Mechanical Systems and Signal Processing 23 (2009) 2488–2499

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/jnlabr/ymssp

A divide and conquer approach to anomaly detection, localization and diagnosis

Jianbo Liu [a], Dragan Djurdjanovic [b,*], Kenneth A. Marko [c], Jun Ni [d]

[a] Department of Electrical and Computer Engineering, Michigan State University, 2120 Engineering Building, East Lansing, Michigan, 48824-1226, USA
[b] Department of Mechanical Engineering, University of Texas at Austin, 1 University Station, Austin, TX 78712-0292, USA
[c] ETAS Inc., 3021 Miller Rd, Ann Arbor, MI 48103, USA
[d] Department of Mechanical Engineering, University of Michigan, 2350 Hayward Street, Ann Arbor, MI 48109-2125, USA

ARTICLE INFO

Article history:
Received 10 June 2007
Received in revised form
4 June 2008
Accepted 27 May 2009
Available online 6 June 2009

Keywords:
Anomaly detection
Fault diagnosis
Self-organizing maps
Time–frequency analysis

ABSTRACT

With the growing complexity of dynamic control systems, the effective diagnosis of all possible failures has become increasingly difficult and time consuming. The virtually infinite variety of behavior patterns of such systems due to control inputs and environmental influences further complicates system characterization and fault diagnosis. To circumvent these difficulties, we propose a new diagnostic method, consisting of three elements: the first, based on anomaly detection, identifies any performance deviation from normal operation; the second, based on anomaly/fault localization, localizes the problem, as best as possible, to the specific component or subsystem that does not operate properly and the third, fault diagnosis, discriminates known and unknown faults and identifies the type of the fault if it is previously known. Our prescriptive method for diagnostic design relies on the use of self-organizing maps (SOMs) for regionalization of the system operating conditions, followed by the performance assessment module based on time-frequency distributions (TFDs) and principal component analysis (PCA) for anomaly detection and fault diagnosis. The complete procedure is described in detail and demonstrated with an example of automotive engine control system.

Published by Elsevier Ltd.

1. Introdcution

Driven by increasing customer demand for safety, reliability and maintainability, as well as strict environmental legislations, the development of dynamic control systems shows a rapidly increasing integration of sensors, actuators and microelectronics. As the system complexity keeps increasing, the effective diagnosis of all possible failures has become increasingly difficult.

A variety of diagnostic techniques, ranging from analytical methods to artificial intelligence and statistical approaches, has been developed during the last two decades. Fig. 1 shows a classification of commonly used diagnostic techniques in the literature. Based on the underlying assumptions about the dynamic system, diagnostic techniques can be roughly divided into three categories: model-based, expert-knowledge-based, and knowledge-discovery-based.

* Corresponding author. Tel.: +1 512 232 0815; fax: +1 734 936 0363.
E-mail addresses: ryukenpa@gmail.com (J. Liu), dragand@me.utexas.edu (D. Djurdjanovic), Kenneth_Marko@yahoo.com (K.A. Marko), junni@umich.edu (J. Ni).

0888-3270/$ - see front matter Published by Elsevier Ltd.
doi:10.1016/j.ymssp.2009.05.016

