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Hybrid fault diagnosis of nonlinear systems using neural parameter estimators

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ABSTRACT

This paper presents a novel integrated *hybrid* approach for fault diagnosis (FD) of nonlinear systems taking advantage of both the system's mathematical model and the adaptive nonlinear approximation capability of computational intelligence techniques. Unlike most FD techniques, the proposed solution *simultaneously* accomplishes fault detection, isolation, and identification (FDII) within a unified diagnostic module. At the core of this solution is a bank of adaptive neural parameter estimators (NPEs) associated with a set of single-parameter fault models. The NPEs continuously estimate *unknown* fault parameters (FPs) that are indicators of faults in the system. Two NPE structures, *series–parallel* and *parallel*, are developed with their exclusive set of desirable attributes. The *parallel* scheme is extremely robust to measurement noise and possesses a simpler, yet more solid, fault isolation logic. In contrast, the *series–parallel* scheme displays short FD delays and is robust to closed-loop system transients due to changes in control commands. Finally, a fault tolerant observer (FTO) is designed to extend the capability of the two NPEs that originally assumes full state measurements for systems that have only *partial state measurements*. The proposed FTO is a neural state estimator that can estimate *unmeasured* states even in the presence of faults. The *estimated* and the *measured* states then comprise the inputs to the two proposed FDII schemes. Simulation results for FDII of reaction wheels of a three-axis stabilized satellite in the presence of disturbances and noise demonstrate the effectiveness of the proposed FDII solutions under partial state measurements.

1. Introduction

Increasing demand for reliable operation of safety-critical control systems such as intelligent vehicles and future planned autonomous spacecraft/probes has made fault detection, isolation, and identification an essential component of an autonomous system. There is a high demand for developing intelligent systems that are able to autonomously detect and isolate the location of faults occurring in different components of complex systems. Furthermore, accurate estimation of fault severities is essential for development of reliable autonomous recovery procedures as well as component health monitoring and condition-based maintenance, where accurate estimation of a component's health state and consequently prediction of its remaining useful life is of utmost importance.

In general, autonomous on-line health monitoring and fault diagnosis is essential for mission-critical and safety-critical systems as opposed to fail-operational systems, where off-line health monitoring and fault diagnosis is usually sufficient in order to perform maintenance. In this work, the main focus is on developing a fault diagnosis methodology that enables on-line health monitoring of nonlinear systems; however, the proposed approach can also be applied for off-line monitoring purposes.

Furthermore, accurate identification of fault severities is an invaluable asset for system maintenance as well as development of reliable autonomous recovery procedures. More precisely, accurate estimation of severities in the case of incipient faults allows system operators and controllers to either very quickly schedule a maintenance service for the faulty component, to switch to the redundant component if maintenance is not possible, or to intelligently plan and execute preemptive actions in advance, in order to avoid catastrophic failures.

Accurate identification of fault severities is an invaluable asset for system maintenance operations. Accurate estimation of fault

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severities facilitates the early detection of incipient faults and the identification of out-of-spec behaviors. This consequently allows system operators and controllers to intelligently plan and execute *a priori* preemptive actions to avoid system breakdown, catastrophic failures, and mission abortion. Furthermore, recent interest by the aerospace industry in preventive maintenance (as opposed to corrective maintenance) systems, has called for a technological shift in system monitoring and maintenance operations from traditional scheduled time-based (or distance-based) fixed interval maintenance practices (which tend to reduce system lifetime and increase system down-time, resulting in loss of profit) to condition-based maintenance (CBM) systems (Mitchell, 1998; Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006; Wu, Gebraeel, Lawley, & Yih, 2007; Yang, 2003).

The objective of this paper is to develop integrated fault detection, isolation and identification (FDII) schemes for nonlinear systems that are robust to sensor noise and system disturbances and that are able to operate even in presence of partial state measurements. The FDII schemes are not only able to reliably detect the presence and isolate the location of anomalies in nonlinear systems but also accurately estimate their severities after their occurrence. Furthermore, the FDII system is robust with respect to system disturbances and measurement noise in order to minimize false alarms while the system is in a healthy mode of operation. Moreover, the FDII system is able to operate sufficiently accurately even in cases where some of the system states are not available for measurement (i.e., partial state measurement). Thus, another objective of the work is to develop a state estimation algorithm that can provide accurate estimates of the unmeasured states of the system even in presence of faults or anomalies (that is robust to occurrence of faults) and that is eventually integrated into the FDII system.

Finally, the effectiveness of the developed integrated FDII scheme in diagnosis of faults in a practical engineering system will be verified. For this purpose, the integrated FDII scheme is applied for detection, isolation, and identification of faults in reaction wheel (RW) actuators of a satellite's attitude control system (ACS) in the presence of measurement noise, satellite and reaction wheel disturbances, and partial measurement of the states of the reaction wheel.

