A Survey of Fault Diagnosis and Fault-Tolerant Techniques Part I: Fault Diagnosis with Model-Based and Signal-Based Approaches

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***Abstract*—With the ever increase of complexity and expense of industrial systems, there is less tolerance for performance degradation, productivity decrease and safety hazards, which greatly stimulates to detect and identify any kinds of potential abnormalities and faults as early as possible, and implement real-time fault-tolerant operation for minimizing performance degradation and avoiding dangerous situations. During the last four decades, fruitful results were reported about fault diagnosis and fault-tolerant control methods and their applications in a variety of engineering systems. The three-part survey paper aims to give a comprehensive review for real-time fault diagnosis and fault tolerant control with particular attention on the results reported in the last decade. In the first-part review, fault diagnosis approaches and their applications are reviewed comprehensively from model-based and signal-based perspectives, respectively.**

***Index Terms*—Analytical redundancy, model-based fault diagnosis, signal-based fault diagnosis, real-time monitoring, fault tolerance**

I. Introduction

As is known, many engineering systems, such as aero engines, vehicle dynamics, chemical processes, manufacturing systems, power network, electric machines, wind energy conversion systems, and industrial electronic equipment and so forth, are safety-critical systems. There is an ever increasing demand on reliability and safety of industrial systems subjected to potential process abnormalities and component faults. As a result, it is paramount to detect and identify any kinds of potential abnormalities and faults as early as possible, and implement fault-tolerant operation for minimizing performance degradation and avoiding dangerous situations.

A fault is defined as an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable/usual/standard condition [1]. Examples of such malfunctions are the blocking of an actuator, the loss of a sensor (e.g., a sensor gets stuck at a particular value or has a variation in the sensor scalar factor), or the disconnection of a system component. Therefore, the faults are often classified as actuator faults, sensor faults and plant faults (or called component faults or parameter faults), which either interrupt the control action from the controller on the plant, or produce substantial measurement errors, or directly change the dynamic input/output properties of the system, leading to system performance degradation, and even the damage and collapse of the whole system. In order to improve the reliability of a system concerned, fault diagnosis is usually employed to monitor, locate and identify the faults by using the concept of redundancy, either hardware redundancy or software redundancy (or called analytical redundancy). The basic idea of the hardware redundancy is to use identical components with the same input signal so that the duplicated output signals can be compared leading to diagnostic decision by a variety of methods such as limit checking, and majority voting *etc*. The hardware redundancy is reliable, but expensive and increasing weights and occupying more space. It is necessary for key components to equip with the redundant duplicate, but would not be applicable if the hardware redundancy is applied to the whole system due to the cost or the difficulty for physical installing when the space and/or weight are strictly constrained. With the mature of modern control theory, the analytical redundancy technique has become the main stream of the fault diagnosis research since the 1980s, whose schematic diagram can be depicted by Fig.1. For a controlled system subjected to actuator fault f_a, process/component fault f_c, and sensor fault f_s, the input u and output y are used to construct a fault diagnosis algorithm, which is employed to check the consistency of the feature information of the real-time process carried by the input and output data against the pre-knowledge on a healthy system, and a diagnostic decision is then made by using diagnostic

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logics. Compared with hardware redundancy methods, analytical redundancy diagnostic methods are more cost effective, but more challenging due to environmental noises, inevitable modelling error, and the complexity of the system dynamics and control structure.

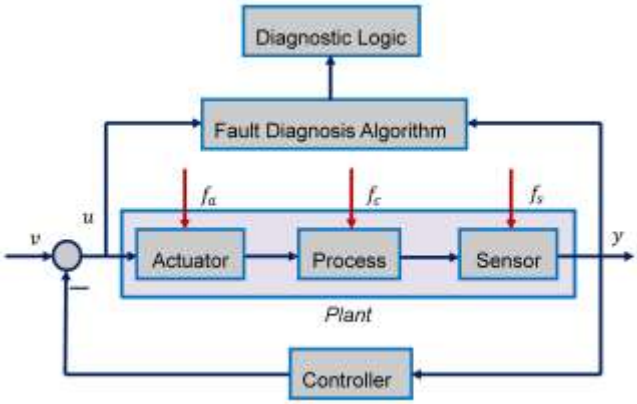

Fig. 1. Analytical redundancy based fault diagnosis

Fault diagnosis includes three tasks, that is, fault detection, fault isolation and fault identification. Fault detection is the most basic task of the fault diagnosis, which is used to check whether there is malfunction or fault in the system and determine the time when the fault occurs. Furthermore, fault isolation is to determine the location of the faulty component, and fault identification is to determine the type, shape and size of the fault. Clearly, the locations of the faulty components and their severe degrees of the malfunctions described by the types, shapes and sizes of the faults are vital for the system to take fault-tolerant responses timely and appropriately to remove the adverse effects from the faulty parts to the system normal operation.

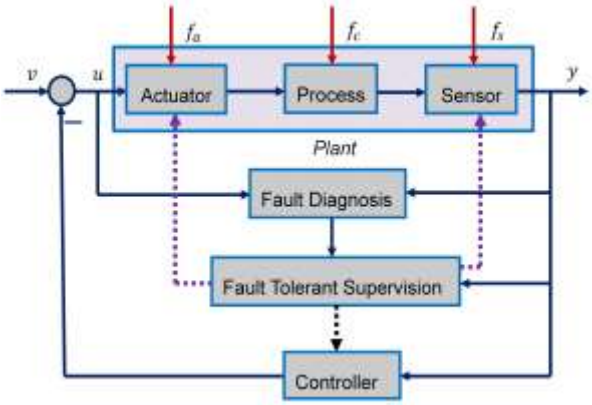

Fig. 2. Schematic diagram of fault tolerant control

The schematic of fault-tolerant control is depicted by Fig. 2, which is shown that fault tolerant control is integrated with fault diagnosis in essence. Real-time fault diagnosis can detect whether the system is faulty, and tell where the fault occurs and how severe the malfunction is. Based on the valuable information, the supervision system can thus take appropriate fault-tolerant actions such as off-setting the faulty signals by actuator/sensor signal compensation, tuning or reconfiguring the controller, and even replacing faulty components by redundant duplicates, so that the adverse effects from faults are accommodated or removed.

During the last four decades, fruitful results have been reported on fault diagnosis methods, fault-tolerant control techniques and their applications in various industrial processes and systems. A number of survey papers were written, for instance [2-38], which are depicted by Table 1, categorized in terms of years and methods/applications.

TABLE 1
SURVEY PAPERS FOR FAULT DIAGNOSIS AND FAULT TOLERANCE

Years	Fault Diagnosis Methods	Fault Diagnosis Applications	Fault Tolerance Methods	Fault Tolerance Applications
1970s	[2]			
1980s	[3,4]			
1990s	[5-8]	[18]	[27-29]	
2000s	[9-14], [33]	[19, 20], [22-24]	[30-32], [34]	[36]
2010s	[15-17], [35]	[21], [25,26]	[33], [35]	[37, 38]

Specifically, in 1976, Willsky presented the key concepts of analytical redundancy for model-based fault detection and diagnosis in the early survey paper [2]. More comprehensive model-based fault diagnosis methods such as parity space approaches, observer-based methods and parameter estimation techniques are reviewed by [3-9]. A three-part survey paper [10-12] on fault diagnosis was presented in 2003, respectively from the viewpoint of quantitative mode-based methods, qualitative model-based methods and process history based methods. In [13], a structured and comprehensive overview of the research on anomaly detection is provided, which is referred to the problem of finding patterns in data that do not conform to expected behavior, and has an extensive use in a wide variety of applications such as intrusion detection for cyber-security, military surveillance for enemy activities, as well as fault detection in safety critical systems. In [14-16], comprehensive fault diagnostic methods were reviewed respectively from the data-driven perspective. In [17], a short review on fault detection in sensor networks was provided. With respect to fault diagnosis methods for various processes/systems applications, a couple of survey papers were addressed for mining equipment [18], electric motors [19-21], building systems (such as heating, ventilating, air-conditioning and refrigeration) [22, 23], machinery system [24, 25], and swarm systems (consisting of multiple intelligent interconnected nodes and possessing swarm capability) [26], respectively.

For fault-tolerant control, an early review paper was presented by [27] in 1991, which introduced the basic concepts of fault-tolerant control and analyzed the applicability of artificial intelligence (e.g., neural network and expert systems) to fault-tolerant control systems. In 1997, an overview of fault-tolerant control was given from the system

development view [28]. In the same year, a comprehensive review was contributed by [29], which presented the key issues of the fault-tolerant control systems and outlined the state of the art in this field. Reconfigurable fault-tolerant control systems are reviewed extensively respectively by [30-32]. Some results on fault-tolerant control for nonlinear systems were reviewed by [33]. Along with fault diagnosis, brief reviews on data-driven fault-tolerant control and model-based fault-tolerant reconfiguration were presented by [34, 35] respectively. From the viewpoint of industrial applications, fault tolerance techniques were reviewed for electric drive systems [36] and power electronics systems [37, 38], respectively.

The three-part survey paper aims to give a comprehensive overview for real-time fault diagnosis and fault tolerant control with particular attention on the results reported in the last decade. Generally, fault diagnosis methods can be categorized into model-based methods, signal-based methods, knowledge-based methods, hybrid methods (the combination methods of at least two methods) and active fault diagnosis methods. In the first-part survey paper, fault diagnosis techniques will be reviewed from the model-based and signal-based perspectives, and the knowledge-based, hybrid, and active fault diagnosis techniques will be reviewed in the second-part survey paper. The first-part and second-part survey papers aim to review the existing fault diagnosis methods and applications within a framework by using the up-to-date references.

