Reliable operation of sensors in structural health monitoring (SHM) systems is important, as sensor faults may affect the quality of monitoring by causing erroneous judgments of structural conditions. Detecting and isolating sensor faults falls within the scope of fault diagnosis (FD), which has been widely applied in SHM. From a wireless SHM perspective, recent studies have proposed so-called “analytical redundancy” approaches for detecting and isolating sensor faults. Analytical redundancy refers to methods using information inherently redundant to the SHM system to produce virtual sensor outputs, which are then compared to actual sensor outputs. In FD approaches using analytical redundancy, FD is achieved through machine learning methods, such as artificial neural networks, the virtual sensor outputs being obtained using the correlation between structural response data sets. In this paper, an analytical redundancy FD approach for wireless SHM systems based on support vector regression (SVR) is presented, representing a computationally efficient machine learning approach for preserving the constrained resources of wireless sensor nodes. The FD-SVR approach is implemented into a prototype wireless SHM system, enabling automated, decentralized sensor fault detection and isolation. The ability of the embedded SVR algorithm to detect and isolate sensor faults is showcased in laboratory experiments, proving the ability of the FD-SVR approach to ensure the reliable, i.e. non-faulty, operation of sensors in wireless SHM systems.

Keywords: Fault detection and isolation, fault diagnosis, structural health monitoring, analytical redundancy, wireless sensor networks, support vector regression

1 Introduction

Information obtained from structural health monitoring (SHM) systems aims to issue alerts for taking further action against potential hazards posed to structural integrity (LYNCH et al., 2016). Furthermore, in wireless SHM systems, embedded computing is often leveraged towards conducting SHM tasks on board wireless sensor nodes so as to avoid the power-consuming transmission of entire data sets (DRAGOS & SMARSLY, 2015). The consequent scarcity of raw SHM data renders manual detection of anomalies, such as sensor faults, within the data burdensome. A sensor fault is usually caused by malfunctions or by external factors, resulting in an error and, eventually, in SHM system failure. According to QIN & LI (1999), the five most common sensor fault types are bias, drift, complete failure, gain, and precision degradation. Bias introduces a constant offset in the SHM data, while drift is represented by a linear (incrementing) offset with respect to the actual SHM data (i.e. the SHM data if the fault does not occur). Complete failure results in constant values or noise in the SHM data, gain introduces a scaling factor to the SHM data, and precision degradation contaminates the SHM data with white noise. To ensure reliable operation of
wireless SHM systems, sensor faults need to be effectively handled. Referred to as “fault diagnosis”, managing sensor faults encompasses four stages: i) fault detection, where anomalies in SHM data are recognized, ii) fault isolation, in which the exact location of faults is determined, iii) fault identification, where the type of fault is determined, and iv) fault accommodation, which involves corrective action to alleviate the fault effects.

Fault diagnosis has been a topic of ongoing research since the middle of the last century (MOORE & CHANNON, 1956; VON NEUMANN, 1956; WILLSKY, 1976). Fault diagnosis approaches are usually based on comparisons between virtual sensor outputs and actual sensor outputs (SMARSLY & PETRYNA, 2014). In SHM approaches, virtual sensor outputs are obtained either from installing redundant sensors (physical redundancy) or by exploiting the abundance of structural response data and the inherent correlations between responses from different structural locations (analytical redundancy) (KRAEMER & FRITZEN, 2007). The correlation between structural response data sets is either defined via physics-based models or using data-driven models, if no a priori knowledge is available. For example, artificial neural networks have been used in several studies as data-driven models for fault diagnosis (BASIRAT & KHAN, 2009; SMARSLY & LAW, 2014; DRAGOS & SMARSLY, 2016).

Despite the good results obtained from data-driven analysis, methods such as artificial neural networks are classified as “big data methods” requiring large data sets to ensure high quality results. In this paper, a novel computationally efficient data-driven approach towards fault diagnosis is applied. The fault diagnosis approach is based on support vector regression (SVR), which usually performs better with small data sets compared to big data methods, and it enables a conceptually easier implementation, thus allowing embedding algorithms into wireless sensor nodes performing SVR. As a result, wireless sensor nodes are essentially enabled to autonomously self-diagnose sensor faults, enhancing the decentralization of the SHM system. The work in this paper focuses on fault detection and isolation, but the FD-SVR approach can be easily extended to the other two stages of fault diagnosis. The accuracy and the computational efficiency of the approach is validated through laboratory tests using a prototype wireless SHM system installed on a shear frame structure, which showcase the capability of the FD-SVR approach to detect sensor faults. The paper is structured as follows: First, the background and the underlying theory of the FD-SVR approach is elucidated. Then, the implementation of an embedded SVR algorithm in the SHM system is described. Finally, the validation tests are presented followed by a summary and conclusions as well as suggestions for future research directions.

