An analytical redundancy approach towards decentralized autonomous fault detection in wireless structural health monitoring

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Abstract

Sensor faults can affect the dependability and the accuracy of structural health monitoring (SHM) systems. Recent studies have demonstrated that analytical redundancy can be used to detect sensor faults. In this paper, decentralized artificial neural networks (ANNs) are implemented on each sensor node of a wireless SHM system to evaluate analytical redundancy in structural response data. Evaluating the deviations (or residuals) between measured and predicted data, sensor faults are autonomously detected by the wireless sensor nodes in a fully decentralized manner. The proposed approach has been validated in laboratory experiments, to optimize the ANNs towards performance and accuracy.

Zusammenfassung

Sensorfehler können die Zuverlässigkeit und die Genauigkeit von Bauwerksmonitoringsystemen (engl. Structural Health Monitoring, SHM) beeinflussen. Studien haben belegt, dass das Konzept der analytischen Redundanz verwendet werden kann, um Sensorfehler zu detektieren. In diesem Beitrag werden künstliche neuronale Netze (ANN) dezentral in jedem Sensorknoten eines drahtlosen Bauwerksmonitoringsystems implementiert, um die analytische Redundanz im Schwingungsverhalten des überwachten Bauwerks auszuwerten. Durch die Auswertung von Abweichungen zwischen gemessenen und vorhergesagten Daten werden Sensorfehler automatisch direkt auf den drahtlosen Sensorknoten erfasst. Das vorgeschlagene Konzept wurde in Laborversuchen validiert, und die implementierten ANN wurden nach Leistung und Genauigkeit optimiert.

1 Introduction

To evaluate the conditions and to ensure the structural integrity of civil engineering structures, Structural health monitoring (SHM) systems are used. To eradicate problems related to cost and installation time in conventional wired SHM systems, wireless sensor nodes are employed. An advantage of wireless sensor nodes is the collocation of processing power with sensing modules; hence, embedded computing has been utilized to perform a variety of SHM tasks (DRAGOS & SMARSLY 2015). However, the wireless sensor nodes can become inaccurate, faulty, or may even break when deployed over long periods of time. To ensure the dependability and the accuracy of the SHM system and the integrity of the structure, sensor faults must be reliably detected in real time (BISBY 2014).

Artificial neural networks (ANN) have been used for sensor fault detection in several engineering disciplines. SMARSLY & LAW (2014), for example, have proposed the use of ANNs for sensor fault detection by utilizing the analytical redundancy in the correlations between sensor outputs. OBST (2009) has presented a distributed recurrent neural network with local communication to detect sensor faults. BASIRAT & KHAN (2009) have introduced a neural network approach to distinguish accurate sensor data from faulty sensor data. YUEN & LAM (2006) have presented a method to develop ANN designs for damage detection in structural health monitoring. VENKATASUBRAMANIAN et al. (1990) have tested various neural network topologies for detecting process failures, such as sensor faults.

In this paper, a wireless SHM system is presented capable of decentralized, autonomous fault detection is presented. Fault detection is conducted by evaluation analytical redundancy within the sensor network via artificial neural networks. Each sensor node embeds a distinct ANN and feeds it with structural response data obtained from adjacent sensor nodes. The SHM system is tested on a test structure and the ANNs are optimized, enabling efficient and accurate sensor fault detection. Preliminary results have been presented in JAHR et al. (2015).

In the first part of the paper, background information on sensor fault detection using analytical redundancy is given, followed by a description of artificial neural networks and the functionality of the proposed SHM system. In the second part of the paper, the implementation of the SHM system is shown, and laboratory experiments, devised to validate the SHM system, are presented. Several topologies, training algorithms and types of data transfer of the embedded ANNs are tested with simulated sensor faults. The performance of the ANNs is investigated with respect to the dependability and the accuracy of the fault detection approach, the results are discussed and an optimal ANN configuration for the presented test structure is defined.

2 Sensor fault detection using artificial neural networks

In the following section, a brief overview of sensor fault detection using artificial neural networks for evaluating analytical redundancy is given, and the general architecture of the proposed SHM system is shown.

