A Survey of Fault Diagnosis and Fault-Tolerant Techniques—Part II: Fault Diagnosis With Knowledge-Based and Hybrid/Active Approaches

Article *in* IEEE Transactions on Industrial Electronics · June 2015

DOI: 10.1109/TIE.2015.2419013

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***Abstract*—This is the second-part paper of the survey on fault diagnosis and fault-tolerant techniques, where fault diagnosis methods and applications are overviewed, respectively, from the knowledge-based and hybrid/active viewpoints. With the aid of the first-part survey paper, the second-part review paper completes a whole overview on fault diagnosis techniques and their applications. Comments on the advantages and constraints of various diagnosis techniques, including model-based, signal-based, knowledge-based, and hybrid/active diagnosis techniques, are also given. An overlook on the future development of fault diagnosis is presented.**

***Index Terms*—Active fault diagnosis, analytical redundancy, fault tolerance, hybrid fault diagnosis, knowledge-based fault diagnosis, real-time monitoring.**

I. Introduction

FAULT diagnosis techniques are composed of hardware-redundancy-based fault diagnosis and analytical-redundancy-based fault diagnosis. The analytical redundancy technique has become the main stream of fault diagnosis research since the 1980s, which can be generally categorized into the classes of model-based fault diagnosis, signal-based fault diagnosis, knowledge-based fault diagnosis, hybrid fault diagnosis, and active fault diagnosis. For model-based fault diagnosis approaches, a system model, which explicitly describes the relationship among the system variables, is available to the designer. Based on the model, fault diagnosis schemes/algorithms can be designed and then implemented online for monitoring and diagnosing the real-time system/process. For signal-based fault diagnosis methods, the signal pattern/symptom of a system under a healthy status is *a priori*, and the fault diagnosis is carried out by checking the consistency between the known healthy signal pattern and the signal symptom of the real-time process extracted either by using time-domain, frequency-domain, or time-frequency signal processing techniques. For complicated industrial processes, a large amount of historical data, rather than a model or a signal pattern, is available. The underlying knowledge, which implicitly represents the dependence of the system variables, can be extracted by using various artificial intelligent techniques and the available historic data. Fault diagnosis is carried out by checking the consistency of the obtained underlying knowledge and the real-time system feature extracted from the online monitored data. Hybrid fault diagnosis is an integration or combination of more than one diagnosis method. Active fault diagnosis is to enhance the detectability of potential faults by injecting a suitably designed input signal under a test interval so that faulty modes can be distinguished from normal modes quickly and accurately. In the first-part survey paper [1], model-based and signal-based diagnosis approaches were reviewed. In the second-part review paper, knowledge-based fault diagnosis, hybrid fault diagnosis, and active fault diagnosis will be reviewed comprehensively. The distinctive advantages and various constraints of these diagnosis methods are to be discussed. Moreover, the overlook on the future development of the fault diagnosis will be presented.

The organization of this paper is as follows. After the introduction in Section I, knowledge-based fault diagnosis methods are reviewed in Section II. The hybrid and active fault diagnosis methods are overviewed in Section III. This paper is ended in Section IV with the conclusion and comments on the future development of the fault diagnosis and applications.

Manuscript received November 13, 2014; revised January 24, 2015 and March 8, 2015; accepted March 19, 2015. Date of publication April 1, 2015; date of current version May 8, 2015.

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Digital Object Identifier 10.1109/TIE.2015.2419013

II. Knowledge-Based Fault Diagnosis Methods

Different from model-based methods and signal-based approaches that require either an *a priori* known model or signal patterns, knowledge-based fault diagnosis methods start from where only a large volume of historic data is available. Applying a variety of artificial intelligent techniques (either symbolic intelligence or computing intelligence) to the available historic data of the industrial processes, the underlying knowledge, which implicitly represents the dependence of the system