The rest of this paper is organized as follows. Following the introduction session, model-based fault diagnosis techniques are reviewed in Section II. Signal-based fault diagnosis is reviewed in Section III. The paper is ended by Section IV with conclusions.

II. Model-Based Fault Diagnosis Methods

Model-based fault diagnosis was originated by Beard [39] in 1971 in order to replace hardware redundancy by analytical redundancy, and comprehensive results were documented in some well-written books (*i.e.,* see [40, 41]). In model-based methods, the models of the industrial processes or practical systems are required to be available, which can be obtained by using either physical principles or systems identification techniques. Based on the model, fault diagnosis algorithms are developed to monitor the consistency between the measured outputs of the practical systems and the model predicted outputs. In this section, model-based fault diagnosis methods are reviewed following the four categories: deterministic fault diagnosis methods, stochastic fault diagnosis methods, fault diagnosis for discrete-events and hybrid systems, and fault diagnosis for networked and distributed systems, which are classified in terms of types of the models used.

A. Deterministic fault diagnosis methods

Observer plays a key role in model-based fault diagnosis for monitored systems/processes characterized by deterministic models. The schematic diagram of the observer-based fault diagnosis is depicted by Fig. 3, which includes fault detection, fault isolation and fault identification (or called fault reconstruction or fault estimation).

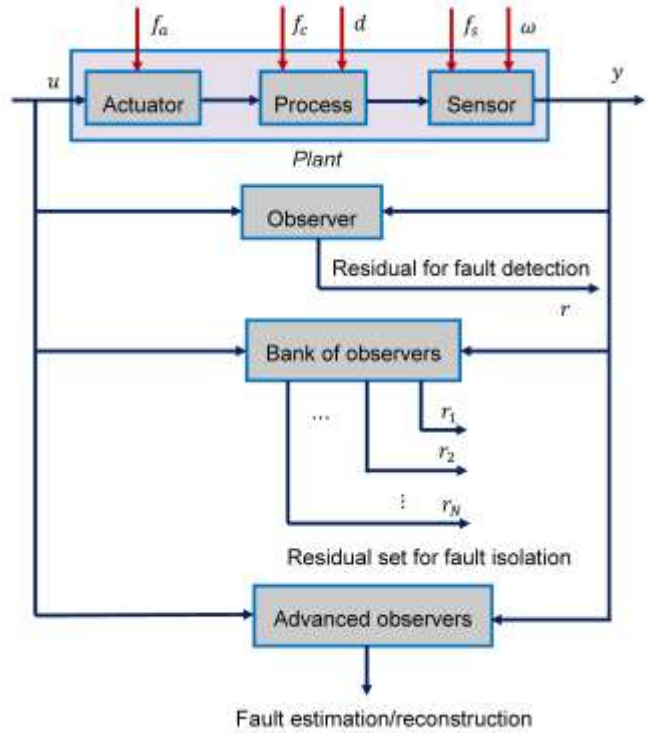

Fig. 3. Scheme of model-based fault diagnosis

For simplicity, the model of the process in Figure 3 is assumed to be linearized state-space model, which is described by the following:

$$\begin{cases} x(k+1) = (A+\Delta A)x(k) + (B+\Delta B)u(k) + B_d d(k) \\ \qquad\qquad + B_a f_a(k) + B_c f_c(k) \\ y(k) = (C+\Delta C)x(k) + D_s f_s(k) + D_\omega \omega(k) \end{cases} \tag{1}$$

where $x(k) \in R^n$, $u(k) \in R^m$, $y(k) \in R^p$, $f_a(k) \in R^{l_a}$, $f_c(k) \in R^{l_c}$, $f_s(k) \in R^{l_s}$, $d(k) \in R^{l_d}$, and $\omega(k) \in R^\omega$ are the system state, control input, measured output, unexpected actuator fault, component/parameter fault, sensor fault, process disturbance and measurement noises, respectively. $A, B, C, B_d, B_a, B_c, D_s$ and D_ω are known parameter matrices, and $\Delta A, \Delta B$ and ΔC are unknown modelling parameter errors.

An observer-based *fault detection* filter is given in the following form:

$$\begin{cases} \hat{x}(k+1) = A\hat{x}(k) + Bv(k) + Kr(k) \\ r(k) = y(k) - \hat{y}(k) \\ \hat{y}(k) = C\hat{x}(k) \end{cases} \tag{2}$$

where $\hat{x}(k)$ and $\hat{y}(k)$ are the estimates of the state and output, respectively; $r(k)$ is the residual signal and K is the observer gain to be designed. Let $e(k) = x(k) - \hat{x}(k)$, the frequency-domain residual signal can be described by

$$r(z) = G_{\bar{d}}(z)\bar{d}(z) + G_{\bar{f}}(z)\bar{f}(z) \tag{3}$$

where

$$G_{\bar{d}}(z) = C(zI - A + KC)^{-1}\bar{B}_{\bar{d}} + \bar{D}_{\bar{d}}$$
$$G_{\bar{f}}(z) = C(zI - A + KC)^{-1}\bar{B}_{\bar{f}} + \bar{D}_{\bar{f}}$$
$$\bar{B}_{\bar{d}} = (\Delta A - K\Delta C \quad \Delta B \quad B_d \quad -KD_\omega)$$

$$\bar{B}_{\bar{f}} = (B_a \quad B_c \quad -KD_s)$$
$$\bar{D}_{\bar{d}} = (\Delta C \quad 0 \quad 0 \quad D_\omega)$$
$$\bar{D}_{\bar{f}} = (0 \quad 0 \quad D_s)$$
$$\bar{d}(z) = (x^T(z) \quad v^T(z) \quad d^T(z) \quad \omega^T(z))^T$$
$$\bar{f}(z) = (f_a^T(z) \quad f_c^T(z) \quad f_s^T(z))^T.$$

It is indicated from (3) that the residual signal is subjected to both fault signals and disturbance signals (including modelling errors, process disturbances and measurement noises). In order that the residual signal is sensitive to faults, but robustness against disturbances, the observer gain can be designed by solving an optimization problem over a specific frequency range:

$$\text{minimize}\left(\|G_{\bar{d}}(z)\| / \|G_{\bar{f}}(z)\|\right) \tag{4}$$

In order to solve (4), the parametric eigenstructure assignment approach for fault diagnosis was initialized by [42] and further revisited in [43], in which the observer gain K is formulated as the function of the eigenvalues and eigenvectors, therefore seeking an optimal K is transformed to the problem of finding optimal eigenvalues and eigenvectors. Recently, eigenstructure assignment based fault diagnosis approaches have been applied to vehicles [44], gas turbine engines [45], spacecraft [46] and wind turbine systems [47]. Alternatively, the multi-object optimization problem described by (4) can be reformulated by linear matrix inequality (LMI), which has been a popular method for fault diagnosis research and applications owing to its wide applicability to a variety of dynamic systems. Recent development of the LMI-based fault diagnosis can be found for various systems such as Lipschitz nonlinear systems [48], TS fuzzy nonlinear systems [49, 50], time-delay systems [51], switching systems [52], and application to structure damage detection [53], and shaft crack detection [54] etc.

A bank of observer-based residuals is generally required in order to realize *fault isolation*. A nature idea is to make a single residual is sensitive to the fault concerned but robustness against other faults, disturbances and modelling errors, which is called *structure residual fault isolation* [4]. Alternative fault isolation logic is to make each residual signal sensitive to all but one fault, and robustness against modelling errors and disturbances, which is called *generalized residual fault isolation* [5]. Recent results on robust fault isolation are developed for nonlinear systems [55,56], and various applications such as for aircraft engine [57], robotic manipulators [58], and lithium-ion batteries [59]. The *unknown input observer,* proposed by [60], is another fault isolation tool by decoupling input disturbance, modelling errors and other faults in the corresponding residuals. Recently, the unknown input observer based fault isolation techniques are extended to nonlinear systems [61, 62] and applied to aircraft systems [63], inductor motors [64] and waste water treatment plant [65].

Fault identification (or called fault reconstruction/fault estimation) is to determine the type, size and shape of the fault concerned, which is vital information for fault tolerant operation. *Advanced observer techniques* such as proportional and integral (PI) observers [66, 67], proportional multiple-integral (PMI) observers [68-70], adaptive observer [71-73], sliding mode observers [74, 75], and descriptor observers [76, 77] are usually utilized for fault estimation/reconstruction. The essence of the advanced observers is to construct an augmented system by introducing the concerned fault as an additional state and the extended state vector is thereafter estimated, leading to the estimates of the concerned fault signal together with original system states. Therefore, the advanced observers are also called simultaneous state and fault observers. The above advanced observer techniques are in an advantage position either for reconstructing slow-varying additive faults (PI, and PMI observers), slow-varying parameter faults (adaptive observers), actuator faults with sinusoidal waveforms (sliding mode observers), and high-frequency sensor faults (descriptor system approaches). Actually the above observer techniques may be integrated or combined in order to solve engineering-oriented problems. For instance in [78], integral observer, sliding observers and adaptive observers are combined to reconstruct sensor faults for satellite control systems. In [79], PI observer and descriptor observer techniques are integrated to estimate parameter faults for an aero engine system.