A well-known approach towards fault detection is the installation of physically redundant sensors. Faulty sensors can be identified through the deviation of their measurements from the measurements of correlated sensors. Physical redundancy, although efficient for sensor fault detection, causes increased installation and maintenance costs due to the installations of multiple sensors. Representing a more efficient approach, analytical redundancy typically uses mathematical functions, mapping the characteristics of the structure and the correlations of the installed sensors (SMARSLY & PETRYNA 2014). Specifically, virtual sensor measurements are computed for each sensor and then compared to the actual measurements. If the properties of a structure are known, physics-based models, e.g. finite element models, can be used in combination with data from adjacent sensor nodes to predict measurements of a sensor. However, to use numerical models, a priori knowledge about the structure is required.

Without a priori knowledge, analytical redundancy can be implemented in wireless sensor nodes based on data-driven models, such as artificial neural networks. ANNs are a class of algorithms that are inspired by biological nervous systems, such as the human brain. ANNs are used to approximate non-linear functions by adapting to given data sets. Applications of ANNs are used in several areas, i.e. cancer detection, pattern recognition in image analysis, and sensor fault detection.

As depicted in Figure 1, ANNs essentially consist of interconnected data processing units, called "artificial neurons" (FIESLER & BEALE 1996). Feed forward neural networks are grouped in different layers: one input layer, one output layer, and one or more hidden layers. The connections between the neurons, termed "synapses", have adaptive weights according to the connection strength between two neurons. The connections are used for data exchange between the neurons: the output of the neurons of one layer is used as the input of the neurons of the next layer. ANNs adapt to different applications by learning, which is achieved by adjusting the weights of the synapses until a set of given input values results in the desired output values. ANNs can be customized to various objectives by using different topologies, neuron functions, and learning strategies (MEHROTRA et al. 1997).

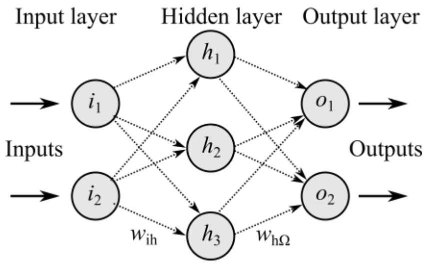

Figure 1:
Example of an artificial neural network with two input neurons, two hidden neurons and two output neurons, connected by synapses

The SHM system prototype proposed in this study consists of wireless sensor nodes and a host computer, both linked through a base station. The components of the SHM system perform different tasks, as shown in the data flow in Figure 2. During system operation, the sensor nodes collect acceleration response data. The fundamental frequency and the corresponding Fourier magnitude of the acceleration response data of the structure are estimated by the sensor nodes using the fast Fourier transform (FFT) and a peak picking algorithm. Each sensor node transmits the determined fundamental frequency and Fourier magnitude to the adjacent sensor nodes for decentralized sensor fault detection, as can be seen in Figure 3. A distinct artificial neural network is embedded into each sensor node, where a sensor node is represented either by an input neuron or by an output neuron of the ANN. The magnitudes of neighbor sensor nodes are used as input, the predicted magnitude of a sensor node is returned as output. The processed data is transmitted wirelessly to the base station and then to the host computer. On the host computer, the data is stored in a MySQL database. Additional diagnostics and information retrieval are conducted on the host computer in further steps.

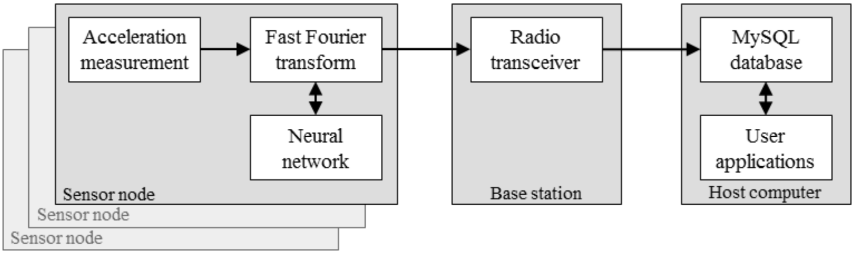

Figure 2: Hardware components and dataflow of the proposed SHM system

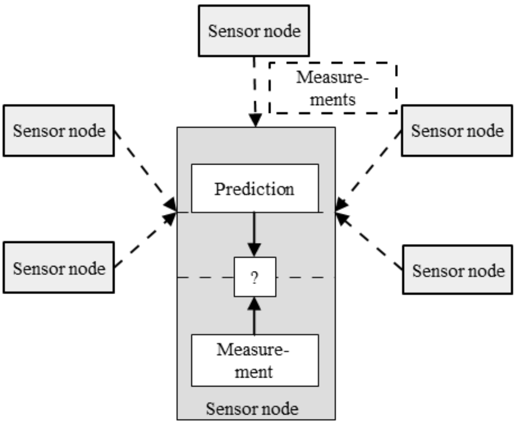

Figure 3:
Simplified diagram showing the decentralized fault detection algorithm: Each sensor node receives data from the other sensor nodes, predicts the expected value and compares prediction and measurement