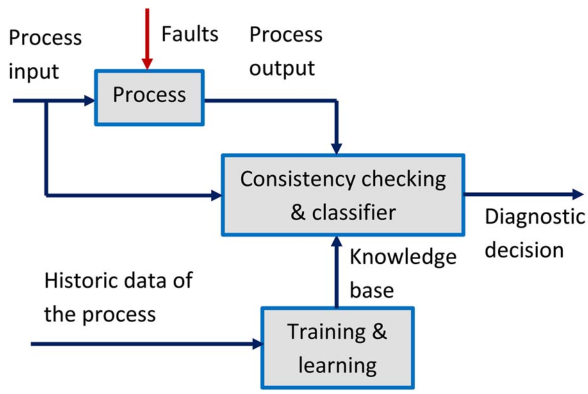

Fig. 1. Schematic of the knowledge-based fault diagnosis.

variables, can be extracted. The consistency between the observed behavior of the operating system and the knowledge base is then checked, leading to a fault diagnosis decision with the aid of a classifier. It is worthy to point out that model-based diagnosis methods, signal-based diagnosis approaches, and knowledge-based diagnosis algorithms all have to utilize real-time data when doing real-time monitoring and online fault diagnosis; however, only knowledge-based diagnosis approaches need to employ a large volume of historic data available. From this point of view, knowledge-based fault diagnosis is also referred to as *data-driven fault diagnosis*. The schematic of the knowledge-based fault diagnosis is depicted in Fig. 1.

The extraction process of the knowledge base can be either qualitative or quantitative in nature. Therefore, knowledge-based fault diagnosis methods can be classified into qualitative methods and quantitative methods.

A. Qualitative Knowledge-Based Fault Diagnosis

One of the most known qualitative fault diagnosis methods is the *expert-system*-based method. The expert system emerged in the late 1960s as a branch of artificial intelligence, which is a rule-based system by presenting a human's expertise in a set of rules [2], [3]. Expert-system-based fault diagnosis was initialized in the 1980s [4], [5], which was performed based on the evaluation of online monitored data in terms of a set of rules, which is learned by human experts from past experience. Owing to the advantages such as ease of development, transparent reasoning, the ability to reason under uncertainty, and the capability to explain the solutions provided, expert-system-based fault diagnosis methods received much attention, particularly in the 1980s and the 1990s, which have been successfully applied to a variety of engineering systems such as gas turbine combustion chambers [6], energy systems [7], chemical processes [8], vehicles [9], etc. However, it is noticed that expert-system-based fault diagnosis methods are system specific, having low generality and low expandability. Motivated by this, a task-based diagnosis expert system has been proposed in [10] recently, where object-oriented knowledge representation methods were utilized so that the rules of a specific machine can be flexibly customized on the basis of general rules. In [11], a universal fault diagnostic expert system framework was presented, where the object-oriented paradigm and the rule-based expert system were integrated, providing a flexible and powerful environment for the fault diagnosis process.

In many practical industrial processes, process malfunctions leave a distinct trend in the sensors monitored, which can be suitably employed to identify the underlying abnormalities in the process. Therefore, it is motivated to classify and analyze the process trends. *Qualitative trend analysis* (QTA) is a data-driven technique to identify the process trends from noisy process data and to associate the extracted trends to fault trends in the database, which was comprehensively reviewed in [12]. The QTA technique has been widely applied to fault diagnosis in complex industrial processes, particularly for chemical processes. Recent developments of the QTA have integrated with other qualitative tools such as signed directed graphs (SDGs) in order to enhance their advantages while compensating for their disadvantage. For instance, an integrated SDG and QTA framework was proposed in [13] for incipient fault diagnosis by combining the completeness property of an SDG and the high diagnostic resolution property of the QTA. In [14], an SDG–QTA fault diagnosis approach was addressed for a distillation power unit, which not only met the fundamental requirements of diagnosis, such as correctness, completeness, and real time, but also provided a good resolution.

B. Quantitative Knowledge-Based Fault Diagnosis

A quantitative knowledge-based method is to essentially formulate the diagnostic problem solving as a pattern recognition problem. Quantitative information (or features) can be extracted by using either statistical or nonstatistical methods. Therefore, the quantitative knowledge-based fault diagnosis can be roughly classified into statistical-analysis-based fault diagnosis and nonstatistical-analysis-based fault diagnosis.