Another well-known model-based fault diagnosis is *parity relation approach*, which was developed in the early of 1980s [80, 81]. The parity relation approach is to generate residuals (parity vector) which is employed to check the consistency between the model and process outputs. The parity relation approach can be applied to either time-domain state-space model or frequency-domain input-output model, which is well revisited by the books [40,41,82]. Recently, the parity relation method is extended for fault diagnosis for more complex models such as TS fuzzy nonlinear systems [83] and fuzzy tree models [84], and applied to various industrial systems such as aircraft control surface actuators [85] and electromechanical brake systems [86].

Stable factorization approach is frequency-domain fault diagnosis method, which was initiated in 1987 by [87] and further extended by [88] in 1990. The basic idea is to generate a residual, based on the stable coprime factorization of the transfer function matrix of the monitored system, which is made sensitive to the fault, but robustness against disturbances by selecting an optimal weighting factor. Recent developments of stable factorization approach can be found in [89] for nonlinear systems, and [90, 91] for applications in auto-balancing two-wheeled cart and thermal process, respectively.

It is worthy to point out that the parity relation method and stable factional approach both have some kind of connections with observers. For instance, the parity relation approach is equivalent to the use of a dead-beat observer, and the coprime factorization realization includes the design of observer gain (together with state-feedback gain).

B. Stochastic Fault diagnosis methods

In parallel with the development of the fault diagnosis for deterministic systems, stochastic approaches were also developed for fault diagnosis in the early 1970s. A general

fault detection and diagnosis procedure was first proposed in [92] by using residuals (or innovations) generated by *Kalman filters* with similar structure to observers, where the faults were diagnosed by statistic testing on whiteness, mean and covariance of the residuals. A variety of statistical tools, such as generalized likelihoods [93], χ^2 testing [94], cumulative sum algorithms [95] and multiple hypothesis test [96], were further developed for testing Kalman-filter based residuals in order to check the likelihood that a particular fault occurs. Further researches have led to a couple of modified Kalman filter techniques for fault diagnosis, such as extended Kalman filters, unscented Kalman filters, adaptive Kalman filters, and augmented state Kalman filters. Unlike the conventional Kalman filters, the extended Kalman filter (EKF) can be used to diagnose the faults in a nonlinear industrial process [97]. The unscented Kalman filter (UKF), depending on a more accurate stochastic approximation, i.e., unscented transform, can better capture the true mean and covariance leading to better diagnosis performance [98, 99]. Adaptive Kalman filters can be employed to tune process noise covariance matrix, or measurement noise covariance matrix in order to obtain satisfactory fault diagnosis [100,101]. The augmented state Kalman filters can be utilized to simultaneously estimate system states and fault signals [102]. Recent application examples of Kalman filter-based fault diagnosis can be found in [103-105] respectively for combustion engines, electronic systems under mechanical shock, and permanent-magnet synchronous motors.

Another important stochastic fault diagnosis method is *parameter estimation* on the basis of system identification techniques (e.g., least-square error and its derived methods), which was initialized by [106]. In this approach, the faults are assumed to be reflected in system parameters, and only the model structure is needed to be known. The basic idea of the detection method is to identify the parameters of the actual process on-line which are compared with the reference parameters obtained initially under healthy conditions. The parameter estimation based fault diagnosis methods are very straightforward if the model parameters have an explicit mapping with the physical coefficients. This method was well reviewed in the early survey papers [3,9] and book [107]. Recent development of this approach can be found in [108-110].

Motivated by combustion processes, paper making systems and chemical processes, the monitored system outputs can be described by probability density functions. For this class of stochastic systems, fault diagnosis was first addressed by [111], where the probability density function outputs are approximated by using B-spline expansion techniques, and random noises/errors can be non-Gaussian. In order to improve robustness against measurement noises, modelling errors and process disturbances, an integration of descriptor estimator and parametric eigenstructure assignment was utilized to detect faults in [112]. Recent development of fault diagnosis for nonlinear systems can be found in [113]. In addition, fault diagnosis methods were also developed for other classes of stochastic systems such as stochastic processes with Brownian motions [114, 115] and Markovian jumps [116].

C. Fault diagnosis for discrete-events and hybrid systems

In industrial processes, the signals of some dynamic systems switch from one value to another rather than changing their values continuously. This kind of systems is called *discrete-event systems*. Fault diagnosis of discrete-event systems was initialized by [117] in 1990s, and the underlying theory of fault diagnosis for discrete-event systems was proposed. The basic event-driven fault diagnosis problem is to perform model-based inferring at run-time to determine whether a given unobservable fault event has occurred or not in the past by using sequences of observable events [118]. According to the model used, the fault diagnosis methods for discrete-event system can be roughly classified into automata based fault method and Petri net based method. In order to overcome the complexity of the task, the automata-based fault diagnosis method has evolved into decentralized method [119], symbolic method [120] and the combination of decentralized and symbolic methods [121]. On the other hand, Petri net has intrinsically distributed nature where the notions of state and action are local, which has been an asset to reduce the computational complexity of solving fault diagnosis problems [122]. Nevertheless, improved results were developed for avoiding complexity by either applying integer linear programming to Petri nets [123] or using partially observed Petri nets [124]. Recently, event-based approaches were applied to fault isolations for continuous dynamic processes where a high-level discrete-event system fault diagnoser was employed to improve the robustness of the fault diagnosis against large environment disturbances [125] or isolate abrupt parameter faults [126].

Some complex industrial systems are both driven by time-based continuous dynamics and event-driven discrete dynamics, which are called hybrid systems, emerging from complex mechatronic systems, manufacturing systems, complex chemical processes, aerospace engineering systems, automotive engine control and embedded control systems. Monitoring and fault diagnosis for hybrid systems entails challenges due to the fact that the continuous dynamics and discrete event changes are mutually dependent and interacted. Hybrid automata are the most common models to represent hybrid systems, which can be utilized to design fault diagnosis algorithms to detect and isolate faults [127, 128]. Bond graph has become a powerful model to be used for fault diagnosis due to its capability of modelling complex systems in a unified way, and the ease for obtaining analytical redundancy relation from the causalities on the graph. Recent results on Bond graph based fault diagnosis and their applications for hybrid systems can be found in [129-132].

D. Fault diagnosis for networked and distributed systems

The rapid developments in network technologies have much stimulated the real-time control and monitoring via communication channels, that is called networked control and

monitoring, which have valuable advantages such as cost effectiveness, less weight and power requirements, easier for installation and maintenance as well as resources sharing [133]. It is noted that the introduction of limited-capacity network cables or wireless sensors into control and monitoring loops has unavoidably brought some unanticipated problems such as random communication delays, data dropout, and scheduling confusion, which make the network based monitoring and fault diagnosis more challenging compared with conventional point-to-point control and monitoring systems. Therefore, in the network based fault diagnosis, the residual or fault estimation error should be not only robust against modelling errors, process disturbance, and measurement noises, but also robust against transmission delays, data dropouts, and incomplete measurements caused by the limit capacity of communication channels [134]. Recently, a variety of fault diagnosis techniques have been developed for various networked systems. For instance, fault detection filters were developed in [135] for systems subjected to communication delays and missing data, where the network status is assumed to vary in a Markovian fashion. In [136], least-square filters and Kalman filters were integrated for fault detection, isolation and estimation for network sensing systems. In [137], a networked based fault diagnosis technique was addressed for nonlinear systems, which was assessed by an experimental test system with the use of IEEE 802.15.4 wireless sensor networks. In addition, it is also of interest to detect the anomaly of a communication network itself, which may affect the performance of network control systems. In order to monitor the guaranteed quality of service (QoS) of the router and the whole topology, sliding mode observer techniques were employed in [138, 139] for anomaly detection in the transmission control protocol (TCP). Very recently, model-based detection and monitoring approaches were addressed in [140, 141] for monitoring potential intermittent connections or faulty nodes for controller area networks (CANs).

Complex industrial systems can be modelled as an interconnection of subsystems, and each subsystem has a decision marker (intelligent agent) which might have access to local measurements, subsystem models, local estimators/controllers, and constrained communication channels between the agent and its neighbors [142]. This kind of decentralized or distributed structure has become the main stream in complex industrial processes owing to its less use of network resources, cost effectiveness and convenience for expansion. On the other hand, real-time monitoring and fault diagnosis for distributed systems is much challenging due to the constrained information redundancy and limited communication capacity. A general idea of the distributed fault diagnosis is to design local estimators or fault detection filters by intelligent agents according to the local sensing and computing resources, and a consensus strategy is utilized to ensure the whole detection or estimation performance of all the agents in the network. Recent developments on distributed fault detection [143] and distributed fault estimation [144] are developed respectively by using adaptive thresholds and sliding modes techniques to improve the robustness against noises and modelling errors. Moreover, applications on unmanned airships [145] and power networks [146] are reported as well.

III. Signal-Based Fault Diagnosis Methods

Signal-based methods utilize measured signals rather than explicit input-output models for fault diagnosis. The faults in the process are reflected in the measured signals, whose features are extracted and a diagnostic decision is then made based on the symptom analysis and prior knowledge on the symptoms of the healthy systems. Signal based fault diagnosis methods have a widely application in real-time monitoring and diagnosis for induction motors, power converters and mechanical components in a system. A schematic diagram of signal-based fault diagnosis is depicted by Fig. 4.

