A Decentralized Approach towards Autonomous Fault Detection in Wireless Structural Health Monitoring Systems

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A DECENTRALIZED APPROACH TOWARDS AUTONOMOUS FAULT DETECTION IN WIRELESS STRUCTURAL HEALTH MONITORING SYSTEMS

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ABSTRACT

Sensor faults in wireless structural health monitoring (SHM) systems may reduce the monitoring quality and, if remaining undetected, might cause substantial economic loss due to inaccurate or missing sensor data required for structural assessment and life-cycle management of the monitored structure. Usually, fault detection in sensor networks is achieved through a redundant deployment of sensors and further hardware components ("physical redundancy"), which involves considerable penalties in cost and maintainability. Overcoming these drawbacks, in this study the information inherent in the SHM system and the known relationships between the sensors are used for fault detection without the need for additional sensors ("analytical redundancy"). Furthermore, the analytical redundancy approach is implemented in a fully decentralized manner: Partial models of the SHM system, being embedded directly into the wireless sensor nodes, enable each sensor node to autonomously detect sensor faults in real time while efficiently using the limited computing resources.

KEYWORDS : *Autonomous fault detection, structural health monitoring, wireless sensor networks, smart sensors, analytical redundancy, artificial neural networks.*

INTRODUCTION

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, which may cause less accurate sensor data or even sensor faults. Sensor faults, if remaining undetected, can propagate through the overall SHM system and may lead to severe failures that might degrade the overall system performance, decrease the system availability, or even cause a total system collapse [1].

Referred to as "physical redundancy", a key technique towards fault detection in distributed systems is the multiplication, i.e. the redundant installation of hardware components such as sensors, data acquisition units, or computers. For example, for measuring one single parameter of interest, multiple sensors are physically installed. To make a decision whether one of the observed sensors is faulty, the outputs of the redundant sensors are compared with each other [2]. However, physical redundancy involves substantial penalties in cost and maintainability because multiple hardware components must be installed in the monitored structure. Overcoming these problems, the concept of "analytical redundancy" has emerged in the past decades, fostered by the rapid advancements in computer science and information technology.

Instead of physically installing multiple sensors for measuring one single parameter, analytical redundancy takes advantage of the redundant information inherent in the observed system and of the coherences and relationships between the sensors that are regularly installed [3]. For each observed sensor, virtual (i.e. model-based) sensor outputs are predicted based on measured outputs of correlated sensors and on a priori knowledge about the system. The virtual sensor outputs are thus representing non-faulty sensor operation. Comparing actual and virtual sensor outputs, residuals are generated, reflecting inconsistencies between the actual and the virtual sensor behavior. The diagnostic residuals serve as the basis for decision making with respect to potential sensor faults.

In total, analytical redundancy has tremendous potential for reducing cost and power consumption of wireless sensor nodes while substantially increasing system availability, reliability, safety, and maintainability. An efficient approach for implementing fault detection applications based on analytical redundancy is the application of artificial neural networks [4]. Neural networks, composed of a set of processing units (neurons) and weighted connections between the units, are capable of accurately modeling non-linear and dynamic decentralized systems (such as wireless SHM systems) without the need for first-principle models and without a priori knowledge about the complex internal structures of the system observed [5]. Within 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. The neural network estimates the corresponding output values by adapting itself to the new inputs, which can advantageously be used in fault detection applications to estimate virtual sensor outputs based on actual sensor outputs of correlated sensors.

The application of neural networks to fault detection in sensor systems and the design of "intelligent" SHM systems are not new [6, 7]; however, most existing studies tackle the problem of fault detection with centralized approaches. Sensor data originating from different sources is first transferred into a centralized repository and then analyzed with respect to sensor faults, which requires extensive global communication and large amounts of sensor data to be transmitted. This paper, by contrast, presents a decentralized approach towards fault detection in wireless SHM systems. Neural networks are embedded into the wireless sensor nodes that are installed in the monitored structure, enabling each node – that only communicates with its local neighbors – to autonomously detect and isolate sensor faults in real time.