1) Statistical-Analysis-Based Data-Driven Fault Diagnosis: Under a statistical framework, the quantitative knowledge-based fault diagnosis methods are mainly composed of principal component analysis (PCA), partial least squares (PLS), independent component analysis (ICA), statistical pattern classifiers, and the most recently developed support vector machine (SVM). It is evident that the aforementioned methods require a large amount of training data to capture the key characteristics of the process by using statistical analysis.

PCA is the most popular statistically-based monitoring technique, which is utilized to find factors with a much lower dimension than the original data set so that the major trends in the original data set can be properly described. PCA-based fault diagnosis methods have been investigated in depth and have successful applications in complex industrial systems. For instance, a nonlinear extension of the PCA was developed in [15] for diagnosing diesel engines. For a time-varying industrial process (e.g., a nonisothermal continuous stirred tank reactor system), a recursive PCA fault diagnosis method was presented in [16]. Owing to the ability of denoising original signals and improving the signal-to-noise ratio, probabilistic PCA-based fault diagnosis techniques were employed to monitor a rolling bearing with an outer race fault [17]. By integrating y-indexes, residual errors, and faulty sensor identification indexes with the PCA, two readily implementable and computationally efficient fault diagnosis approaches were addressed for gas turbine engines [18].

PLS is one of the dominant data-driven tools for complex industrial processes. Recent development of PLS-based monitoring and fault diagnosis can be found in [19]–[21]. Specifically, in [19], a data-driven scheme of key performance indicator prediction and diagnosis was proposed for both static and dynamic processes, which offered an alternative solution to the PLS method with simplified computation procedures. By combining kernel-based PLS discriminant analysis techniques and pseudosample projection, a fault diagnosis method was presented in [20], providing efficient fault discrimination and enabling a correct identification of the discriminant variables in complex nonlinear processes. An improved structure, i.e., total projection to latent structures (T-PLS), was addressed in [21] on the basis of further decomposition for the obtained PLS structure. The proposed T-PLS-based method can well detect quality-relevant faults in industrial processes subjected to a variety of raw materials and changeable control conditions.

ICA plays an important role in real-time monitoring and diagnosis for practical industrial processes as it allows latent variables not to follow a Gaussian distribution. Recently, a kernel-ICA-based fault isolation method was proposed in [22] for non-Gaussian nonlinear processes. In [23], defect detection was investigated for solar modules by using ICA basis images detection. In [24], an ICA-based fault diagnosis technique was applied to the monitoring and diagnosis of a rolling-element bearing.

As a matter of fact, data-driven statistical tools such as the PCA, the PLS, and the ICA have been widely employed in feature extraction for microarray gene expression data, which facilitate and ease the understanding of biological processes [25]. On the other hand, a microarray enables expressions of tens of thousands of genes to be represented on a small array of colored image dots, which may be utilized for a quick fault diagnosis for industrial processes. Motivated by the microarray visualization and utilizing simple statistical analysis of the measured values of different sensors and the graphical synopsis of the results of such analysis, a quick diagnosis of the key variables/steps that cause the fault in the final quality was achieved in [26].

The *SVM* is a relatively new machine learning technique relying on statistical learning theory, which is capable of achieving high generalization and of dealing with problems with low samples and high input features. The SVM is regarded as a potential technique for classifying all kinds of data sets. The initial attempts of applying the SVM to condition monitoring and fault diagnosis began in the late 1990s [27], [28]. The SVM-based machine condition monitoring and fault diagnosis methods dated to 2006 were well documented and reviewed in [29]. Recent results of the SVM-based fault diagnosis can be found in [30]–[33]. Specifically, by integrating a kernel function and cross validation, an SVM-based fault diagnosis approach was proposed in [30] for the Tennessee Eastman process, which showed a superior fault detection ability over the conventional PLS algorithm. With the aid of a genetic algorithm for parameter tuning, an SVM-based fault diagnosis method was presented in [31], which showed improving diagnosis performance. Utilizing k-nearest neighbor (kNN) algorithms to estimate plausible values to replace the missing values in the data set before SVM learning, an effective SVM-based fault diagnosis technique was addressed in [32] for power transformers. In [33], a smart SVM-based functional fault diagnosis method that exploited multiple kernel functions and utilized incremental learning was proposed. By leveraging a linear combination of single kernels, the multikernel SVM method can achieve accurate faulty component classification on the basis of errors observed, whereas incremental learning can allow the diagnosis system to quickly adapt to a new error observation, leading to even more accurate fault diagnosis.

