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Advances in Fault Detection and Diagnosis Using Filtering Analysis

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Preface I

At the core of many engineering problems is the solution of sets of equations and inequalities, and the optimization of cost functions. Unfortunately, except in special cases, such as when a set of equations is linear in its unknowns or when a convex cost function has to be minimized under convex constraints, the results obtained by conventional numerical methods are only local and cannot be guaranteed. This means, for example, that the actual global minimum of a cost function may not be reached, or that some global minimizers of this cost function may escape detection. By contrast, set-membership analysis makes it possible to obtain guaranteed approximations of the set of all the actual solutions of the problem being considered. This, together with the lack of books presenting set-membership techniques in such a way that they could become part of any engineering numerical tool kit, motivated the writing of this book.

There were at least two ideas on which we easily agreed, though. First, the book should be as simple and understandable as possible, which is why there are so many illustrations and examples. Secondly, readers willing to experiment with set-membership analysis on their own applications should be given the power to do so.

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Preface II

Advances in Fault Detection and Diagnosis Using Filtering Analysis

In practical industrial applications, the operational safety and fault detection and diagnosis of engineering systems have received global attention. For actual engineering systems, how to find an efficient and accurate fault detection and diagnosis method to deal with the fault and ensure the safe and reliable operation of equipment is a very prominent problem in this field. To our knowledge, in the actual engineering system, there will inevitably be a variety of noises. In most cases, there is not enough data to summarize the random characteristics of these noises, and some noises do not have random characteristics, so it is difficult to describe them with statistical laws. Therefore, compared with traditional fault detection and diagnosis methods based on noises conforming to specific distribution laws, it is a meaningful work to conduct accurate and effective fault detection and diagnosis of systems with uncertain noises.

In all, this book proposes some filtering-based fault detection and diagnosis methods for engineering systems with unknown but bounded noises. In order to deal with the uncertain noises in the engineering system reasonably, this book uses the set-membership filtering method, which combines control discipline with space geometry. For different engineering systems, different spatial geometric shapes are used to contain the noises of the system, and the affine contraction process of the geometric space is used to describe the change of the state feasible set. Based on the obtained state feasible set, the process of fault detection and diagnosis can be further completed. On this basis, aiming at the problem of fault detection and diagnosis of engineering systems, from the perspective of filtering, this book not only improves the existing methods but also discusses and studies new methods. This book is of great value to post-graduate students, teachers, engineers, and individual researchers in the field of fault detection and diagnosis based on set-membership filtering.

Chapter 2 studies and analyzes the traditional fault diagnosis method based on filtering, and the Kalman filter algorithm is taken as an example to simulate and verify in the fault diagnosis of power converter. In Chap. 3, the fault detection method of set-membership filtering based on ellipsoid is analyzed and studied. Aiming at the problems of repeated calculation and low data utilization rate of the parameter estimation algorithm of weight ellipsoid, the parameter estimation algorithm of limited data window of weight ellipsoid is proposed. In Chap. 4, based on the polyhedral set-membership algorithm, a fault detection algorithm based on polyhedral set-membership filtering is proposed. In Chap. 5, based on the knowledge of interval operation and the idea of set inversion via interval analysis, a fault observer based on vector set inversion interval filtering is designed for the fault detection of DC motors. In Chap. 6, based on zonotopes and orthotopes, combined with linear programming theory, the fault diagnosis method of set-membership filtering based on polyhedron is studied. At the same time, considering the directional expansion theory and the stratification idea, the targeted research was carried out, respectively. In Chap. 7, two fault diagnosis methods based on composite set-membership filtering are proposed. Finally, in Chap. 8, the research contents of this book are summarized. Also, the future development direction of the fault diagnosis method based on set-membership filtering is prospected.

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Symbol Description

$\mathbb{R}$	Set of real numbers
$\mathbb{R}^n$	Set of n-dimensional real vectors
$\mathbf{B}^n$	Unitary box in $\mathbb{R}^n$
A^{T}	Transpose of matrix A
$\widehat{A}$	Estimated value of matrix A
A^{-1}	Inverse of matrix A
$det(A)$	Determinant of matrix A
$tr(A)$	Trace of matrix A
$A > 0$	General notation for strictly positive definite matrix A
$A \geqslant 0$	General notation for positive definite matrix A
$A < 0$	General notation for strictly negative definite matrix A
$A \leqslant 0$	General notation for negative definite matrix A
$\mathbf{I}_n$	Identity matrix in $\mathbb{R}^{n\times n}$
$\mathbf{0}_n$	Zeros matrix in $\mathbb{R}^{n\times n}$
$\mathrm{diag}(a_1, \ldots, a_n)$	Diagonal matrix of dimension n
$\lvert \cdot \rvert$	Absolute value
$\lVert \cdot \rVert_\infty$	Infinity norm
$\lVert \cdot \rVert_P$	P-norm
$\lVert \cdot \rVert_F$	Frobenius norm
$s.t.$	Subject to
$\in$	Belongs to
$\notin$	Not belongs to
$\subset$	Subset
$\supset$	Contained in
$\cap$	Intersection
$\oplus$	Minkowski sum
$\bigodot$	Linear mapping
$conv(\cdot)$	Convex hull
max	Maximum value

