the most challenging issues. In this section, a brief overview on the most widely used observer-based FDI and FTC approaches for nonlinear systems is given. For this purpose, the state space characterizations of different types of nonlinear systems that have been extensively investigated over the past three decades are introduced first.

2.2.1 Representation of Nonlinear Systems

Without loss of generality, nonlinear systems can be modelled as

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) \\ \mathbf{y}(t) = \mathbf{h}(\mathbf{x}(t), \mathbf{u}(t)) \end{cases} \quad (2.35)$$

where $\mathbf{x}(t) \in \mathcal{R}^{k_x}$, $\mathbf{y}(t) \in \mathcal{R}^{k_y}$, $\mathbf{u}(t) \in \mathcal{R}^{k_u}$ denote the state, output and input vectors, respectively. $\mathbf{f}(\mathbf{x}(t), \mathbf{u}(t))$ and $\mathbf{h}(\mathbf{x}(t), \mathbf{u}(t))$ are continuously differentiable nonlinear function matrices with appropriate dimensions.

To the best of our knowledge, there are few results on FD and FTC studies for the above general type of nonlinear systems since it is difficult to handle the nonlinear dynamics in general. The recent research on nonlinear FD and FTC is mainly dedicated to some special classes of nonlinear systems like Lipschitz nonlinear systems [110, 163], sector bounded nonlinear systems [55], or affine nonlinear systems [1, 73, 72, 151].

Representation of Lipschitz Nonlinear Systems

Without loss of generality, the Lipschitz nonlinear systems can be represented by

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \Gamma(\mathbf{u}, t) + \Phi(\mathbf{x}, \mathbf{u}, t) \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) \end{cases} \quad (2.36)$$

where $\mathbf{A}$, $\mathbf{C}$ and $\mathbf{D}$ are system matrices with appropriate dimensions; $\Gamma(\mathbf{u}, t)$ is nonlinear function matrix. $\Phi(\mathbf{x}, \mathbf{u}, t)$ is Lipschitz nonlinearity [110, 163] if there exists a positive constant γ , such that for $\forall \mathbf{u} \in \mathcal{R}^{k_u}$ and $t \in \mathcal{R}^+$ and $\forall \mathbf{x}_1, \mathbf{x}_2 \in \mathcal{X}$,

$$\|\Phi(\mathbf{x}_1, \mathbf{u}, t) - \Phi(\mathbf{x}_2, \mathbf{u}, t)\| \leq \gamma \|\mathbf{x}_1 - \mathbf{x}_2\| \quad (2.37)$$

where $\mathcal{X}$ is a closed and bounded region containing the origin.

Representation of Sector Bounded Nonlinear Systems

The sector bounded nonlinear systems can be modelled in the following form

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \Psi(\mathbf{x}) \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t) \end{cases} \quad (2.38)$$

where $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D}$ are system matrices with appropriate dimensions. $\Psi(\mathbf{x})$ is a nonlinear function vector satisfying the following sector-bounded condition [55]

$$(\Psi(\mathbf{x}(t)) - \mathbf{T}_1\mathbf{x}(t))^T (\Psi(\mathbf{x}(t)) - \mathbf{T}_2\mathbf{x}(t)) \leq 0 \quad (2.39)$$

for $\mathbf{x}(t) \in \mathcal{R}^{k_x}$. Here, $\mathbf{T}_1$ and $\mathbf{T}_2$ are known real constant matrices and $\mathbf{T} = \mathbf{T}_1 - \mathbf{T}_2$ is symmetric positive definite matrix.

Representation of Affine Nonlinear Systems

The affine nonlinear systems can be described by

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{a}(\mathbf{x}) + \mathbf{b}(\mathbf{x})\mathbf{u}(t) \\ \mathbf{y}(t) = \mathbf{c}(\mathbf{x}) + \mathbf{d}(\mathbf{x})\mathbf{u}(t) \end{cases} \quad (2.40)$$

with $\mathbf{a}(\mathbf{x})$, $\mathbf{b}(\mathbf{x})$, $\mathbf{c}(\mathbf{x})$ and $\mathbf{d}(\mathbf{x})$ being continuously differentiable and of appropriate dimensions. This class of nonlinear systems can be considered as a natural extension of LTI systems (2.1).

2.2.2 Classification of Observer-based FDI Techniques

A review of the literature over the past two decades shows that the application of nonlinear observer theory built the main stream in the nonlinear observer-based FDI study in the 90's [2]. In recent years, much attention has been paid to the application of those techniques to addressing nonlinear FDI issues, which are newly established for dealing with analysis and synthesis of nonlinear dynamic systems more efficiently. For instance, adaptive observer-based FDI, sliding mode observer-based FD, Linear parameter-varying (LPV)-based FDI, geometric approach based FDI, artificial intelligence-based approach or fuzzy technique-based FDI have been reported.