2 Fault detection and isolation based on analytical redundancy using support vector regression

The fault detection and isolation approach presented in this paper is based on machine learning via support vector regression following the concept of analytical redundancy. In this section, the basic principles of the proposed FD-SVR approach are illuminated.

2.1 Correlation between structural response data sets

Analytical redundancy-based approaches depend on correlations between structural response data sets, in that for producing virtual sensor outputs, input data from correlated
sensors is required. In general, correlation between two data sets \( i \) and \( j \) is expressed through the correlation coefficient \( \rho \), as shown in Equation (1).

\[
\rho_{ij} = \frac{\text{cov}(i, j)}{\sigma_i \sigma_j} = \frac{\text{E}[(i - \mu_i) \cdot (j - \mu_j)]}{\sigma_i \sigma_j} = \frac{\sum_{k=1}^{n} (i_k - \bar{i}) \cdot (j_k - \bar{j})}{\sqrt{\sum_{k=1}^{n} (i_k - \bar{i})^2 \cdot \sum_{k=1}^{n} (j_k - \bar{j})^2}}
\]

In Equation (1), “cov” denotes covariance, \( \mu \) and \( \sigma \) represent mean and standard deviation, respectively, \( \text{E} \) is the expected value, and the overbar denotes the sample mean. Furthermore, according to the theory of structural dynamics, structural response data sets, such as acceleration response data sets, essentially consist of harmonic functions at frequencies equal to the eigenfrequencies of structures. These harmonic functions are either positively or negatively correlated to each other depending on the shapes of the corresponding vibration modes describing physical oscillations. While positive correlation is represented by a phase shift between the harmonic functions equal to zero, negative correlation is characterized by a phase shift equal to \( \pi \), as shown in Figure 1. Based on these correlations, structural response data at a specified location can be predicted using structural response data from neighboring locations as input data by applying a machine learning algorithm, such as support vector regression.

![Fig. 1: Correlation between harmonic functions composing structural response data sets.](image)

### 2.2 A support vector regression algorithm for fault diagnosis

Support vector regression is used for building an approximation function \( \hat{f} \) that approximates the behavior of a black box function \( f \), which typically represents numerical models or physical experiments, to reduce the computational cost of calculating all points of \( f \) (FORRESTER et al., 2008). Function \( \hat{f} \) is constructed from “training data” consisting of input points \( x_1, x_2, \ldots, x_n \) within a domain \( D \subset \mathbb{R}^d \) and the responses \( y = [y_1, y_2, \ldots, y_n]^T = [f(x_1), f(x_2), \ldots, f(x_n)]^T \), which are obtained from the numerical model or from the physical
experiment under consideration. SVR strategies vary depending on the application; the strategy employed in this paper is the so-called $\varepsilon$-SVR (SCHÖLKOPF & SMOLA, 2002), in which the approximation function is:

$$\hat{f}(x) = \mu + \sum_{i=1}^{n} w_i \psi(x, x_i).$$

(2)

In Equation (2), $w = [w_1, w_2, \ldots, w_n]^T$ and $\mu$ are unknown model parameters, whose values are determined through optimization, and $\psi$ is a Kernel function, which defines the correlation between a new point $x$ and the training data. In this study, a Gaussian Kernel function with $\psi(x_i, x_j) = \exp(-|x_i - x_j|/\sigma^2)$, with $\sigma^2$ being the variance, is implemented. To define the optimal values for $w$ and $\mu$, the following optimization problem needs is solved:

$$\min_{w, \mu, \xi} ||w||^2 + \sum_{i=1}^{n} (\xi_i^+ + \xi_i^-) : \begin{cases} y_i - \hat{f}(x_i, w) \leq \varepsilon + \xi_i^+ \\ \hat{f}(x_i, w) - y_i \leq \varepsilon + \xi_i^- \quad \forall i \in [1, n]. \\ \xi_i^+, \xi_i^- \geq 0 \end{cases}$$

(3)

In the optimization problem shown in Equation (3), the goal is twofold: On the one hand, $\hat{f}$ should deviate from responses $y_i$ for $i = 1 \ldots n$ by a value lower than $\varepsilon$. On the other hand, $\hat{f}$ should be as flat as possible, which is ensured by the minimization of $||w||^2$. The equation is expanded by slack variables $\xi_i^+$ and $\xi_i^-$ to avoid the appearance of infeasible constraint. As a result of introducing the slack variables, some deviations larger than $\varepsilon$ may be allowed, but the sum of these deviations should be minimal. Parameter $C$ controls the trade-off between the flatness of $\hat{f}$ and the maximum tolerable deviation higher than $\varepsilon$. Equation (3) is a convex optimization problem, which can be reformulated into a dual quadratic optimization problem by the Lagrangian function and the Karush-Kuhn-Tucker conditions (KUHN & TUCKER, 1951), and it can be easily solved by quadratic programming algorithms for defining the optimal values for $w$ and $\mu$.