1 IMPLEMENTATION OF A PROTOTYPE WIRELESS SHM SYSTEM

The prototype SHM system, in essence, is composed of a number of wireless sensor nodes, type "Oracle SunSPOT", that are employed (i) to autonomously collect sensor data from the observed structure, (ii) to locally analyze the data, (iii) to aggregate the data, and (iv) to communicate with other wireless sensor nodes as well as with an Internet-enabled local computer. The local computer is primarily deployed to process and to store the sensor data and to support further (remote) data processing.

For collecting, analyzing, aggregating and communicating the data sets, modular Java-based software programs, referred to as "SHM modules", are embedded into the wireless sensor nodes. In addition to the SHM modules, further software programs, labeled "fault detection modules", are embedded into the sensor nodes facilitating autonomous detection of sensor faults. In the following subsections, the design of the fault detection modules is presented. For details on the SHM modules, the reader is referred to [8, 9, 10].

1.1 Fault detection modules

The fault detection modules embedded into the wireless sensor nodes integrate two major sub-modules. As shown in Figure 1, each fault detection module includes a mathematical *system model* of the SHM system for computing the virtual sensor outputs and a *decision logic* for comparing actual and virtual sensor outputs. To illustrate the conceptual design of the fault detection modules, a typical SHM system is considered in Figure 1. The dynamic system has an input vector **x** and an output vector **z**. For a realistic system representation it is important to model all effects that can affect the system, such as sensor faults, modeling errors as well as system and measurement noise. These effects are included in the fault vector **f**, which is $\mathbf{f} = 0$ in the fault-free case and $\mathbf{f} \neq 0$ in a faulty case. Further effects relevant to fault detection are summarized in the vector of unknown inputs **d**. The mathematical system model, using the actual system inputs **x** (i.e. actual sensor outputs), estimates the virtual system outputs $\hat{\mathbf{z}}$ (i.e. virtual sensor outputs) that represent the outputs of the system in non-faulty operation. The residuals **r** between actual system outputs **z** and virtual system outputs $\hat{\mathbf{z}}$ are evaluated through the decision logic.

1.2 Neural network architecture

The mathematical model of the SHM system is divided into partial system models, each of which being embedded into one wireless sensor node. The partial system models are implemented by means of artificial neural networks that allow modeling the non-linear nature of the observed SHM system and estimating virtual sensor outputs without detailed knowledge about the complex internal structures of the system. The partial system models, in detail, are implemented based on multi-layer backpropagation feedforward neural networks, which have proven their effectiveness in parameter estimation problems in several engineering applications [11].

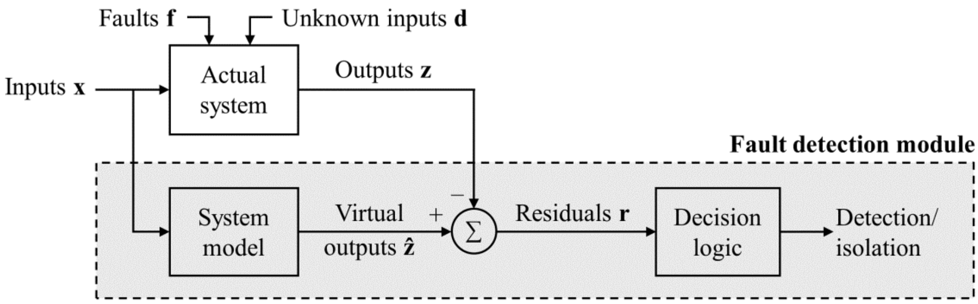

Figure 1: Conceptual structure of the embedded fault detection modules

Before porting specific neural network instances on the wireless sensor nodes, the optimum network topology is determined on a desktop PC using training data recorded in preliminary laboratory tests [12]. As shown in Figure 2, the number of neurons on the input layer and the number of neurons on the output layer are predetermined by the sensors of the wireless SHM system; more precisely, the output layer contains the virtual outputs of an observed sensor estimated by the neural network, and the input layer corresponds to the correlated sensors. The optimum number of hidden layers, the optimum number of neurons per hidden layer as well as further network parameters (such as input functions, activation functions and learning parameters) are determined using a heuristic search followed by trial and error, which results in 2 hidden layers with 3 neurons each (Figure 2).