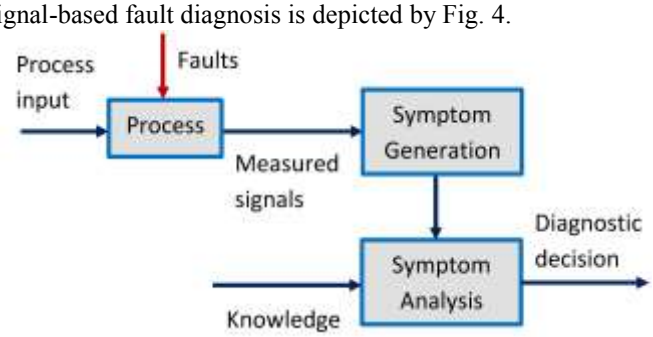

Fig. 4. Scheme of signal-based fault diagnosis

The feature signals to be extracted for symptom (or pattern) analysis can be either time-domain (*e.g.,* mean, trends, standard deviation, phases, slope, and magnitudes such as peak and root mean square) or frequency-domain (*e.g.,* spectrum). Therefore signal-based fault diagnosis methods can be thus classified into time-domain signal based approach, frequency-domain signal based approach and time-frequency signal based method.

A. Time-domain signal based methods

For a continuous dynamical process to be monitored, it is natural to extract time-domain features for fault diagnosis. For instance in [147], by analyzing the changes of the measured root-mean-square current characteristics between healthy conditions and the situations under single/dual transistor short circuit or open circuit, a fault diagnosis method was developed for power converters of switched reluctance motors. In [148], the absolute value of the derivative of the Park's vector phase angle was used as a fault indicator, which was employed for diagnosing multiple open-circuit faults in two converters of permanent magnet synchronous generators (PMSG) drives for wind turbine applications. By observing the slope of the induction current over time, a fault diagnosis method was addressed in [149] for open and short circuits switch fault diagnosis in non-isolated DC-DC converters, and the field programmable gate array (FPGA) digital target was then used for real-time experimental implementation. In [150], by using the measured motor phase currents and their corresponding

reference signals, a real-time algorithm was developed for detecting and locating multiple power switch open circuit faults in inverted-fed AC motor drives. In [151], it was shown that, under balanced supply voltage, the phase angle, the magnitude of the negative and zero-sequence currents can be considered as reliable indicators of stator faults in the induction motors. In [152], a statistical method for the detection of sensor abrupt faults in aircraft control systems was presented, where the covariance of the sensing signals was used for feature extraction. Recently, a time-domain signal-based diagnostic algorithm was developed in [153] for monitoring of gear faults, by combining fast dynamic time warping (Fast DTW) as well as correlated kurtosis (CK) techniques. The fast DTW algorithm was employed to extract the periodic impulse excitations caused from the faulty gear tooth, and the extracted signal was then resampled for subsequent diagnostic analysis using the CK technique. Taking advantages of the periodicity of the geared faults, the CK algorithm can identify the position of the local gear fault in the gearbox.

Different from the approaches for fault detection and diagnosis using features of the measured signal in one-dimension domain, a two-dimension signal-based method was proposed in [154], where the vibration signal was translated into an image (two dimensions), and the local features were then extracted from the image using scale invariant feature transform (SIFT) for fault detection and isolation under a pattern classification framework. Very recently, a two-dimension approach was reported in [155] for fault diagnosis of induction motors, where time-domain vibration signals acquired from the operating motor were firstly converted into two-dimension gray-scale images, and the discriminating texture features were then extracted from these images utilizing local binary patterns (LBP) technique. The extracted texture features were finally used for fault diagnosis with the aid of a classifier. It is noted that, when converting signals into images, the added noise acts as illumination variation. As both the SIFT technique and the LBP operator have illumination invariance capability to some extent, the proposed fault diagnosis methods in [154, 155] have robustness even in a high level of background noises.

B. Frequency-domain signal based methods

Frequency-domain signal based method is to detect changes or faults by using spectrum analysis tool such as discrete Fourier transformation (DFT). One of the most powerful frequency-domain methods for diagnosing motor faults is motor-current signature analysis (MCSA), which utilizes the spectral analysis of the stator current to sense rotor faults associated with broken rotor bars and mechanical balance. Without requiring access to the motor, the MCSA approach has received much attention, which was well reviewed in [19, 20]. Recent development of current based spectrum signature analysis for fault diagnosis can be found in [156, 157].

Vibration signal analysis is a common method for condition monitoring and diagnosis for mechanical equipment such as gear box, as machine sound indicates a lot about working condition of the machine. In [158], an acoustic fault detection method was addressed for gear box on the basis of the improved frequency domain blind de-convolution flow. Recently in [159], Fourier spectrum and the demodulated spectra of amplitude envelope were employed to detect and locate multiple gear faults in planetary gearboxes.

C. Time-Frequency signal based methods

For machines under an unloaded condition, or unbalanced supply voltages, varying load, or load torque oscillations, the measured signals are generally transient and dynamic under the concerned time section. Therefore, analysis of the stationary quantities in some cases finds difficult to monitor or detect faults via either a pure time-domain or frequency-domain method. Due to the time-varying frequency spectrum of the transient signals, suitable time-frequency decomposition tools are needed for real-time monitoring and fault diagnosis.

Time-frequency analysis can identify the signal frequency components, and reveal their time variant features, which has been an effective tool for monitoring and fault diagnosis by extracting feature information contained in non-stationary signals [25].

Various time-frequency analysis methods have been proposed and applied to machinery fault diagnosis. Among the time-frequency methods, short-time Fourier transform (STFT), wavelet transforms (WT), Hilbert-Huang transform (HHT), and Wigner-Ville distribution (WVD) are most common used approaches. For instance, STFT method allows determining signal frequency contents of local sections as the signal changes in time, which has been widely applied to detect both stator and rotor faults in inductor motors [160]. However, the STFT method suffers the high computational cost if it is required to obtain a good resolution. As a linear decomposition, WT based method can provide a good resolution in time for high-frequency components of a signal and a good resolution in frequency for low-frequency components, which has demonstrated the effectiveness for tracking fault frequency components under non-stationary conditions [161]. In [162], the STFT and discrete WT were integrated to do early diagnosis and prognosis of the abnormalities in the monitored industrial systems. It is noticed that STFT and WT may suffer some uncertain limitations. For instance, the selection of a suitable window size in STFT is required, but it is generally not a known priori. The type of the basic wavelet function in WT has a direct effect on the effectiveness in identifying transient elements hidden within a dynamic signal. However, on the basis of the instantaneous frequencies resulting from the intrinsic-mode functions of the signal being analyzed, HHT method is not constrained by the uncertain limitations with respect to the time and frequency resolutions suffered by some time-frequency techniques (e.g., STFT and WT), which has shown quite interesting performance in terms of fault severity evaluation [163]. WVD method features a relatively low computational cost and high resolution, as the entire signal is utilized to obtain the energy at each time-frequency bin, which has been successfully applied to the fault diagnosis along with current analysis [164] or vibration analysis [165]. A significant defect of the

conventional WVD method is the appearance of the cross terms in the distribution of artifacts, which hinders the application of WVD methods. Very recently, via combining advanced notch FIR filters and the conventional WVD method, an improved WVD based fault diagnosis algorithm was proposed in [166], which can effectively minimize the cross terms and provide seamless high-resolution time-frequency diagrams enabling the diagnosis of rotor asymmetries and eccentricities in induction machines directly connected to the grid even in the worst cases. In [167], a self-adaptive WVD method, based on local mean decomposition, was addressed, which can evidently remove the cross-terms of WVD to improve the performance of the defect diagnosis.

IV. Conclusion

In the first-part survey paper, fault diagnosis techniques and their applications have been comprehensively reviewed from model-based and signal-based perspectives, respectively. Specifically, model-based fault diagnosis is reviewed following the categories of fault diagnosis approaches for deterministic systems, stochastic fault diagnosis methods, discrete-event and hybrid system diagnosis approaches, and networked and distributed system diagnosis techniques, respectively. Meanwhile, signal-based fault diagnosis is surveyed following the classifications of time-domain, frequency-domain, and time-frequency-domain approaches, respectively. The overview on knowledge-based fault diagnosis, hybrid and active fault diagnosis is to be carried out in the second-part review paper, which will complete the whole overview on the fault diagnosis techniques and their applications.

References

[1] D. Schrick, ``Remarks on terminology in the field of supervision, fault detection and diagnosis,'' *Proc. IFAC Symp. Fault Detection, Supervision Safety for Techn. Process*, pp.959-964, Hull, UK, Aug. 1997.

[2] A. Willsky, ``A survey of design methods for failure detection in dynamic systems,'' *Automatica*, vol.12, no.6, pp.601-611, Nov. 1976.

[3] R. Isermann, ``Process fault detection based on modelling and estimation methods: A survey,'' *Automatica*, vol.20, no.4, pp.387-304, Jul. 1984.

[4] J. Gertler, ``Survey of model-based failure detection and isolation in complex plants,'' *IEEE Contr. Syst. Mag*., vol.8, no.6, pp.3-11, Dec. 1988.

[5] P. Frank, ``Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy-A survey and some new results,'' *Automatica*, vol.26, no.3, pp.459-474, May 1990.

[6] E. Garcia, and P. Frank, ``Deterministic nonlinear observer-based approaches to fault diagnosis: A survey,'' *Contr. Eng. Practice*, vol.5, no.5, pp.663-670, May 1997.

[7] R. Isermann, ``Trends in the application of model-based fault detection and diagnosis of technical processes,'' *Contr. Eng. Practice*, vol.5, no.5, pp.709-719, May 1997.

[8] P. Frank, and X. Ding, "Survey for robust residual generation and evaluation methods in observer-based fault detection systems," *J. Proc. Contr.*, vol.7, no.6, pp. 403-424, Dec. 1997.

[9] R. Isermann, ``Model-based fault-detection and diagnosis – status and applications,'' *Annu. Rev. Contr.,* vol.29, no.1, pp.71–85, Jan. 2005.