2) Nonstatistical-Analysis-Based Data-Driven Fault Diagnosis: Owing to its powerful ability in nonlinear approximation and adaptive learning, A *neutral network* (NN) has been the most well-established nonstatistical-based data-driven fault diagnosis tool. In terms of topology, the NN can be classified into radial basis networks, recurrent dynamic networks, self-organizing maps, backpropagation networks, and extension networks. According to the learning strategy, NN-based fault diagnosis can be categorized into supervised-learning-based fault diagnosis and unsupervised-learning-based fault diagnosis. By using unsupervised learning, the knowledge base can be extracted from the historical data to emulate normal system behavior, which is utilized to check whether the behavior of the real-time process deviates from the normal system behavior. By using supervised learning, the knowledge bases for normal systems and faulty conditions are all extracted, which are then utilized for real-time monitoring. Recent developments of the NN can be found in a variety of real-time applications, e.g., for combustion engines [34], steam turbine generators [35], nuclear processes [36], induction machines [37], [38], and power network quality [39].

Fuzzy logic (FL) is an approach of partitioning a feature space into fuzzy sets and utilizing fuzzy rules for reasoning, which essentially provide approximate human reasoning. FL has been successfully employed for fault diagnosis. For instance, in [40], FL was employed to represent a fuzzy knowledge base that was extracted from the current analysis and applied to detect misfiring in the switches in a pulsewidth modulation (PWM) source inverter induction motor drive. Recent developments have shown an interest to combine FL with other knowledge-based techniques such as expert systems or an NN for solving an engineering-oriented diagnosis issue or getting better diagnosis performance. For instance, in [8], by integrating FL and an expert system, a real-time fault diagnosis algorithm was developed and tested in a real industry situation by using the Advanced Reactive System Screening Tool. In [41], a novel architecture of a fuzzy-neural data fusion engine was proposed, which was composed of three layers for monitoring and diagnosis. The first layer utilized the known thresholds of the normal operating conditions to monitor process anomalies. The second layer was composed of the self-organizing FL system that was trained offline by using previously observed normal behavioral patterns. An online processing engine was used to check the similarity between the current system behavior and the normal behavioral pattern by interpreting each fuzzy rule of the FL system. The third layer employed an NN predictor to process the temporary historical data so that the expected near-future behavioral patterns can be predicted, where the predicted values were used to replace these missing data to maintain the coherent status awareness of the monitored system.

3) Joint Data-Driven Fault Diagnosis: In some practical applications, the statistic and nonstatistic fault diagnosis data-driven methods are often utilized jointly. For instance, in [42], a Bayesian network and a recurrent NN were integrated to diagnose and isolate faults in induction motors, where the NN was used to train the data from the system under normal operating conditions and known faulty conditions, whereas the stochastic Bayesian network was employed to produce random residuals. In [43], a combined algorithm of dynamic PCA and a feedforward propagation NN was applied to detect stator insulation failures, broken rotor bars, and bearing faults. The PCA was used to extract distinctive features called residuals, which were then sent to the NN for training to produce signals to identify potential faults. The algorithm was real time implemented by utilizing Matlab, C++, and a National Instruments data acquisition (DAQ) board. In [44], based on a fuzzy SVM and a self-organizing map NN, a fault diagnosis method was presented to monitor and diagnose rotating machinery systems, which showed satisfactory classification precision for systems subjected to multifaults.

A supervised method and an unsupervised method are two major training and search manners in data-driven fault diagnosis. For the unsupervised approach, the data recorded from the normal operation of the practical system are trained to form a knowledge base, which is then utilized to monitor the deviations against a real-time process. In the supervised method, a classifier is trained on the annotated historical data recorded from both normal and faulty conditions, which is then employed for fault prediction. The supervised and unsupervised methods have their own advantages and disadvantages. In order to enhance their advantages, a natural idea is to combine the supervised method and the unsupervised method for fault diagnosis. Recently, a cold start fault detection framework was proposed in [45], where only normal operating data were available at the beginning and the faulty operation data became available as the faults occur. The proposed method integrated decisions from the initial unsupervised training and the incrementally updated supervised training, leading to an overall improvement in the accuracy of the fault detection.