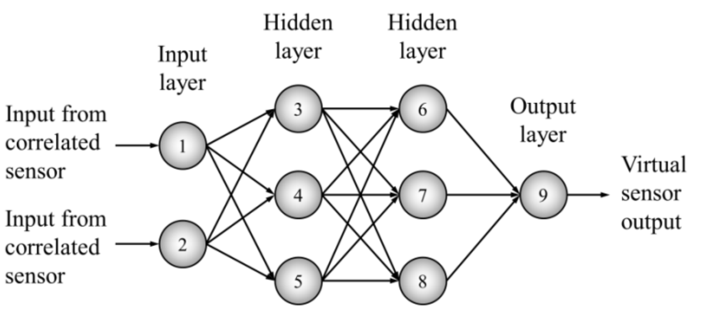

Figure 2: Topology of the neural network embedded into the wireless sensor nodes

2 LABORATORY EXPERIMENTS

The prototype SHM system is mounted on a laboratory test structure shown in Figure 3. The test structure, a steel tower of 4.10 m height, is designed to map the main properties of a wind turbine [13]. The tower is connected to the ground through elastomeric spring elements that can be exchanged to vary the characteristics of the wind turbine foundation. On top of the test structure, steel plates are mounted, which represents nacelle and rotor of the wind turbine. The wireless sensor nodes, labeled *A*, *B* and *C*, are attached to the tower. According to the structural sections of the tower, the sensor nodes are installed at h_A = 4.07 m, h_B = 2.55 m and h_C = 1.11 m as shown in Figure 3. In addition, a base station, connecting the wireless sensor nodes to the local computer, is placed next to the test structure.

Two laboratory experiments are devised. In the first laboratory experiment, the performance of the SHM system under normal operation (i.e. in the absence of sensor faults) is validated. Then, in the second experiment the sensor data recorded from the test structure in the first experiment is used to train the neural networks of the wireless sensor nodes allowing the nodes to "learn" non-faulty sensor signatures or, in other words, to distinguish between non-faulty and faulty sensors. Furthermore, faults are injected into the wireless sensor nodes to investigate the fault detection capabilities of the SHM system.

2.1 Real-time wireless monitoring under normal sensor operation

In the first laboratory experiment, the wireless sensor nodes are deployed to analyze the modal properties of the test structure. For that purpose, the test structure is excited at the top of the tower by a horizontal deflection, forcing the tower to vibrate freely at its characteristic frequencies. Acceleration data is recorded through the nodes' internal three-axis accelerometers, as shown in Figure 4, and it is analyzed directly on the nodes. For data analysis, each node calculates the frequency response function from the recorded acceleration time histories using an embedded FFT algorithm that is implemented to convert the measured accelerations from the time domain into the frequency domain [10].