[10] V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S. Kavuri, ``A review of process fault detection and diagnosis part I: quantitative model-based methods,'' *Comput. Chem. Eng*., vol.27, no.3, pp. 293-311, Mar. 2003.

[11] V. Venkatasubramanian, R. Rengaswamy, and S. Kavuri, ``A review of process fault detection and diagnosis part II: qualitative models and search strategies,'' *Comput. Chem. Eng*., vol.27, no.3, pp. 313-326, Mar. 2003.

[12] V. Venkatasubramanian, R. Rengaswamy, S. Kavuri, and K.Yin ``A review of process fault detection and diagnosis part III: process history based methods,'' *Comput. Chem. Eng*., vol.27, no.3, pp. 313-326, Mar. 2003.

[13] V. Chandola, A. Banerjee, and V. Kumar, ``Anomaly detection: A survey,'' *ACM Comput. Survey*., vol.41, no.3, pp.1-58, Jul. 2009.

[14] C. Angeli, and A. Chatzinkolaou, ``On-line fault detection techniques for technical systems: A survey,'' *Int. J. Comput. Sci. Appli*, vol.1, no.1, pp.12-30, 2004.

[15] X. Dai, and Z. Gao, ``From model, signal to knowledge: a data-driven perspective of fault detection and diagnosis,'' *IEEE Trans. Ind. Inf*., vol. 9, no.4, pp.2226-2238, Nov. 2013.

[16] S. Yin, S. Ding, X. Xie, and H. Luo, ``A review on basic data-driven approaches for industrial process monitoring,'' *IEEE Trans. Ind. Electron.*, vol.61, no.11, pp.6418-6428, Nov. 2014.

[17] H. Dong, Z. Wang, S. Ding, and H. Gao, ``A survey on distributed filtering and fault detection for sensor networks,'' *Math. Problem Eng*., Article ID 858624, 7 pages, 2014.

[18] J. Jr, and L. Holloway, ``An overview of fault monitoring and diagnosis in mining equipment,'' *IEEE Trans. Ind. Appl*, vol.30, no.5, pp.1326-1332, Oct. 1994.

[19] M. Benbouzid, ``A review of induction motor signature analysis as a medium for faults detection,'' *IEEE Trans. Ind. Electron*., vol.47, no.5, pp.984-993, Oct. 2000.

[20] S. Nandi, H. Toliyat, and X. Li, ``Condition monitoring and fault diagnosis of electric motors-A review,'' vol.20, no.4, *IEEE Trans. Energy Conv*., vol.20, no.4, pp.719-725, Dec. 2005.

[21] S. Mortazavizadeh, and M. Mousavi, ``A review on condition monitoring and diagnostic techniques of rotating electric machines,'' *Physical Sci. Int. J.,* vol.4, no.3, pp.310-338, May 2014.

[22] S. Katipamula, and M. Brambley, ``Methods for fault detection, diagnostics and prognostics for building systems-A review, part I,'' *HVAC & R Research*, vol.11, no.1, pp.3-25, Jan. 2005.

[23] S. Katipamula, and M. Brambley, ``Methods for fault detection, diagnostics and prognostics for building systems-A review, part II,'' *HVAC & R Research*, vol.11, no.2, pp.169-187, Apr. 2005.

[24] A. Widodo, and B. Yang, ``Support vector machine in machine condition monitoring and fault diagnosis,'' *Mech. Syst. Sig. Proc*., vol.21, no.6, pp.2560-2574, Aug. 2007.

[25] Z. Feng, M. Liang, and F. Chu, ``Recent advances in time–frequency analysis methods for machinery fault diagnosis: A review with application examples,'' *Mech. Syst. Sig. Proc.,* vol.38, no.1, pp.165-205, Jul. 2013.

[26] L. Qin, X. He, and D. Zhou, ``A survey of fault diagnosis for swarm systems,'' *Syst. Sci. Contr. Eng*.: vol.2, no.1, pp.13-23, Jan. 2014.

[27] R. Stengel, ``Intelligent failure-tolerant control,'' *IEEE Contr. Sys. Mag*., vol.11, no.4, pp.14-23, Jun. 1991.

[28] M. Blanke, R. Izadi-Zamanabadi, S. Bogh, and C. Lunau, ``Fault-tolerant control systems-A holistic view,'' *Contr. Eng. Practice*, vol.5, no.5, pp.693-702, May 1997.

[29] R Patton, ``Fault-tolerant control systems: The 1997 situation,'' *Proc. IFAC Symp. Fault Detection, Supervision Safety for Techn. Process*, pp.1033-1054, Hull, UK, Aug. 1997.

[30] J. Jiang, ``Fault-tolerant control systems—An introductory overview,'' *Acta Automatica Sinica*, vol.31, no.1, pp.161-174, Jan. 2005.

[31] J. Lunze, and J. Richter, ``Reconfigurable fault-tolerant control: A tutorial introduction,'' *Eur. J. Contr*., vol.14, no.5, pp.359-386, 2008.

[32] Y. Zhang, and J. Jiang, ``Bibliographical review and reconfigurable fault-tolerant control systems,'' *Annu. Rev. Contr.,* vol.32, no.2, pp.229-252, Dec. 2008.

[33] M. Benosman, ``A survey of some recent results on nonlinear fault tolerant control,'' *Math. Problem Eng*., Article ID 586169, 25 pages, 2010.

[34] H. Wang, T. Chai, J. Ding, and B. Martin, ``Data driven fault diagnosis and fault tolerant control: some advances and possible new directions,'' *Acta Automatica Sinica*, vol.35, no.6, pp.739-747, Jun. 2009.

[35] I. Hwang, S. Kim, Y. Kim, and C. Seah, ``A survey of fault detection, isolation, and reconfiguration methods,'' *IEEE Trans. Contr. Syst. Tech.,* vol.18, no.3, pp.636-653, May 2010.

[36] D. Campos-Delgado, D. Espinoza-Trejo, and E. Palacios, ``Fault-tolerant control in variable speed drives: A survey,'' *IET Elec. Power Appl.*, vol.2, no.2, pp.121-134, Apr. 2008.

[37] Y. Song, and B. Wang, ``Survey of reliability of power electronic systems,'' *IEEE Trans. Power Elec.*, volo.28, no.1, pp.591-604, Jan. 2013.

[38] B. Mirafzal, ``Survey of fault-tolerance techniques for three-phase voltage source inverters,'' *IEEE Trans. Ind. Electron.*, vol.61, no.10, pp.5192-5202, Oct. 2014.

[39] R. Beard, Failure Accommodation in Linear System Through Self Reorganization. PhD Dissertation, USA: MIT, 1971.

[40] J. Chen, and R. Patton, Robust Model-Based Fault Diagnosis for Dynamic Systems. Boston, MA, USA: Kluwer Academic, 1999.

[41] S. Ding, Model-based Fault Diagnosis Techniques: Design Schemes, Algorithms, and Tools. Berlin, Germany: Springer, 2008.

[42] R. Patton, S. Willcox, and S. Winter, ``A parameter insensitive techniques for aircraft sensor fault analysis,'' *J. Guid. Contr. Dynam.*, vol.10, no.3, pp.359-367, Jul. 1987.

[43] R. Patton, and J. Chen, ``On eigenstructure assignment for robust fault diagnosis,'' *Int. J. Ada. Contr. Sig. Proc.*, vol.10, no.14, pp.1193-1208, Dec. 2000.

[44] L. Xu, and H. Tseng, ``Robust model-based fault detection for a roll stability control system,'' *IEEE Trans. Contr. Syst. Tech.*, vol.15, no.3, pp.519-528, May 2007.

[45] X. Dai, Z. Gao, T. Breikin, and H. Wang, ``Disturbance attenuation in fault detection of gas turbine engines: a discrete robust observer design,'' *IEEE Trans. Syst. Man Cybert., Part C*, vol.39, no.2, pp.234-239, Mar. 2009.

[46] R. Fonod, D. Henry, C. Charbonnel, and E. Bornschlegl, `` Robust thruster fault diagnosis : application to the rendezvous phase of the mars sample return mission,'' *Proc. 2nd CEAS Specialist Con. Guid., Navi. Contr.*, pp.1496-1510, Delft, Apr. 2013.

[47] Y. Zhu, and Z. Gao, ``Robust observer-based fault detection via evolutionary optimization with applications to wind turbine systems,'' *Proc. IEEE 9th Conf. Ind. Electron. Appl.*, pp.1627-1632, Hangzhou, Jun. 2014

[48] A. Pertew, H. Marquez, and Q. Zhao, ``LMI-based sensor fault diagnosis for nonlinear Lipschitz systems'' *Automatica*, vol.43, no.8, pp.1464-1469, Aug. 2007.

[49] D. Zhang, H. Wang, B. Lu, and Z. Wang, ``LMI-based fault detection fuzzy observer design with multiple performance constraints for a class of non-linear systems: comparative study,'' *Int. J. Innovative Comput. Inf. Contr.*, vol.8, no.1, pp.633-645, Jan. 2012.

[50] S. Aouaouda, M. Chadli, V. Cocquempot, and M. Khadir, ``Multi-objective H_-/H_∞ fault detection observer design for Takagi–Sugeno fuzzy systems with unmeasurable premise variables: descriptor approach,'' *Int. J. Ada. Signal Proc.*, vol.27, no.12, pp.1031-1042, Dec. 2013.