III. Hybrid and Active Fault Diagnosis Approaches

A. Hybrid Fault Diagnosis Approach

Model-based, signal-based, and knowledge-based fault diagnosis methods have their *distinctive advantages and various constraints*. Specifically, model-based fault diagnosis can monitor and diagnose unknown faults by using a small amount of real-time data, but it requires an explicit model representing the input–output relationship; the diagnosis performance relies on the model accuracy. On the other hand, signal-based and knowledge-based approaches do not require an explicit or complete model, which are particularly suitable for monitoring and diagnosis for complex industrial processes where explicit system models are unavailable or challenging to derive. The signal-based method generally extracts the major features of the output signals for fault diagnosis, but it pays less attention on system dynamic inputs, whose diagnosis performance may be thus degraded under unknown input disturbances or unbalanced conditions (e.g., in power supplies or loads). Due to the high dependence on a large amount of historical data for training, the knowledge-based method suffers high computational costs and may not work well for identifying unknown fault types. In order to leverage the strength of the various fault diagnosis methods, an integration or combination of two or more fault diagnosis methods, which is called a hybrid fault diagnosis approach, is often exploited for a variety of engineering applications. For instance, in [46], the signal-based method and the data-driven method were hybridized to monitor and diagnose plastic bearing faults, where a statistical approach was utilized to separate the outer race fault from other types of faults based on the frequency-domain fault features extracted by using the fast Fourier transform, and other types of faults were diagnosed using the data-driven kNN fault classifier on the basis of time-domain features extracted by a time-domain signal-based algorithm. In [47], a hybrid signal-based and data-driven method was presented for the detection and diagnosis of faults in induction motors, where a number of features sensitive to electrical and mechanical faults were extracted by signal processing (including spectral analysis), and a data-driven classifier, which is called artificial ant clustering, was then employed to classify operation modes, enabling a diagnostic decision by checking the degree of resemblance between the new data and the obtained knowledge base (classified operation modes). By integrating signal processing and data-driven techniques, a vibration-analysis-based fault diagnosis algorithm was addressed in [48] for diagnosing interturn faults in induction machines, where a dual tree complex wavelet transform (WT) was used to capture features (faults or imbalances) from the measured vibration signals, and the PCA and the probabilistic NN were employed as classifiers to distinguish healthy from faulty features. In [49], a WT signal processing method was used to extract the features from stator currents, the data-based PCA method was employed for dimension reduction and the elimination of linear dependence of the features, and the fuzzy SVM was then utilized as classifiers, enabling the detection of eccentricity occurrence and the determination of the fault type and degree in a permanent-magnet synchronous generator motor. In [50], a hybrid data-driven and model-based fault diagnosis method was proposed for chemical reactors subjected to high nonlinearities and a high variability of dynamics. The SVM was implemented for fault detection, but it was found to have difficulty in locating faults due to the highly transitional dynamics. In order to enhance the fault isolation ability, an observer, which is based on a simplified initial model, was combined to the SVM, where the model was corrected and updated by the information provided by the SVM in the case without faults. The SVM-observer algorithm showed effectiveness in isolating the faults.