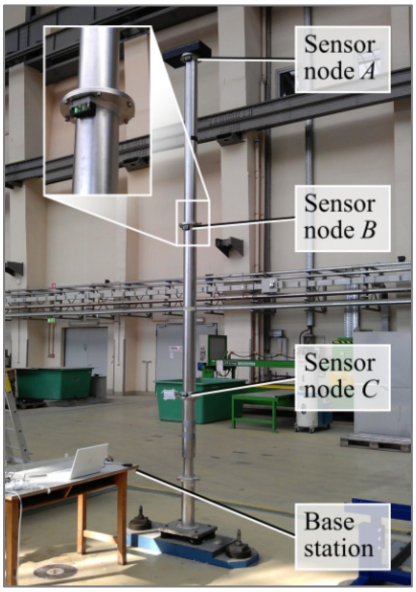

Figure 3: Wireless SHM system mounted on the test structure

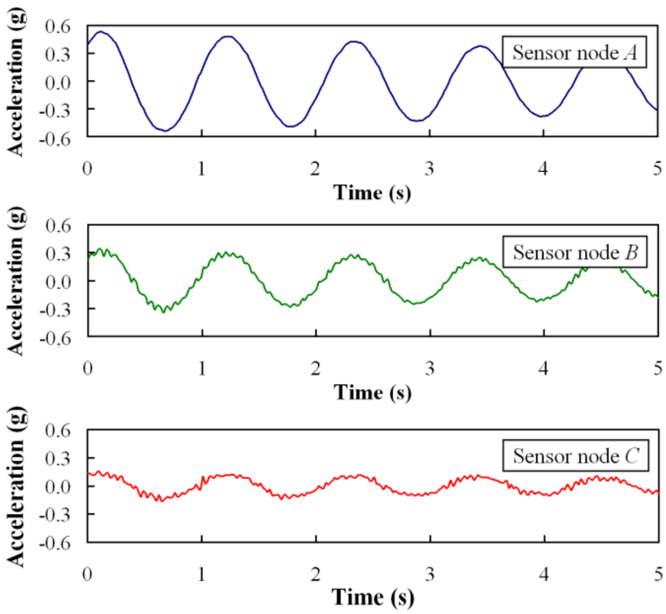

Figure 4: Horizontal acceleration response recorded by the wireless sensor nodes

Thereupon, the primary modes of the test structure are derived through peak picking. The first fundamental frequency of the structure is calculated by the wireless sensor nodes in this experiment as 0.96 Hz, showing close agreement with the theoretical response analytically determined from a numerical model of the test structure. The test procedure conducted in this experiment is repeated 10 times to obtain sufficient quantities of sensor data to be used in the second laboratory experiment.

2.2 Autonomous detection of sensor faults

In the second laboratory experiment, the previously obtained acceleration data is used (i) to train, (ii) to validate, and (iii) to test the neural networks of the wireless sensor nodes. For every sensor node, a total of 2,560 data points originating from the 10 test procedures is randomly subdivided into three disjoint subsets, 80% of which serving as training data (*training set*), 10% are used for cross validation (*validation set*), and 10% are used for testing the neural networks (*test set*). First, the training set is applied to adjust the weights of the neuron connections of each neural network using a backpropagation algorithm as introduced in [12]. Each network is trained several times with random initial weights to avoid local minima problems when determining the optimum connection weights. The validation set is used to monitor the network error during training and to stop training when the error – the mean squared error between the desired and the estimated outputs – is less than the predefined threshold of 0.002.

Once the connection weights are fixed, the test set is applied to evaluate the fully trained neural network of each sensor node and to confirm the predictive power when estimating sensor outputs. Therefore, the data points of the test set are fed into each neural network, and the estimated sensor outputs are compared with the desired sensor outputs included in the test set. By the example of sensor node *B*, Figure 5 illustrates a time history of horizontal acceleration (recorded during excitation of the test structure) and the corresponding acceleration estimated by the neural network. The goodness of fit of the embedded neural network to the measured acceleration data is determined by the coefficient of determination R^2. As can be seen from Figure 6, the neural network is able to predict the acceleration of the test structure with $R^2 = 0.984$, which is above the minimum regression coefficient $R^2_{min} = 0.950$ that is defined in this study as a threshold to be met for applying a fully trained network for fault detection.

Upon completing the training procedure, the fault detection capabilities of the SHM system are validated. Several faults are simulated by changing the code of the software that is embedded into sensor node *B* for collecting and analyzing acceleration data. The fault injection is exemplarily illustrated by simulating a sensor drift – a fault type known to be most difficult to detect [14]. While sensor node *B* is affected by the simulated fault, sensor node *A* and sensor node *C* are able to continue running in normal operation.

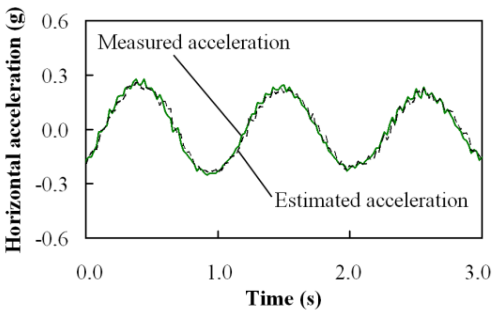

Figure 5: Acceleration measured (solid line) and estimated (dashed line)