[51] H. Karimi, M. Zapateiro, and N. Luo, ``A linear matrix inequality approach to robust fault detection filter design of linear systems with mixed time-varying delays and nonlinear perturbations,'' *J. Franklin Inst.*, vol.347, no.6, pp.957-973, Aug. 2010.

[52] D. Wang, P. Shi, and W. Wang, ``Robust fault detection for continuous-time switched delay systems: an linear matrix inequality approach,'' *IET Contr. Theory Appl.*, vol.4, no.1, pp.100-108, Jan. 2010.

[53] B. Chen, and S. Nagarajaiah, ``H_-/H_∞ structural damage detection filter design using an iterative linear matrix inequality approach,'' *Smart Mater. Struct.*, vol.17, no.3, pp.1-9, Apr. 2008.

[54] Z. Kulesza, J. Sawicki, and A. Gyekenyesi, ``Robust fault detection filter using linear matrix inequalities' approach for shaft crack diagnosis,'' *J. Vibration Contr.,* vol.19, no.9, pp.1421-1440, Jul. 2013.

[55] X. Zhang, M. Polycarpou, and T. Parisini, ``Fault diagnosis of a class of nonlinear systems with Lipschitz nonlinearities using adaptive estimation,'' *Automatica*, vol.46, no.2, pp.290-299, Feb. 2010.

[56] M. Du, and P. Mhaskar, ``Isolation and handling of sensor faults in nonlinear systems,'' *Automatica*, vol.50, no.4, pp.1066-1074, Apr. 2014.

[57] X. Zhang, L. Tang, and J. Decastro, ``Robust fault diagnosis of aircraft engines: A noninear adaptive estimation-based approach,'' *IEEE Trans. Contr. Syst. Tech.*, vol.21, no.3, pp.861-868, May 2013.

[58] F. Caccavale, A. Marino, G. Muscio, and F. Pierri, ``Discrete-time framework for fault diagnosis in robotic manipulators,'' *IEEE Trans. Contr. Syst. Tech.*, vol.21, no.5, pp.1858-1873, Sep. 2013.

[59] W. Chen, W. T. Chen, M. Saif, M. Li, and H. Wu, ``Simultaneous fault isolation and estimation of lithium-ion batteries via synthesized design of Luenberger and learning observers,'' *IEEE Trans. Contr. Syst. Tech.,* vol.22, no.1, pp.290-298, Jan. 2014.

[60] J. Chen, and H. Zhang, ``Robust fault detection of faulty actuators via unknown input observers,'' *Int. J. Syst. Sci.*, vol.22, no.10, pp.1829-1839-105, Oct. 1991.

[61] W. Chen, and M. Saif, ``Fuzzy nonlinear unknown input observer design with fault diagnosis applications,'' *J. Vibration Contr.*, vol.16, no.3, pp.377-401, Mar. 2010.

[62] J. Zarei, and E. Shokri, ``Robust sensor fault detection based on nonlinear unknown input observer,'' *Measurement*, vol.48, no.2, pp.355-367, Feb. 2014.

[63] D. Wang, and K. Lum, ``Adaptive unknown input observer approach for aircraft actuator fault detection and isolation,'' *Int. J. Ada. Contr. Sig. Proc.*, vol.21, no.1, pp.31-48, Mar. 2007.

[64] K. Gaeid, and H. Ping, ``Induction motor fault detection and isolation through unknown input observer,'' *Sci. Res. Essays,* vol.5, no.20, pp.3152-3159, Oct. 2010.

[65] S. Methnani1, F. Lafont, J. Gauthier, T. Damak, and A. Toumi, ``Actuator and sensor fault detection, isolation and identification in nonlinear dynamical systems, with an application to a waste water treatment plant,'' *J. Comput. Eng. Inf.*, vol.1, no.4, pp.112-125, Oct. 2013.

[66] Z. Gao, ``Discrete-time proportional and integral observer and observer-based controller for systems with both unknown input and output disturbances,'' *Opt. Contr. App. Meth.*, vol.29, no.3, pp. 171-189, May 2008.

[67] K. Zhang, B. Jiang, V. Cocquempot, and H. Zhang, ``A framework of robust fault estimation observer design for continuous-time/discrete-time systems,'' *Opt. Contr. App. Meth.*, vol.34, no.4, pp. 442-457, Aug. 2013.

[68] Z. Gao, and D. Ho, ``Proportional multiple-integral observer design for descriptor systems with measurement output disturbances,'' *IEE Pro. Contr. Theory App.*, vol.151, no.3, pp.279-288, May 2004.

[69] D. Koenig, ``Unknown input proportional multiple-integral observer design for linear descriptor systems: application to state and fault estimation,'' *IEEE Trans. Automat. Contr.*, vol.50, no.2, pp.212-217, Feb. 2005.

[70] Z. Gao, S. Ding, and Y. Ma, ``Robust fault estimation approach and its application in vehicle lateral dynamic systems,'' *Opt. Contr. App. Meth.*, vol.28, no.3, pp. 143-156, May 2007.

[71] Q. Zhang, and G. Besancon, ``An adaptive observer for sensor fault estimation in a class of uniformly observable non-linear systems,'' *Int. J. Mod. Indent. Contr.*, vol.4, No.1, pp.37-43, Jan. 2008.

[72] K. Zhang, B. Jiang, and V. Cocquempot, ``Adaptive observer-based fast fault estimation,'' *Int. J. Contr. Automat. Syst.,* vol. 6, no. 3, pp. 320-326, Jun. 2008.

[73] M. Gholizadeh, and F. Salmasi, ``Estimation of state of charge, unkown nonlinearities, and state of health of a lithium-ion battery based on a comprehensive unobservable model,'' *IEEE Trans. Ind. Electron.,* vol.61, no.3, pp.1335-1344, Mar. 2014.

[74] H. Alwi, and C. Edwards, ``Robust fault reconstruction for linear parameter varying systems using sliding mode observers,'' *Int. J. Robust Nonlin. Contr.*, vol.24, no.14, pp.1947-1968, Sep., 2014.

[75] X. Han, F. Emilia, and S. Sarah, ``Sampled-data sliding mode observer for robust fault reconstruction: A time-delay approach,'' *J. Franklin Inst.*, vol.351, no.4, pp. 2125-2142, Jun. 2014.

[76] Z. Gao, and H. Wang, ``Descriptor observer approaches for multivariable systems with measurement noises and application in fault detection and diagnosis,'' *Syst. Contr. Lett.*, vol.55, no.4, pp.304-313, Apr. 2006.

[77] Z. Gao, X. Shi, and S. Ding, ``Fuzzy state/disturbance observer design for T–S fuzzy systems with application to sensor fault estimation,'' *IEEE Trans. Syst. Man Cyber., part B,* vol.38, no.3, pp.875-880, Jun. 2008.

[78] J. Zhang, A. Swain, and S. Nguang, ``Robust sensor fault estimation scheme for satellite attitude control systems,'' *J. Franklin Inst.*, vol. 350, no.9, pp.2581-2604, Nov. 2013.

[79] Z. Gao, X. Dai, T. Breikin, and H. Wang, ``Novel parameter identification by using a high-gain observer with application to a gas turbine engine,'' *IEEE Trans. Ind. Inf.*, vol.4, no.4, pp.271-279, Nov. 2008.

[80] L. Mironovski, ``Functional diagnosis of linear dynamic systems,'' *Auto. Remo. Contr.,* vol.40, no.8, pp.1198-1205, Aug. 1980.

[81] E. Chow, and A. Willsky, ``Analytical redundancy and the design of robust detection systems,'' *IEEE Trans. Automat. Contr*., vol.29, no.7, pp.603-614, 1984.

[82] J. Gertler, Fault Detection and Diagnosis in Engineering Systems. New York: Marcel Dekker, 1998.

[83] S. Nguang, P. Zhang, and S. Ding, ``Parity relation based fault estimation for nonlinear systems: an LMI approach,'' *Int. J. Automat. Compute.*, vol.4, no.2, pp.164-168, Apr. 2007.

[84] Z. Zhang, J. Hu, and H. Hu, ``Parity space approach to fault detection based on fuzzy tree model,'' *Int. J. Adv. Comput. Tech*.,vol.5, no.2, pp.657-665, Jan. 2013.

[85] H. Odendaal, and T. Jones, ``Actuator fault detection and isolation: An optimized parity space approach,'' *Contr. Eng. Prac*., vol.26, no.5, pp.222-232, May 2014.

[86] W. Huang, and K. Huh, ``Fault detection and estimation for electromechanical brake systems using parity space approach,'' *J. Dyn. Sys., Meas., Contr.*, vol.137, no.1, Aug. 2014.

[87] N. Viswanadham, J. Taylor, and E. Luce, ``A frequency-domain approach to failure detection and isolation with application to GE-21 turbine engine control systems,'' *Contr:-Theory and Adv. Tech*., vol. 3, no.1, pp. 45-72, Mar. 1987.

[88] X. Ding, and P. Frank, ``Fault detection via factorization approach,'' *Syst. Contr. Lett*., vol.14, no.5, pp.431-436, Jun. 1990.

[89] M. Abid, A. Khan, W. Chen, and S. Ding, Optimal residual evaluation for nonlinear systems using post filter and threshold,'' *Int. J. Contr*., vol.84, no.3, pp.526-539, Mar. 2011.

[90] J. Hu, and M. Tsai, ``Design of robust stabilization and fault diagnosis for an auto-balancing two-wheeled cart,'' *Adva. Robotics*, vol.22, no.2, pp.319-338, Mar. 2008.

[91] M. Deng, I. Akira, and E. Kazunori, ``Fault detection system design for actuator of a thermal process using operator based approach,'' *Acta Automat. Sinica*, vol.36, no.4, pp.580-585, Apr. 2010.