Adaptive Observer-based Approach

Generally speaking, adaptive observers adopt recursive algorithms for joint estimation of states and parameters [161]. Due to its constructive nature and the global convergence ensured by an easy-to-check persistent excitation condition, it has been widely investigated for nonlinear FD purpose [145, 163, 140, 17, 36, 51, 61], in particular when the parameters are directly or indirectly related to fault variables. For instance, [61] has addressed the FD problem for a class of nonlinear systems with uncertainties by transforming the systems into two different subsystems under some geometric conditions. Furthermore, [145] has proposed an adaptive fault diagnosis scheme by nontrivially combining a high gain observer and a linear adaptive observer, which is applicable to a class of systems which are truly nonlinear in the sense that they cannot be linearized by coordinate change and output injection. [163] has presented an FDI approach for a class of Lipschitz nonlinear systems with nonlinearity and unstructured modeling uncertainty by adopting an adaptive FD estimator and a bank of fault isolation estimator. In general, the adaptive observer-based FDI approach is more applicable to nonlinear systems with linear parametric uncertainties or faults.

Sliding Mode Observer-based Approach

Sliding mode observers have good robustness against system uncertainties and external disturbances [39, 127], which provides potential for solving robust FDI and FTC problems of nonlinear systems

[62, 42, 149, 148, 27, 147, 3, 86]. In [62], a robust fault estimation scheme has been proposed for affine nonlinear systems in a geometric context. [42] has presented a sliding mode disturbance observer to deal with robust fault detection problem for the affine nonlinear systems. However, both of these two schemes require strict geometric conditions, thus their applicability in practice is restricted. In [147], a robust fault estimation and reconstruction approach for a class of nonlinear systems with uncertainties has been proposed with the aid of convex optimization technique. It has been proved that the reconstructed signal can approximate the fault signal to any accuracy even in the presence of uncertainties. Moreover, the application to a class of nonlinear large-scale systems and civil aircrafts has been reported in [148, 3]. To sum up, sliding mode observer-based FD approach has been widely applied to systems with bounded or Lipschitz nonlinear terms.

LPV-based Approach

LPV techniques have received considerable attention and been intensively investigated for vehicle and aerospace control [15]. It can be considered as an extension of the gain-scheduled control for nonlinear systems. However, this approach is mainly dedicated to nonlinear plants that can be treated as linear systems with on-line measurable and time-varying parameters [15]. More design schemes of integrated fault detection and control problem for LPV systems and FDI filter for LPV systems under a sensitivity constraint can be found in the literatures [7, 141].

Geometric Approach

Geometric approach was first proposed in [97, 98, 79] to solve the design problems of FDF for linear systems. The basic idea behind these approaches is to reconstruct a subsystem which is decoupled from disturbance and only affected by faults. A differential-geometric method has been presented in [109] to address FDI issues for affine nonlinear systems. A basic existence condition of the changes of coordinates in the output space and in the state space has been derived under a mild hypothesis. In [38], the development of residual generators of a class of input affine nonlinear systems has been studied for the purpose of fault reconstruction by means of dynamic system inversion. However,

this requires strict geometric conditions which limit its application in practice.

Artificial Intelligence-based Approach

Associated with the rapid development of computer techniques, artificial intelligence-based FD approach has attracted considerable attention in recent years [68, 76]. It has been recognized to be a promising tool for solving FD issues for nonlinear systems when no accurate mathematic model is provided. Signal processing- and knowledge-based approaches serve as the major methodologies. Among the approaches, neural network-based FD methods have been widely investigated due to their adaptation ability to practical processes. However, further efforts are needed for determining the structure and scale of the network, improving the convergence rate and real-time ability and guaranteeing the integrity of training examples.

Fuzzy Technique-based Approach

Over the past decades, the application of Takagi-Sugeno (T-S) fuzzy-model-based analysis and synthesis techniques to deal with nonlinear systems or even non-analytic systems have received intensive attention from both research and application fields [77, 40]. It has been demonstrated that by means of fuzzy dynamic modelling technique, the controller/filtering design issues for nonlinear systems can be transformed into solving a class of linear matrix inequalities (LMIs) in the Lyapunov-function-based framework [128, 60, 48, 155, 100, 21, 23]. Under such circumstances, fault detection problems have been studied in [49, 102, 37, 166, 144, 20, 167]. Among involved studies, [167] has proposed a parity-equation FD approach and a fuzzy-observer-based FD approach for NCSs represented by T-S fuzzy model with different network-induced delays. [102] has proposed a multi-objective FD filter for uncertain T-S fuzzy models so that the residual signal is sensitive to fault signal and meanwhile robust to exogenous input. In [49], a novel fuzzy observer-based design approach is developed to achieve a sensor fault estimation for T-S fuzzy systems with unknown output disturbances. [144] has presented two robust FD schemes (fuzzy-rule-independent and fuzzy-rule-dependent) for T-S fuzzy Itô stochastic systems such that a prescribed noise attenuation level is guaranteed in the $\mathcal{H}_\infty$ sense. In [37],

a robust FD approach is developed for a class of uncertain discrete-time T-S fuzzy systems in NCSs with mixed time delays and successive packet dropouts. In [20], an $\mathcal{H}_-/\mathcal{H}_\infty$ FD filter has been proposed for nonlinear systems described by T-S fuzzy models with sensor faults and unknown bounded disturbances by using descriptor approach and non-quadratic Lyapunov functions. Some work on the FD issues for fuzzy systems in presence of unmeasurable premise variables is reported in [6].