3 Implementation and validation of the prototype SHM system

The implementation and validation of the proposed SHM system is described in the following section. Laboratory experiments of the SHM system are presented and the test results are discussed.

3.1 Implementation

The sensor nodes and the base station used in this paper are of type “Oracle Sun SPOT”. The main board of the Sun SPOTs features a 400 MHz ARM main processor, 1 MB of memory, 8 MB of flash memory and an IEEE 802.15.4 radio transceiver. The application board contains a 3-axis digital output accelerometer, an ambient light sensor, a temperature sensor, and eight tricolor LEDs. The accelerometer ranges between ±2 g and ±8 g and has a maximum sampling rate of 125 Hz (SUN SPOT 2009). The SHM system is implemented in an object-oriented way using Java programming language.

3.2 Laboratory experiments

As shown in Figure 4a, the sensor fault detection approach is validated by installing the sensor nodes on a test structure. The test structure is a 4-story frame structure consisting of steel plates of 25 cm×50 cm×0.75 mm. The plates are mounted on threaded rods with a vertical clearance of 23 cm. At the bottom of the structure, the rods are fixed into a solid block of 40 cm×60 cm×30 cm. The SHM system is installed on the test structure by mounting one wireless sensor node in the middle of story 3 and story 4, and two sensor nodes on story 2, one in the middle and one at a distance of 20 cm from the middle, as the response is too low on story 1.

a) Regular sensor arrangement **b)** Simulated sensor fault

Figure 4: Instrumentation of the test structure

The structure is excited by deflecting the top story. Each test run includes a training phase and a data collection phase, performed simultaneously on every sensor node. The training phase of the SHM system consists of the initialization and the training of an artificial neural network. The training of the ANN is completed through several sampling events used as training input. A sampling event includes the excitation of the structure, sampling of 512 acceleration measurements, on-board estimation of the fundamental frequency and corresponding Fourier magnitude, and wireless data exchange with the other sensor nodes. The data collection phase consists of any desired number of sampling events, sensor fault detection, and data storage. After every sampling event, the predicted magnitude of each sensor node is calculated by using the measured magnitudes of the other sensor nodes as input to the neural network. The deviation of the measured magnitude and the predicted magnitude is calculated by the sensor node. A deviation exceeding a predetermined threshold is indicative of a sensor fault.

To determine a suitable artificial neural network architecture for the laboratory test setup, several different topologies and neuron behaviors are tested offline. Finally, the optimal ANN is embedded into each sensor node to validate the fault detection online. To train and to test the ANNs, 100 test samples are generated. To this end, the test structure is excited and acceleration response data is collected and stored in the database. The acceleration response data is split randomly into 70 % of training data and 30 % of test data. Then, sensor faults are simulated to validate the autonomous sensor fault detection. For each simulated sensor fault, 30 test cases are generated. Different types of sensor faults are simulated through

a) substituting the readings of one sensor node with randomized values

b) rotating one of the sensor nodes by 45°

c) shifting one of the sensor nodes by 20 cm (Figure 4b)

Finally, three criteria are used to optimize the ANNs: prediction accuracy, ability of sensor fault detection, and time consumption during training. To optimize the topology, various numbers of hidden layers and hidden neurons per layer are tested. Interlayer connections, allowing only synapses between neurons in adjacent layers, as well as supralayer connections, allowing synapses between neurons in distant layers, are applied. As for the neuron behaviors, different training algorithms, backpropagation (RUMELHART et al. 1986), and resilient backpropagation (RIEDMILLER & BRAUN 1993), are tested. The training and testing of each type of fault is repeated five times. As a performance measure, the root mean square errors (RMSEs) between the measured and the predicted data are calculated and averaged for all iterations.