[92] R. Mehra, and J. Peschon, ``An innovation approach to fault detection and diagnosis in dynamic systems,'' *Automatica*, vol.7, no.5, pp.637-640, Sep. 1971.

[93] A. Willsky, and H. Jones, ``A generalized likelihood ratio approach to the detection and estimation of jumps in linear systems,'' *IEEE Trans. Automat. Contr*., vol.21, no.1, pp.108-121, Feb. 1976.

[94] R. Da, and C. Lin, ``Sensitivity analysis algorithm for the state chi-square test,'' *J. Guid. Contr. Dynam.*, vol.19, no.1, pp.219-222, Jan. 1996.

[95] I. Nikiforov, V. Varavva, and V. Kireichikov, ``Application of statistical fault-detection algorithms to navigation system monitoring,'' *Automatica*, vol.29, no.5, pp. 1275-1290, Sep. 1993.

[96] S. Bogh, ``Multiple hypothesis-testing approach to FDI for the industrial actuator benchmark,'' *Contr. Eng. Practice*, vol.3, no.12, pp.1763-1768, Dec. 1995.

[97] R. Li, and J. Olson, ``Fault detection and diagnosis in a closed-loop nonlinear distillation process: application of extended Kalman filters,'' *Ind. Eng. Chem. Res.,* vol.30, no.5, pp 898–908, May 1991.

[98] H. Liu, D. Liu, C. Lu, and X. Wang, ``Fault diagnosis of hydraulic servo system using the unscented Kalman filter,'' *Asian J. Contr*., vol.16, no.6, pp.1713-1725, Nov. 2014.

[99] M. Laila, N. Naveen, and K. Vishakh, ``Comparison of estimation capabilities of extended and unscented Kalman Filter in an RLV,'' *Int. J. Adv. Res. in Elec. Electron. Instrument. Eng*., vol. 2, no.7, pp.3480-3488, Jul. 2013.

[100] C. Hajiyev, H. Soken, ``Robust adaptive Kalman filter for estimation of UAV dynamics in the presence of sensor/actuator faults,'' *Aerospace Sci. Tech.*, vol.28, no.1, pp.376–383, Jul. 2013.

[101] A. Izadian, ``Self-tuning fault diagnosis of MEMS,'' *Mechatronics*, vol.23, no.8, pp.1094-1099, Dec. 2013.

[102] F. Hmida, K. Khemiri, J. Ragot, and M. Goss, ``Three-stage Kalman filter for state and fault estimation of linear stochastic systems with unknown inputs,'' *J. Franklin Inst*., vol.349, no.7, pp.2369–2388, 2012, Sep. 2012.

[103] S. Helm, M. Kozek, and S. Jakubek, ``Combustion torque estimation and misfire detection for calibration of combustion engines by parametric Kalman filtering,'' *IEEE Trans. Ind. Electron.,* vol.59, no.12, pp.4326-4337, Nov. 2012.

[104] P. Lall, R. Lowe, and K, Goebel, ``Prognostics health management of electronic systems under mechanical shock and vibration using Kalman filter models and metrics,'' *IEEE Trans. Ind. Electron*., vol.59, no.11, pp.4301-4314, Nov. 2012.

[105] G. Foo, X. Zhang, and D. Vilathgamuwa, ``A sensor fault detection and isolation method in interior permanent-magnet synchronous motor drives based on an extended Kalman filter,'' *IEEE Trans. Ind. Electron.,* vol.60, no.8, pp.3485-3495, Aug. 2013.

[106] C. Bakiotis, J. Raymond, and A. Pault, ``Parameter and discriminant analysis for jet engine mechanical state diagnosis,'' *Proc. Conf. Decision Contr*., pp.648-650, Fort Lauderdale, Dec. 1979.

[107] S. Simani, C. Fantuzzi, R. Patton, Model-based Fault Diagnosis in Dynamic Systems Using Identification Techniques. Berlin, Germany: Springer, 2002.

[108] R. Doraiswami, C. Diduch, and J. Tang, ``A new diagnostic for identifying parametric faults,'' *IEEE Trans. Contr. Syst. Tech.*, vol.18, no.3, pp.533-544, May 2010.

[109] M. Dohler, and L. Mevel, ``Subspace-based fault detection robust to changes in the noise covariances,'' *Automatica*, vol.49, no.9, pp.2734-2743, Sep. 2013.

[110] A. Akhenak, E. Duviella, L. Bakoa, and S. Lecoeuchea, ``Online fault diagnosis using recursive subspace identification: application to a dam-gallery open channel system,'' *Contr. Eng. Practice*, vol.21, no.6, pp.797-806, Jun. 2013.

[111] H. Wang, H., and W. Lin, ``Applying observer based FDI techniques to detect faults in dynamic and bounded stochastic distributions,'' *Int. J. Control*, vol.73, no.15, pp. 1424–1436, Aug. 2000.

[112] Z. Gao, H. Wang, and T. Chai, ``A robust fault detection filtering for stochastic distribution systems via descriptor estimator and parametric gain design,'' *IET Contr. Theory Appli*., vol.1, no.5, pp.1286-1293, Jan, 2007.

[113] S. Cao, Y. Yi, and L. Guo, ``Anti-disturbance fault diagnosis for non-Gaussian stochastic distribution systems with multiple disturbances,'' *Neurocomput*., vol.136, no.20, pp.315–320, Jul. 2014.

[114] L. Wu, and D. Ho, ``Fuzzy filter design for Itô stochastic systems with application to sensor fault detection,'' *IEEE Trans. Fuzzy Syst*., vol.17, no.1, pp.233-242, Feb. 2009.

[115] M. Liu, X. Cao, and P. Shi, ``Fault estimation and tolerant control for fuzzy stochastic systems,'' *IEEE Trans. Fuzzy Syst*., vol.21, no.2, pp.221-229, Apr. 2012.

[116] H. Dong, Z. Wang, and H. Gao, ``Fault detection for Markovian jump systems with sensor saturations and randomly varying nonlinearities,'' IEEE Trans. Circuits Syst. I, vol.59, no.10, pp.2354-2362, Oct. 2012.

[117] M. Sampath, R. Sengupta, S. Lafortune, K. Sinnamohideen, and D. Teneketzis, ``Diagnosability of discrete-event systems,'' *IEEE Trans. Automat. Contr*., vol.40, no.9, pp.1555-1575, Sep. 1995.

[118] L. Carvalho, M. Moreira, J. Basilio, and S. Lafortune, ``Robust diagnosis of discrete-event systems against permanent loss of observations,'' *Automatica,* vol.49, no.1, pp.223-231, Jan. 2013.

[119] Y. Pencole, and M. Cordier, ``A formal framework for the decentralized diagnosis of large scale discrete event systems and its application to telecommunication network,'' *Artif. Intell*., vol.164, no.2, pp.121-170, May 2005.

[120] A. Shumann, Y. Pencole, and S. Thiebaux, ``A spectrum of symbolic on-line diagnosis approaches,'' *Proc. 19th National Conf. Artif. Intell*., pp.335-340, 2007.

[121] A. Grastien, and A. Anbulagan, ``Diagnosis of discrete event systems using satisfiability algorithms: a theoretical and empirical study,'' *IEEE Trans. Automat. Contr*., vol.58, no.12, pp.3070-3083, Dec. 2013.

[122] M. Cabasino, A. Giua, and C. Seatzu, ``Fault detection for discrete event systems using Petri nets with unobservable transitions,'' *Automatica,* vol.46, no.9, pp.1531-1539, Sep. 2010.

[123] M. Dotoli, M. Fanti, A. Mangini, and W. Ukovich, ``On-line fault detection in discrete event systems by Petri nets and integer linear programming,'' *Automatica*, vol.45, no.11, pp.2665-2672, Nov. 2009.

[124] D. Lefebvre, ``On-line fault diagnosis with partially observed Petri nets,'' *IEEE Trans. Automat. Contr*., vol.59, no.7, pp.1919-1924, Jul. 2014.

[125] N. Meskin, K. Khorasani, and C. Rabbath, ``A hybrid fault detection and isolation strategy for a network of unmanned vehicles in presence of large environmental disturbances,'' *IEEE Trans. Contr. Syst. Tech.*, vol.18, no.6, pp.1422-1429, Nov. 2010.

[126] M. Daigle, X. Koutsoukos, and G. Biswas, ``A qualitative event-based approach to continuous systems diagnosis,'' *IEEE Trans. Contr. Syst. Tech.,* vol.17, no.4, pp.780-793, Jul. 2009.

[127] F. Zhao, K. Koutsoukos, H. Haussecker, J. Reich, and P. Cheung, ``Monitoring and fault diagnosis of hybrid systems,'' *IEEE Trans. Syst. Man Cybern*., vol.35, no.6, pp.1225-1240, Dec. 2005.