min	Minimum value
$\emptyset$	Empty set

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Chapter 1
Introduction

1.1 Fault Detection and Diagnosis Problem

With the further development of industrialization, the scale of electric power [1], chemical industry [2], machinery [3] and other industries has been expanding, and the system structure has become more and more complex. Affected by many unpredictable and unavoidable factors, these large industrial systems may have various faults at any time. Therefore, fault detection and diagnosis plays a key role in the operation and maintenance of equipment. In the process of industrial production, the synchronous guarantee of production efficiency and system safety has always been the focus of people's attention. Once the system components or subsystems fail, the system usually can not operate as expected. In this case, if the system continues to run, it will bring significant losses to the economic benefits, equipment maintenance, and the employee safety [4, 5].

As a renewable energy source, wind energy has the advantages of large energy storage, pollution-free, sustainable, and renewable energy. It is one of the most economical green energy sources in the world [6]. Wind turbine is a complex electromechanical system responsible for converting wind energy into electric energy, and it is generally composed of system components such as hubs, transmission shafts, gearboxes, generators and so on [7]. Wind turbines are exposed to the environment of large temperature differences between day and night, big load change and random wind impact all year round. The working environment is very harsh, and they are prone to failure. At the same time, the remote industrial environment of the wind turbine is remote, faults are usually difficult to find and repair in the first time, and it is easy to evolve into major accidents, which greatly increases the maintenance cost [8, 9]. It is reported that in 2004, Danish motor suppliers lost 40 million Euro due to the motor faults of wind turbines. Power converter is a widely used power conversion device in system energy conversion and transmission, and it plays a key role in power, industry, agriculture and other fields [10]. With the expansion of the application field of power electronic technology, the application field of power converters will be broader. However, as an intermediate link of power system conversion,

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power converter is vulnerable to higher switching frequencies. At the same time, its work is also accompanied by electric heating, which leads frequent faults of power converter components [11, 12]. In addition, the safety and reliability of industrial products such as air conditioners, electric vehicles and elevators that are commonly used in daily life are also issues that cannot be ignored.

Fault detection and diagnosis play a key role in the operation and maintenance of equipment in these industries. Regular maintenance of the system is usually more economical and safer than dealing with faults after they occur. When the system fails, the performance of the components or subsystems of the system cannot meet the requirements, which will lead to the increase of resource consumption, the decrease of system performance or the loss of its intended functions, or damaging the mechanical equipment, causing the entire system to paralyze and resulting in a huge economy loss in the worst case, and even endangering the personal safety of employees. Therefore, fault detection and diagnosis is also important in cost management, efficiency improvement and environmental protection. The development of science and technology has promoted the progress of industrialization, and the strict requirements on industrial safety has been put forward while the demand for product quality and production efficiency in various industries has further improved. Therefore, using safe and reliable fault detection and diagnosis methods for timely and effective fault detection and diagnosis of the system has important practical significance to ensure the reliable performance of the system, improve the economic benefits of the system, and avoid casualties and environmental pollution.

1.2 Classification of Fault Detection and Diagnosis Methods

The research of fault diagnosis technology originated from Beard's doctoral dissertation published in 1971 [13]. With the investment of a large amount of capital, manpower and material resources, fault diagnosis technology gradually developed. Based on the researched contents of fault detection and diagnosis, Willsky published the first review article related to fault detection and diagnosis in Automatica in 1975 [14]. Subsequently, the first academic work in the field of fault detection and diagnosis was published in 1978, laying a solid theoretical foundation for the development of subsequent fault detection and diagnosis technology [15]. With the research and discussion of scholars for nearly half a century, fault diagnosis technology has shown a good development trend along the way. Various fault diagnosis algorithms have been proposed, developed, improved and matured, which can effectively deal with various systems and various situations. Under the fault diagnosis problem, and at the same time have good diagnosis accuracy and speed. At present, fault diagnosis methods are mainly divided into three categories: analytical model-based method [16–18], knowledge-based method [19, 20] and signal-processing-based method [21–23].

Furthermore, numerous experts and scholars have applied these methods to fields of real industries. For example, Qiu and Dai [17] proposed a chemical process fault diagnosis model and applied it to the Tennessee Eastman process. Jiang et al. [18]