In fact, the basic idea behind these approaches lies in lumping the design schemes into finding a common Lyapunov function of a set of LMIs for all subsystems. The conservatism inherent in these common Lypuanov-function-based approaches has motivated investigations on the design methods by means of piecewise/fuzzy Lyapunov functions [166, 159, 41, 66, 157, 111, 112, 114]. The FD problem for fuzzy systems with intermittent measurements has been investigated using basis-dependent Lyapunov functions in [166]. More significantly, both robust full-order fault estimation observer and reduced-order fault estimation observer have been studied for discrete-time T-S fuzzy systems based on piecewise Lyapunov functions in [159]. Roughly speaking, most of these studies have been mainly dedicated to FD design issues for affine systems.

2.2.3 Classification of FTC Techniques for Nonlinear Systems

In the following, the state-of-the-art of FTC techniques for nonlinear systems is reviewed.

Reliable FTC Approach

The basic idea behind a reliable FTC approach lies in taking into account the prior knowledge of potential faults in the controller design. Significant effort has been devoted to study the FTC design for affine nonlinear systems or a class of nonlinear systems with norm-bounded uncertainties in terms of solutions of Hamilton-Jacobi inequalities (HJIs) [85, 90, 150, 115]. Moreover, [13] introduced a passive FTC scheme for affine nonlinear systems with actuator faults. The Lyapunov-based feedback controllers have been addressed to ensure the local uniform asymptotic stability of the systems under additive and loss-of-effectiveness faults. The drawback of these approaches is that the solvability of HJIs is difficult to evaluate.

Adaptive FTC Approach

In order to limit the restrictions on process model accuracy, adaptive techniques have been applied to estimate states and parameters. Based on state and parameter estimation, fault-tolerant performance can be achieved. In [162], a unified approach for FDI and fault accommodation has been proposed for a type of multivariable nonlinear systems by invoking a neural network-based adaptive technique. In [64], a fault accommodation scheme is developed for Lipschitz nonlinear systems with an embedded adaptive fault estimation module. The inherent drawback of an adaptive observer limits its application to more general types of nonlinear systems.

Sliding Mode Based FTC Approach

It is known that sliding mode control has good robustness against uncertainties and external disturbances. In [87], a novel proportional and derivative (PD) sliding mode observer is proposed for nonlinear Markovian jump systems with time delay to simultaneously estimate the state and fault variables. Based on this estimation, an observer-based FTC scheme is developed to guarantee the stochastic stability of the closed-loop system. Furthermore, the application of integral sliding mode FTC approach for the longitudinal control of an aircraft can be found in [4]. For detailed discussions on FTC using sliding mode observers, the readers can refer to [5]. Similar to adaptive observer-based FD approaches, the application of adaptive FTC methods are mainly restricted to some special types of nonlinear systems.

Artificial Intelligence-based FTC Approaches

In recent years, the application of artificial intelligence techniques to deal with nonlinear FTC issues has received significant attention [29, 122]. Generally speaking, this FTC approach is realized by following two steps: (i) adopting the neural network-based learning method to approximate fault models or weighting factors of faults for nonlinear systems, and (ii) re-configuring the control law based on the parameter changes. However, there are few results on the systematic design of neural network, which limits the application of artificial intelligence in solving practical control problems.

Fuzzy Technique-based FTC Approach

As mentioned earlier, T-S fuzzy-model-based analysis and synthesis technique has been well recognized as a simple and effective tool to controlling nonlinear systems or even nonanalytic systems [126, 156, 18]. More recently, there have also appeared some results on fuzzy-model-based FTC for nonlinear systems [59, 132]. It has been demonstrated that by using the fuzzy dynamic modelling technique, the FTC design issues for nonlinear systems can be transformed to solving a class of LMIs in the Lyapunov-function-based framework. This inherent advantage motivates its application in real industrial processes [70, 28, 120].

2.3 Concluding Remarks

This chapter represents FD and FTC techniques for both linear and nonlinear systems. A brief description on the developments of FD and FTC configurations for linear systems has been provided. It is worth mentioning that the parametrization forms of residual generators and controllers play an essential role in obtaining the associated configurations. However, the generalization of the parametrization forms to nonlinear systems seems to be left out of investigation. Therefore, the configurations of observer-based FD and FTC for nonlinear systems will be studied in Chapters 3 and 7. Then, different types of nonlinear processes have been introduced. The major FD and FTC methodologies have been recalled for nonlinear systems. It can be observed that only some of these studies have dealt with residual generator and evaluation as well as decision making in an integrated way. Most of efforts have been made on the FD system design but little on the analysis issues. Thus, the forthcoming chapter discusses the analysis and integrated design issues for nonlinear observer-based FD systems. The integrated design of observer-based FD systems is now basically a blank field for the research of general types of nonlinear processes. To deal with the nonlinear issues, a mathematical and systematic tool is needed. Inspired by the T-S-Fuzzy controller design for nonlinear systems, the investigations on fuzzy observer-based FD systems for general types of nonlinear systems are addressed in Chapters 4-5.

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