[128] J. Guo, D. Ji, S. Du, S. Zeng, and B. Sun, ``Fault diagnosis of hybrid systems using particle filter based hybrid estimation algorithm,'' *Chemical Eng. Tran*., vol.33, no.1, pp.145-150, Sep. 2013.
[129] S. Arogeti, D. Wang, C. Low, and M. Yu, ``Fault detection isolation and estimation in a vehicle steering system,'' *IEEE Trans. Ind. Electron.,* vol.59, no.12, pp.4810-4820, Dec. 2012.
[130] M. Yu, and D. Wang, ``Model-based health monitoring for a vehicle steering system with multiple faults of unknown types,'' *IEEE Trans. Ind. Electron.,* vol.61, no.7, pp.3574-3586, Jul. 2014.
[131] P. Levy, S. Arogeti, and D. Wang, ``An integrated approach to model tracking and diagnosis of hybrid systems,'' *IEEE Trans. Ind. Electron*, vol.61, no.4, pp.1024-1040, Apr. 2014.
[132] M. Yu, D. Wang, and M. Luo, ``Model-based prognosis for hybrid systems with mode-dependent degradation behaviors,'' *IEEE Trans. Ind. Electron*, vol.61, no.1, pp.546-554, Jan. 2014.
[133] G. Walsh, H. Ye, and L. Bushnell, ``Stability analysis of networked control systems,'' *IEEE Trans. Contr. Syst. Tech*., vol.10, no.3, pp.438-446, May 2002.
[134] D. Zhou, X. He, Z. Wang, G. Liu, and Y. Ji, ``Leakage fault diagnosis for an internet-based three-tank system: an experimental study,'' *IEEE Trans. Contr. Syst. Tech.*, vol.20, no.4, pp.857-870, Jul. 2012.
[135] X. He, Z. Wang, and D. Zhou, ``Robust fault detection for networked systems with communication delay and data missing,'' *Automatica*, vol.45, no.11, pp.2634-2639, Nov. 2009.
[136] X. He, Z. Wang, Y. Liu, and D. Zhou, ``Least-square fault detection and diagnosis for networked sensing systems using a direct state estimation approach,'' *IEEE Trans. Ind. Inf*., vol.9, no.3, pp.1670-1679, Aug. 2013.
[137] S. Alavi, and M. Saif, ``Fault detection in nonlinear stable systems over lossy networks,'' *IEEE Trans. Contr. Syst. Tech.*, vol.21, no.6, pp.2129-2142, Nov. 2013.
[138] S. Rahme, Y. Labit, F. Gouaisbaut, and T. Floquet, ``Second order sliding mode observer for anomaly detection in TCP networks: from theory to practice,'' *Proc. Conf. Decis. Contr*., pp.5120-5125, Atlanta, USA, Dec. 2010.
[139] S. Rahme, Y. Labit, F. Gouaisbaut, and T. Floquet, ``Sliding modes for anomaly observation in TCP networks: from theory to practice,'' *IEEE Trans. Contr. Syst. Tech.*, vol.21, no.3, pp.1031-1038, May. 2013.
[140] Y. Lei, Y. Yuan, and J. Zhao, ``Model-based detection and monitoring of the intermittent connections for CAN networks,'' *IEEE Trans. Ind. Electron*., vol.61, no.6, pp.2912-2921, Jun. 2014.
[141] S. Kelkar, and R. Kamal, ``Adaptive fault diagnosis algorithm for controller area network,'' *IEEE Trans. Ind. Electron*, vol.61, no.10, pp.5527-5537, Oct. 2014.
[142] S. Stankovic, M. Stankovic, and D. Stipanovic, ``Consensus based overlapping decentralized estimation with missing observation and communication faults,'' *Automatica*, vol.45, no.6, pp.1397-1406, Jun. 2009.
[143] C. Keliris, M. Polycarpou, and T. Parisini, ``A distributed fault detection filtering approach for a class of interconnected continuous-time nonlinear systems,'' *IEEE Trans. Automat. Contr*., vol.58, no.8, pp.2032-2047, Aug. 2013.
[144] P.Menon, and C. Edwards, ``Robust fault estimation using relative information in linear multi-agent networks,'' *IEEE Trans. Automat. Contr*., vol.59, no.2, pp.477-482, Feb. 2014.
[145] N. Lechvin, and C. Rabbath, ``Decentralized detection of a class of non-abrupt faults with application to formations of unmanned airships,'' *IEEE Trans. Contr. Syst. Tech*., vol.17, no.2, pp.484-493, Mar. 2009.
[146] A. El-Zonkoly, ``Fault diagnosis in distribution networks with distributed generation,'' *Electric Power Syst. Res.*, vol.81, no.7, pp.1482-1490, Jul. 2011.
[147] H. Chen, and S. Lu, ``Fault diagnosis digital method for power transistors in power converters of switched reluctance motors,'' *IEEE Trans. Ind. Electron*., vol.60, no.2, pp.749-763, Feb. 2013.
[148] N. Freire, J. Estima, and A. Cardoso, ``Open-circuit fault diagnosis in PMSG drives for wind turbine applications,'' *IEEE Trans. Ind. Electron.,* vol.60, no.9, pp.3957-3967, Sep. 2013.
[149] M. Shahbazi, E. Jamshidpour, P. Poure, S. Saadate, and M. Zolghadri, ``Open and short-circuit switch fault diagnosis for noisolated DC-DC converters using field programmable gate array,'' *IEEE Trans. Ind. Electron.,* vol.60, no.9, pp.4136-4145, Sep. 2013.
[150] J. Estima, and A. Cardoso, ``A new algorithm for real-time multiple open-circuit fault diagnosis in voltage-fed PWM motor drives by the reference current errors,'' *IEEE Trans. Ind. Electron.,* vol.60, no.8, pp.3496-3505, Aug. 2013.
[151] M. Bouzid, and G. Champenois, ``New expression of symmetrical components of the inductor motor under stator faults,'' *IEEE Trans. Ind. Electron*., vol.60, no.9, pp.4093-4102, Sep. 2013.
[152] P. Samara, G. Fouskitakis, J. Sakellariou, and S. Fassois, ``A statistical method for the detection of sensor abrupt faults in aircraft control systems,'' *IEEE Trans. Contr. Syst. Tech.,* vol.16, no.4, pp.789-798, Jul. 2008.
[153] L. Hong, and J. Dhupia, ``A time domain approach to diagnose gearbox fault based on measured vibration signals,'' *J. Sound Variation*, vol.333, no.7, pp.2164-2180, Mar. 2014.
[154] V. Do, and U. Chong, ``Signal model-based fault detection and diagnosis for induction motors using features of vibration signal in two-dimension domain,'' *J. Mechan. Eng*., vol.57, no.9, pp.655-666, Sep. 2011.
[155] M. Shahriar, T. Ahsan, and U. Chong, ``Fault diagnosis of induction motors utilizing local binary pattern-based texture analysis,'' EURASIP *J. Image Video Proc*., vol.2013, no.1, 11 pages, May 2013.
[156] G. Joksimovic, J. Riger, T. Wolbank, N. Peric, and M. Vasak, ``Stator-current spectrum signature of healthy cage rotor induction machines,'' *IEEE Trans. Ind. Electron.,* vol.60, no.9, pp. 4025-4033, Sep. 2013.
[157] X. Gong, and W. Qiao, ``Bearing fault diagnosis for direct-drive wind turbines via current-demodulated signals,'' *IEEE Trans. Ind. Electron.,* vol.60, no.8, pp.3419-3428, Aug. 2013.
[158] N. Pan, X. Wu, Y. Chi, X. Liu, and C. Liu, ``Combined failure acoustical diagnosis based on improved frequency domain blind deconvolution,'' *J. Phy.: Conf. Series*, vol.364, no.1, pp.1-7, Jan. 2012.
[159] Z. Feng, and M. Zuo, ``Fault diagnosis of planetary gearboxes via torsional vibration signal analysis,'' *Mech. Syst. Proc*., vol.36, no.2, pp.401-421, Apr. 2013.
[160] S. Nandi, T. Ilamparithi, S. Lee, and D. Hyun, ``Detection of eccentricity faults in induction machines based on nameplate parameters,'' *IEEE Trans. Ind. Electron*., vol.58, no.5, pp.1673-1683, May 2011.
[161] Y. Gritli, L. Zarri, C. Rossi, F. Filippetti, G. Capolino, and D. Casdei, ``Advanced diagnosis of electrical faults in wound-rotor induction machines,'' *IEEE Trans. Ind. Electron.,* vol.60, no.9, pp.4012-4024, Sep. 2013.
[162] E. Cabal-Yepez, A. Garcia-Ramirez, R. Romero-Troncoso, A. Garcia-Perez, and R. Osornio-Rios, ``Reconfigurable monitoring system for time-frequency analysis on industrial equipment through STFT and DWT,'' *IEEE Trans. Ind. Inf*., vol.9, no.2, pp.760-771, May 2013.
[163] R. Yan, and R. Gao, ``Hilbert-Huang transform-based vibration signal analysis for machine health monitoring,'' *IEEE Trans. Instrum. Meas*., vol.55, no.6, pp.2320-2329, Dec. 2006.
[164] R. Burnett, J. Watson, and S. Elder, ``The application of modern singal processing techniques for use in rotor fault detection and location within three-phase induction motors,'' *Signal Processing*, vol.49, no.1, pp.57-70, Feb. 1996.
[165] B. Tang, W. Liu, and T. Song, ``Wind turbine fault diagnosis based on Morlet wavelet transformation and Wigner-Ville distribution,'' *Renewable Ener.* Vol.35, no.12, pp.2862-2866, Dec. 2010.
[166] V. Climente-Alarcon, J. Antonino-Daviu, M. Riera-Guasp, and M. Vlcek, ``Induction motor diagnosis by advanced notch FIR filters and the Wigner-Ville distribution,'' *IEEE Trans. Ind. Electron.,* vol.61, no.8, pp.4217-4227, Aug. 2014.
[167] L. Xiang, and X. Yan, ``A self-adaptive time-frequency analysis method based on local mean decomposition and its application in defect diagnosis,'' *J. Vibrat. Contr*., Jun. 2014.

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