3.3 Test results

Sensor faults are identified by increased RMSEs between the measured and the predicted magnitude of the sensor node. Benchmarks for different neural network topologies are shown in Table 1. For non-faulty sensor data, small RMSEs indicate a good approximation. The smallest RMSEs between 0.063 and 0.144, representing the best results, are retrieved with interlayer connected topologies and backpropagation. Using topologies with supralayer connections or the resilient backpropagation training algorithm leads to RMSEs between 0.132 and 0.208. When propagating data of simulated sensor faults through the ANNs, increased RMSE indicate efficient sensor fault detection. The RMSEs of all ANNs increase by a factor of 1.5 to 12 for different simulated sensor faults. Run times during training deviate by a factor of up to 40 between 4.6 s and 172.4 s. In general, the time increases with the number of hidden neurons within an ANN. Using resilient backpropagation, compared to backpropagation, increases the training time for identical topologies by a factor of around 6.

By comparing the benchmarks of different ANN topologies and taking all criteria and results into consideration, a 3-2-1 interlayer-connected ANN, as shown in Figure 5, with backpropagation is concluded to be the most suitable for the test structure used in this study. The results of the 3-2-1 ANN are marked in Table 1. The RMSE of 0.102 for the test data of the selected ANN is within the lower third of all results. With respect to the simulated sensor faults, the RMSEs of 0.807, 0.603, and 0.410 for randomizing, rotating, and shifting the sensor nodes are within the top quarter of all results. These RMSEs correlate with relative errors of 30.05 %, 27.78 %, and 18.87 % respectively. The training of the 3-2-1 topology, executed in 13 s, is the second fasted.

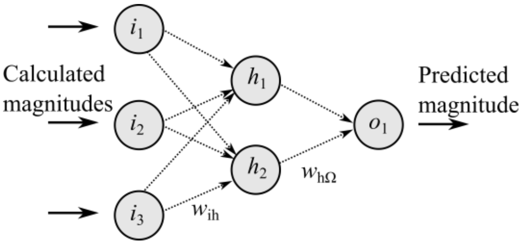

Figure 5:
Optimal ANN topology for sensor fault detection: 3-3-1 feedforward neural network with unidirectional interlayer synapses

Table 1: Arithmetic mean of root mean square errors during training and fault detection, and time consumed during training for several network topologies

			Simulated sensor faults			
	Topology	**Testing**	**Random**	**Rotated**	**Shifted**	**Time [s]**
Interlayer, backpropagation	3-1	0.149	0.767	0.612	0.334	6.6
	3-2-1	**0.102**	**0.807**	**0.603**	**0.410**	**13.0**
	3-3-1	0.144	0.751	0.581	0.283	17.2
	3-5-1	0.081	0.784	0.597	0.370	25.0
	3-7-1	0.063	0.756	0.587	0.294	32.2
	3-2-2-1	0.092	0.813	0.625	0.432	21.0
	3-5-5-1	0.137	1.213	0.752	0.938	46.6
Interlayer and supralayer, backpropagation	3-3-1	0.147	0.762	0.593	0.317	15.2
	3-5-1	0.132	0.764	0.600	0.324	22.6
	3-2-2-1	0.137	0.760	0.601	0.312	19.4
Interlayer, resilient backpropagation	3-3-1	0.153	0.783	0.610	0.364	113.0
	3-5-1	0.143	0.729	0.598	0.249	172.4
	3-2-2-1	0.208	0.744	0.607	0.282	120.6

4 Summary and conclusions

This paper has presented a decentralized autonomous sensor fault detection strategy for wireless structural health monitoring systems based on analytical redundancy. Autonomous sensor fault detection has been implemented by embedding artificial neural networks into the sensor nodes. The ANNs have been trained to predict expected sensor data to be compared to measured sensor data in order to detect sensor faults. To verify the proposed approach, the SHM system has been installed on a test structure for validating tests. Several different ANN models have been tested to identify an efficient, resource-saving configuration. As a result, an artificial neural network with 3-2-1 interconnected topology and backpropagation training algorithm training has been proven to be the optimal solution for the structure tested in this study. In summary, it can be concluded that sensor fault detection using neural networks can improve the dependability and the accuracy of structural health monitoring systems. In future work, different types of artificial neural networks and further topologies may be investigated. The SHM system may be tested under varying conditions on test structures with other stimuli or on site. To ensure portability of the proposed fault detection approach, the SHM system may be implemented on other types of sensor nodes.

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