During the past two decades, a number of approaches have been developed for fault detection and isolation (FDI) of both deterministic and stochastic nonlinear systems. Many techniques utilize either analytical model-based (Isermann, 2005; Jiang, Staroswiecki, & Cocquempot, 2004; Naderi, Meskin, & Khorasani, 2012; Persis & Isidori, 2001; Rengaswamy, Mylaraswamy, Venkatasubramanian, & Arzen, 2001; Simani, Fantuzzi, & Patton, 2003; Vachtsevanos et al., 2006; Zhang, Polycarpou, & Parisini, 2010) or learning-based methodologies (Frank, 1990; Palade, Bocaniala, & Jain, 2006; Patton, Lopez-Toribio, & Uppal, 1999; Rengaswamy et al., 2001; Talebi & Khorasani, 2007; Talebi, Khorasani, & Tafazoli, 2009) using qualitative or quantitative modeling. The problem of FDI of nonlinear stochastic systems often represented by general hidden Markov models has been solved using adaptive change detection (Vaswani, 2007), the likelihood ratio approach with adaptive Monte Carlo as well as particle filters (Li & Kadirkamanathan, 2001, 2004), and entropy optimization filtering (Guo, Yin, Wang, & Chai, 2009). However, only a few works have been reported in the literature that exploit both mathematical models of a system and the adaptive nature of intelligent techniques such as neural networks (Alessandri, 2003; Sobhani-Tehrani, Khorasani, & Tafazoli, 2005; Xiaodong, Polycarpou, & Parisini, 2002). Furthermore, the importance of utilizing an integrated framework to *simultaneously* achieve FDI and fault severity estimation has not been fully addressed.

The fault diagnosis techniques proposed in this work are essentially *hybrid approaches* due to the use of *neural networks* in conjunction with a *mathematical model* of the system as a basis for fault modeling. More precisely, the proposed fault diagnosis methodology simultaneously exploits both the *a priori* mathematical model information of the system and the nonlinear approximation and adaptation capability of neural networks. Specifically, the mathematical model of the system is used as a basis for *fault modeling* and *isolation*, and the capability of neural networks in adaptive nonlinear function approximation is used as a basis for on-line fault *severity identification*. Fault modeling can be accomplished in a variety of ways and perspectives. For example, Sobhani-Tehrani et al. (2005) and Xiaodong et al. (2002) have modeled a fault as an unknown nonlinear function of the system states and inputs. On the other hand, neural networks are used in Patton et al. (1999) to identify the full system dynamics including nominal and faulty dynamics, under different fault scenarios. The fault modeling approach adopted in this paper is based on the notion of fault parameters (FPs) as defined in Alessandri (2003) to parameterize a known mathematical model of the system with unknown parameters that reflect the occurrence of faults.

The idea of using a bank of estimators/observers and models (or multiple models (MMs)) for fault detection and isolation has been previously pursued in the literature by many researchers (see for example, Alessandri, 2003; Barua & Khorasani, 2011a, 2011b; Jiang, Khorasani, & Tafazoli, 2008; Luzar, Czajkowski, Witczak, & Korbicz, 2012; Mehra, Rago, & Seereeram, 1997; Mrugalski, 2013; Tan, Nor, Abu Bakar, Ahmad, & Sata, 2012; Tudoroiu & Khorasani, 2005b; Tudoroiu, Sobhani-Tehrani, & Khorasani, 2006; Yi, Zhan-Ming, & Er-Chao, 2012; Zhang & Li, 1997). However, they have not addressed the problem of fault severity identification.

Ideally, the traditional MM-based approaches to fault diagnosis would be able to accurately identify fault severities *only if* an infinite number of models (or quantization levels) co-exist in the model bank, which makes them computationally unfeasible and thus impractical. The fault diagnosis approach proposed in this work resolves this practical problem by defining multiple parameterized fault models (PFMs), where the parameters can take essentially infinite numbers of values (i.e., the parameter values can vary over a continuum). Thus, the PFM set (or bank) is implicitly unbounded.

Putting the above mentioned synergistic aspects together, we can assert that the fault detection, isolation and identification (FDII) methodology proposed in this work is a *hybrid*, multiple-model, dual (state and parameter) estimation based approach to fault diagnosis of nonlinear systems.

Only a few fault diagnosis methodologies exist in the literature, which simultaneously take advantage of the mathematical model of a system and exclusive capabilities of computational intelligence techniques, especially neural networks, in a hybrid framework. For example, Alessandri (2003), proposed a hybrid approach to fault detection in nonlinear systems. In his work, fault detection and isolation is accomplished by means of a bank of estimators, which provide estimates of parameters that describe actuator, plant, and sensor faults. These estimators, also called finite-memory filters, perform according to a receding-horizon strategy and are designed using a nominal *mathematical model* of the system and models of the failures. The problem of designing such estimators for general nonlinear systems is solved by searching for optimal estimation functions. These functions are approximated by *feed-forward neural networks* and the problem is reduced to finding the optimal neural weights, hence the name *finite-memory neural filters*. The learning process of the neural filters is split into two phases: an off-line initialization phase using any possible "*a priori*" knowledge on the statistics of the random variables affecting the system states, and an on-line training phase for on-line optimization of neural weights.

In another example of a *hybrid* approach to diagnostics, Xiaodong et al. (2002) presented a robust fault detection and