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Decentralized fault detection and isolation in wireless structural health monitoring systems using analytical redundancy

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ABSTRACT

One of the most critical issues when deploying wireless sensor networks for long-term structural health monitoring (SHM) is the correct and reliable operation of sensors. Sensor faults may reduce the quality of monitoring and, if remaining undetected, might cause significant economic loss due to inaccurate or missing sensor data required for structural assessment and life-cycle management of the monitored structure. This paper presents a fully decentralized approach towards autonomous sensor fault detection and isolation in wireless SHM systems. Instead of physically installing multiple redundant sensors in the monitored structure ("physical redundancy"), which would involve substantial penalties in cost and maintainability, the information inherent in the SHM system is used for fault detection and isolation ("analytical redundancy"). Unlike traditional centralized approaches, the analytical redundancy approach is implemented distributively: Partial models of the wireless SHM system, implemented in terms of artificial neural networks in an object-oriented fashion, are embedded into the wireless sensor nodes deployed for monitoring. In this paper, the design and the prototype implementation of a wireless SHM system capable of autonomously detecting and isolating various types of sensor faults are shown. In laboratory experiments, the prototype SHM system is validated by injecting faults into the wireless sensor nodes while being deployed on a test structure. The paper concludes with a discussion of the results and an outlook on possible future research directions.

Introduction

The continuing progress in structural health monitoring (SHM) and wireless sensing technologies has led to prolonged periods of time wireless SHM systems are able to operate autonomously [1,2]. As a consequence, wireless SHM systems, if permanently installed on large-scale engineering structures such as bridges, dams, towers or wind turbines, require sensors operating correctly and precisely over long periods of time. However, when being deployed over extended time periods, sensors are increasingly exposed to harsh environmental conditions as well as ageing and degradation that may cause less accurate sensor data or even sensor faults. It is evident that wireless SHM systems deployed for long-term structural health monitoring require continuous performance monitoring and calibration of the sensors. Monitoring and calibration, in common practice scheduled on a periodic basis, are typically conducted manually within maintenance trips to remote monitoring sites, which are time-consuming and costly. Due to a lack of knowledge about actual sensor conditions, the sensors deployed in wireless SHM systems are usually maintained and calibrated regardless of their performance, causing further maintenance costs and decreased monitoring quality owing to unnecessary and inaccurate sensor calibrations and undetected sensor faults.

To ensure a high quality of monitoring and to reduce maintenance costs, it is essential to continuously monitor the quality of sensor data and to automatically detect and isolate sensor faults. Although much progress has been made in developing intelligent SHM systems [3–6] and structural control systems [7,8], undetected faults still remain an open problem posing substantial challenges in SHM research [9]. Faults in wireless SHM systems can have several reasons, for example malfunctioning hardware, bugs in the software embedded into the wireless sensor nodes, harsh weather conditions, or environmental hazards. While some faults in wireless SHM systems might be easy to detect – for example if sensor data is missing – other faults might be more subtle, e.g. if caused by small sensor drifts. In general, a *fault* can be defined as a defect that leads to an *error*, and an error corresponds to an incorrect system state that may result in a *failure* [10]. A sensor fault, if

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not being detected and isolated, can propagate throughout the entire SHM system causing severe failures that may degrade the overall system performance or even cause a total system malfunction [11,12]. Sensor failures, in general, can be categorized into hard failures and soft failures [13]. Hard failures are, for example, large bias failures that occur instantaneously, and soft failures are small biases or drifts that accumulate relatively slowly over time.

Fault diagnosis, according to [14], can be described as a process that includes (i) fault detection, (ii) fault isolation, (iii) fault identification, and (iv) fault accommodation. It should be noted that unstructured uncertainties, process noise, and measurement noise is usually outside the scope of fault diagnosis. This paper focuses on the area of fault detection and isolation (FDI). The concept of FDI has widely been studied in computer science for several years [15,16], and numerous approaches towards FDI have been proposed including, e.g., model-based approaches, knowledge-based approaches, or a combination of both [14,17–19]. More recently, FDI concepts have also been successfully implemented in a number of engineering disciplines, such as aerospace engineering, mechanical engineering and electrical engineering, to improve the availability and reliability of distributed engineering systems [20–22]. However, the investigation of fault detection and isolation in wireless SHM systems has received little attention.