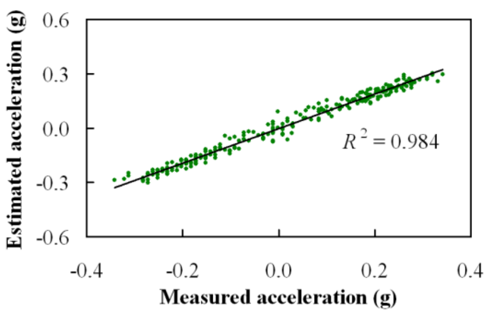

Figure 6: Prediction performance of the neural network (sensor node *B*)

Figure 7 depicts the time history of simulated residuals between the actual measurements and the virtual sensor outputs estimated by the neural network of sensor node *B*. As can be seen from Figure 7, the drift is inserted at $t = 5$ s. The time-varying drift is simulated by adding a ramp with a slope of 0.03 g/s to the regular accelerometer output. In the simulation, the fault is detected by sensor node *B* at about $t = 11$ s once the pre-defined threshold of ±0.2 g is exceeded. At $t = 18$ s, the automated fault correction is triggered, because the residuals are permanently out of the tolerable range since $t = 13$ s, i.e. for more than $\Delta t = 5$ s, where the time span Δt is chosen based on data processing constraints. From this moment on, the virtual sensor outputs of sensor node *B* are used in lieu of the actual measurements recorded by the faulty accelerometer. Otherwise, the faulty sensor would continue feeding incorrect measurements into the SHM system, affecting the monitoring quality of the SHM system and the fault detection capabilities of the other wireless sensor nodes.

Although, for the sake of clarity in this paper, the sensor drift exemplarily injected has a relatively large slope value (0.03 g/s), it is clear that the embedded fault detection modules detect more subtle drifts of smaller slope values with the same accuracy and with a small probability of false alarms; the fault detection of smaller drifts just takes a longer time because the time span between occurrence of the fault and fault detection depends on the fault magnitude and on the thresholds defined for the diagnostic residuals.

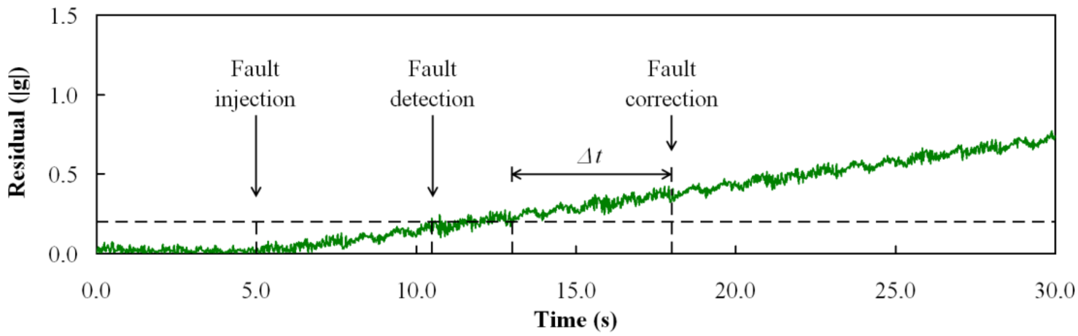

Figure 5: Residuals associated with a sensor drift

SUMMARY AND CONCLUSIONS

A decentralized analytical redundancy approach towards autonomous fault detection in wireless SHM systems has been presented. Instead of physically installing multiple redundant sensors, which would involve substantial penalties in cost and maintainability, the information inherent in the SHM system and the known relationships between the sensors have been used for fault detection. Furthermore, as opposed to traditional centralized approaches towards fault detection that require extensive global communication between the sensor nodes as well as large amounts of sensor data to be transmitted, the analytical redundancy approach presented in this study has been implemented in a fully decentralized fashion.

Partial models of the SHM system, implemented through multi-layer backpropagation feedforward neural networks, have been embedded into the wireless sensor nodes, allowing each node to autonomously detect sensor faults. The results obtained from the laboratory experiments clearly demonstrate that the analytical redundancy approach based on neural networks facilitates reliable real-time fault detection in wireless SHM systems. While efficiently using the limited computing resources, even difficult fault types such as sensor drifts are detected. Furthermore, it could be proven in this study that autonomous, decentralized fault detection is possible without the need for first-principle models and without a priori knowledge about the internal structures of the SHM system observed.

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