B. Active Fault Diagnosis Approach

It is worthy to point out that the aforementioned fault diagnosis methods are not invasive; in other words, the implementation of the monitoring and the diagnosis does not disturb the real-time performance of the industrial processes. On the other hand, in order to enhance the detectability of potential faults in some practical systems, a suitably designed input signal would be allowed to inject into the dynamic processes under a test interval so that faulty modes can be distinguished from normal modes quickly and accurately. This kind of fault diagnosis is called *active fault diagnosis*, where the adverse effects of the added auxiliary input signal on the real-time system performance must be minimized. The early attempts to formulate and solve active fault detection were based on the idea of generating an excitation signal that affects the statistics of the sequential probability ratio test [51], [52], which is called the *stochastic active fault diagnosis* method. In parallel, *deterministic active fault detection* was initialized in [53] in a multimodel framework, where two uncertain candidate models were used to represent nominal and fault systems, respectively, and an auxiliary signal with minimum energy was designed to identify the correct model on a given test period. An extended work can be found in [54], which permitted active fault detection for multiple faults occurring either sequentially or simultaneously. Recently, a hybrid stochastic–deterministic active fault diagnosis method has been proposed in [55], which provided a worst case guarantee of fault diagnosis within a time interval while maximizing the probability of fault diagnosis at some earlier time. The presented hybrid method reduced the average time required for diagnosis and the conservatism of the excitation signal. Recent developments have paid attention to active fault diagnosis under a closed-loop control framework [56], [57]. Specifically, a unified formulation of active fault detection and a control problem was addressed in [56] under a stochastic framework. Three special cases of active fault diagnosis were investigated, including active detector and controller, active detector and input signal generator, and an active detector with a given input signal generator, respectively. The first case was to seek a desired compromise between optimal control and optimal fault detection. The second case was to generate an optimal input signal to improve fault detection. The last case was to design an optimal detector whose decisions can excite the monitored system through the given input signal generator. The aforementioned three cases were formulated as stochastic optimal control problems, which improved the quality of fault detection and provided better understanding on how closed-loop information affected the quality of fault detection. In [57], an optimal exogenous signal was designed under a closed-loop deterministic system framework, which showed that suitable feedback can reduce the cost function compared with the open-loop monitoring and fault detection, indicating better fault detection by introducing closed-loop information. Recent applications of active fault diagnosis methods can be found in [58]–[60]. Specifically, in [58], an active method was proposed for the fault diagnosis of dc-link capacitors in a three-phase ac–dc PWM converter, where a controlled ac component was injected into the input side of the ac–dc converters, and the resulting ac ripples on the dc outputs were then extracted and analyzed for fault detection. In [59], a short pulse of current was injected into the d-axis current to produce an additional set of dq-axis state equations, leading to a full-rank reference/variable model, which was then utilized for online simultaneous estimates of the winding resistance and the rotor flux linage that were employed as indicators for monitoring permanent-magnet synchronous-motor stator winding and rotor permanent magnets. In [60], active fault diagnosis was dealt with for battery systems under a discrete-event model framework. The normal status and the faulty status (including an aged cell and an increased internal resistance) were partitioned into different sets, and a suitable active control algorithm was implemented to excite system evolution along certain trajectories, which were used to check which partitioned set the operation mode of the monitored system belonged to.

IV. Conclusion

In this second-part survey paper, fault diagnosis techniques and their applications have been comprehensively reviewed following the categories of knowledge-based, hybrid, and active methods. Knowledge-based fault diagnosis approaches are reviewed according to the essence of the extracted knowledge base, including qualitative-based approaches and quantitative-based approaches, where quantitative-based approaches are further classified into statistical methods and nonstatistical methods. The hybrid diagnosis methods are reviewed from a variety of combinations/integrations of more than one diagnosis method. The active fault diagnosis methods are reviewed from the stochastic and deterministic views, respectively. Together with the overview on model-based and signal-based diagnosis methods in the first-part survey, the complete survey on the fault diagnosis techniques and applications have been accomplished following the categories of model-based, signal-based, knowledge-based, and hybrid/active methods. We have reviewed over 220 technical studies in total with more attention on the recent developments of the fault diagnosis approaches and their applications during the last decade, shedding light for the readers from various societies and industrial communities to quickly access the recent developments of this field.

Networked and distributed fault diagnosis techniques and their applications may be further stimulated as more and more modern industrial systems have distributed structures equipped with wireless communication networks. Knowledge-based (data-driven) techniques are finding more chances in applications as the supervisory control and data acquisition (SCADA) system and smart meters are commonly installed in today’s industrial automation systems, leading to a large amount data available. The integration of a variety of diagnosis techniques is a trend in order to obtain better real-time monitoring and diagnosis performance. Compared with uninvasive diagnosis methods, active fault diagnosis approaches are far from mature, and further theoretical results and applications are anticipated.

We have tried to include as many as possible up-to-date references following the techniques’ categories. Unfortunately, it is impossible to comprise all the existing publications due to space limitations. In addition, the third-part survey paper focusing on fault-tolerant control techniques is under way.

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