This paper presents a decentralized approach towards fault detection and isolation in wireless SHM systems. Implementing the analytical redundancy approach, neural networks are embedded into the wireless sensor nodes installed in the monitored structure enabling each sensor node autonomously detecting and isolating sensor faults in real time. The paper is organized as follows. First, background information on FDI concepts is given. Then, the design and prototype implementation of a wireless SHM system capable of fault detection and isolation, with strong emphasis on the embedded neural network approach, is described. Next, laboratory experiments are presented that are devised to validate the performance of the wireless SHM system. For the laboratory experiments, the prototype SHM system is installed on a test structure, and sensor data obtained during normal (i.e. non-faulty) system operation is used to train the fault diagnosis capabilities of the SHM system. Thereupon, faults are injected into the wireless sensor nodes to validate the system's capabilities to autonomously detect and isolate sensor faults. The paper concludes with a discussion of the results and an outlook on possible future research directions.

Fault detection and isolation based on analytical redundancy

Traditionally, a key technique towards fault detection and isolation in distributed systems is the multiplication, i.e. the redundant installation of hardware components such as sensors, data acquisition units or computers ("physical redundancy"). For example, for measuring one single parameter of interest, multiple sensors are physically deployed. To make a decision whether one of the observed sensors is faulty, the outputs of the redundant sensors are compared using decision rules that are commonly based on simple majority voting logics [23]. However, physical redundancy involves substantial penalties in cost and maintainability because multiple hardware components must be installed in the monitored structure. Moreover, voting assumes independent faults, and sensors operating in the same environment can hardly be considered independent. Overcoming these problems, the concept of "analytical redundancy" has emerged, fostered by the rapid advancements in computer science and information technology [14].

Instead of physically installing multiple sensors for measuring one single parameter, analytical redundancy takes advantage of the redundant information inherent in the observed SHM system and utilizes the coherences and relationships between the sensors regularly installed [18]. Analytical redundancy, when applied for fault detection and isolation in wireless SHM systems, has tremendous potential to reduce system costs and power consumption of wireless sensor nodes while substantially increasing availability, reliability, safety and maintainability of the SHM system. For each observed sensor, virtual sensor outputs representing non-faulty operation are predicted based on measured outputs of correlated sensors and on a priori knowledge about the system. Comparing actual and virtual sensor outputs, residuals are generated for each sensor. The residuals, reflecting inconsistencies between the actual sensor behavior and the model-based, virtual sensor behavior, serve as the basis for decision making with respect to potential sensor faults.

As opposed to physical redundancy, which often uses simple voting logics to determine faulty sensors, analytical redundancy employs mathematical models of the observed decentralized (SHM) system for mapping the inherent redundancy contained in the system. The mathematical models used to generate the diagnostic residuals between actual and virtual sensor outputs can be either first-principle models derived analytically or black box models obtained empirically. To estimate the virtual sensor outputs as precisely as possible and to correctly interpret the residuals between actual and virtual sensor outputs, analytical redundancy, compared to physical redundancy, requires more sophisticated information processing techniques. For estimating virtual sensor outputs and for generating the residuals, several techniques have been proposed in related disciplines. Widely used and well accepted approaches include, e.g., estimation filters, band-limiting filters as well as innovation testing based on Kalman filters, threshold logic, and generalized likelihood ratio testing. Among the most efficient approaches for estimating virtual sensor outputs is the application of artificial neural networks, because neural networks are capable to accurately model non-linear and dynamic decentralized systems (such as wireless SHM systems) without the need for first-principle models or a priori knowledge about the complex internal structures of the system observed [24]. A plenitude of different types of neural networks has been studied to advance engineering applications in the past decades. On the other hand, due to the efficiency and reliability of such subsymbolic techniques, research in this field is still very active, and new approaches, such as the hierarchical graph neuron (HGN) [25] have emerged and are exploited in different engineering fields in recent years.

Neural networks, consisting of a set of processing units (neurons) and weighted connections between the units, have the ability (i) to find patterns and associations between given input and output values of the network and (ii) to estimate output values based on given input values – even if the input is inaccurate, noisy, or incomplete. During a *training phase*, a neural network learns from existing relationships, i.e. from given pairs of input and output values, resulting in a non-linear black box model that is applied in a subsequent *runtime phase*. In the runtime phase, new input values are presented to the neural network, which estimates the corresponding output values by adapting itself to the new inputs. For fault detection and isolation in wireless SHM systems, these distinct strengths of neural networks can advantageously be used to estimate virtual outputs of a sensor based on actual outputs recorded by correlated sensors presented to the neural network as inputs, which results in a precise and robust residual generation [26].

The characteristics of neural networks, particularly the approximation and adaptation capabilities, have led to a plenitude of neural networks applications deployed to achieve analytical redundancy in various types of engineering systems. Examples