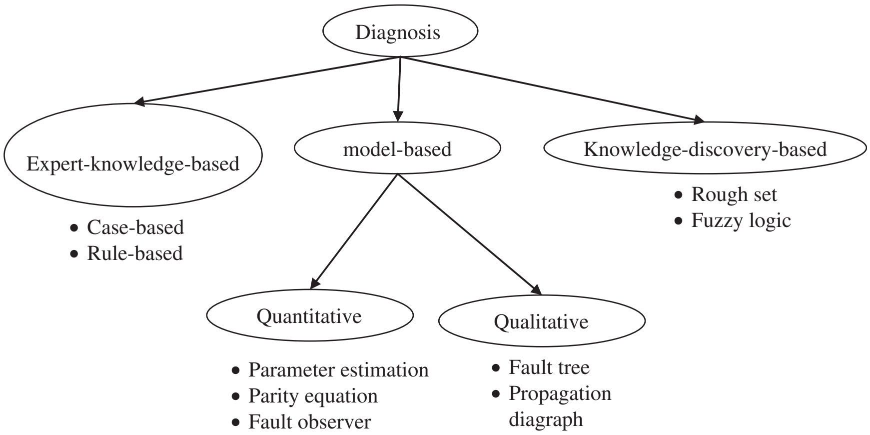

Fig. 1. Classification of diagnostics techniques.

Expert-knowledge-based diagnostic approaches structure analytic reasoning on professional knowledge from field engineers. These approaches do not require exact information about the details of system dynamics. The rationale behind them is that experienced technicians can find faults quickly and reliably based on their experience with failure modes in similar systems, even though without extensive knowledge of the dynamic system. Rule-based or case-based expert systems such as those reported in [31,11] fall into this category.

Compared with expert-knowledge-based diagnostic approaches, knowledge-discovery-based approaches require neither detailed knowledge of the system dynamics nor the field symptom-to-failure knowledge. The knowledge-discovery techniques such as rough sets [16,6] and fuzzy logic [17,18] can extract useful diagnostic information in the form of rules out of large amounts of data. Therefore, knowledge-discovery-based approaches are particularly useful when huge amounts of data, including normal and faulty behavior related data, are available. However, expert-knowledge-based and knowledge-discovery-based approaches can deal with only systems for which prior experimental knowledge or data are available. Therefore, they are relatively incapable of dealing with completely new designs and correctly identifying failure modes that have not been experienced before.

Model-based techniques employ either quantitative or qualitative models of the monitored system [27,28] for fault diagnosis. Most of the model-based approaches are developed based on fundamental understanding of the underlying physical processes and the interrelationships among different vehicle components or subsystems. For quantitative model-based approaches, the knowledge about the system is usually expressed in the form of mathematical functions or mappings, such as differential or difference equations. In contrast, for qualitative model-based approaches, the knowledge is expressed in terms of qualitative functions such as fault trees [1], propagation diagraphs [31] and discrete event systems [20]. Qualitative model-based techniques can accommodate modeling uncertainties and disturbances. Utilization of qualitative model can thus increase the detection and diagnosis accuracy. However, qualitative model-based approaches still require detailed knowledge of the underlying physical processes and most of the qualitative model-based approaches cannot provide quantitative information about the severity of the faults, such as the amount of parameter drift, when such information is of concern. During the last two decades, tremendous efforts have been made on developing quantitative model-based approaches. These approaches require a thorough understanding of the underlying physical system since they are based on generating residual signals that reflect the discrepancies and inconsistencies between the real system and its corresponding model. The approaches are diverse in that there are different ways to generate the residual signals, such as the use of parameter estimation [15,7,3,5], observers [23] and parity equations [24,12,14].

The ‘‘divide-and-conquer’’ dynamic modeling paradigm is an attractive alternative to modeling general nonlinear dynamic systems, such as sub-model decomposition [29]. The newly proposed approach employs a divide-and-conquer strategy for anomaly detection and diagnosis. The system input–output operation space is first partitioned into small regions using self-organizing maps (SOMs) and then a statistical model of the system expected behavior within each region is constructed based on time–frequency distribution (TFD). Any significant deviations from the trained normal behavior are recognized as anomalies. Similarly to the way the anomaly detectors are created in different operational regions, one can construct diagnosers for various known faults within each operational region to identify the types of faults. This divide-and-conquer approach naturally leads to a localized decision-making scheme, where anomaly detection and fault diagnosis can be performed locally within each operational region.

The proposed approach consists of the following three steps.

1. *Anomaly detection*: procedure of identifying abnormal behavior as statistically significant departures of system signatures away from those characterizing normal behavior.