The quadratic optimization problem for the FD-SVR approach assumes structural response data at sensor node $j$ as input points, described by a function of the corresponding data at $k$ other sensor nodes, as shown below:

$$x^{(j)}(t_i) = f_j \left( x^{(1)}(t_i), K, x^{(j-1)}(t_i), x^{(j+1)}(t_i), K, x^{(k)}(t_i) \right)$$

(4)

In Equation (4), $t_i$ is the time step, at which the structural response data has been collected, which is defined by the sampling rate and by the measurement duration. With the $\varepsilon$-SVR, function $\hat{f}_j$ is built based on non-faulty data, and approximates the behavior of $f_j$. To ensure that a close approximation is possible, $f_j$ is reasonably assumed as continuous; this assumption holds only if structural response data from different sensor nodes are correlated.

Based on the $\varepsilon$-SVR principles, a fault diagnosis algorithm is designed, consisting of three phases, the training phase, the implementation phase, and the fault diagnosis phase. In the training phase, training data is collected from each sensor node, and the SVR parameters for each sensor are calculated by solving the optimization problem shown in Equation (3). In the implementation phase, the approximation function $\hat{f}_j$ is applied on node $j$ for $j = 1 \ldots k$. In the fault diagnosis phase, each sensor node collects data from other sensor nodes, produces virtual outputs approximating its own structural response data, and compares the
virtual outputs with the actual outputs (i.e. measured structural response data). In the event of discrepancies between the virtual and the actual outputs, a fault detection alert is issued. It should be noted that fault isolation is implicit in this study, since the FD-SVR approach focuses on each sensor node separately.

2.3 Detection criterion for sensor faults

A common criterion for approximating quality is the coefficient of determination $R^2$ (Netter et al., 1996), which describes the part of the variation of function $f$ that can be mapped by the approximation function $\hat{f}$, given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{f}(x_i))^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}.$$  \hspace{1cm} (5)

In Equation (5), $y_i$ is an actual output of $x_i$, and $\hat{f}(x_i)$ is a virtual output of $x_i$ for $i = 1 \ldots n$. The value $\bar{y}$ denotes the mean value of $y_1 \ldots y_n$. The values of $R^2$ lie between 0 and 1, with values close to 1 indicating good approximation. In the training phase, $R^2$ is calculated using the training data. However, to avoid bias, additional untrained data is collected, called validation data, and applied for validating the value of $R^2$. Using the validation data, a reliable $R^2$ value is obtained and a boundary $\varepsilon$ is defined based on the $R^2$ value. In the fault detection phase, sensor nodes issue fault detection alerts for $R^2$ values lower than $\varepsilon$. Particular attention should be paid to identifying deviations of $R^2$ from values indicating non-faulty operations that may be attributed to changes in the structural state, e.g. due to structural damage. To avoid false fault detection alerts, the outcomes from several sensor nodes need to be collaboratively analyzed; fault detection alerts issued by the majority of sensor nodes may indicate structural damage.

3 Implementation of the embedded SVR algorithm into a wireless SHM system and validation tests

The FD-SVR approach is implemented into a prototype wireless SHM system, as described in this section. First, the prototype wireless SHM system is described including the software for embedding SVR into wireless sensor nodes, and, next, the validation tests are presented.

3.1 Implementation of the FD-SVR approach into a wireless SHM system

The prototype wireless SHM system devised for implementing the FD-SVR approach is composed of (i) wireless sensor nodes, (ii) a base station, and (iii) a host computer. The sensor nodes are assigned to collect acceleration response data through integrated accelerometers and to analyze the data directly on board. The objective of the on-board analysis is to predict the output of a sensor node using the acceleration response data from neighboring sensor nodes as input data and to issue fault detection alerts in the event of discrepancies between the predicted output and the actual output of the sensor node. The outcome of the FD-SVR analysis is transferred wirelessly via the base station to the host computer, where the outcome is stored in a database.
The SHM system is installed on a test structure, which is a four-story shear frame structure consisting of four 300×200 mm (length × width) aluminum plates, resting on four aluminum columns of rectangular 20×2 mm cross sections. The story height is 300 mm, and the short cross section dimension of the columns is aligned with the long dimensions of the plates. The sensor nodes employed in this study are of type “Oracle Sun SPOT” (ORACLE CORP., 2009), each node featuring a programmable 400 MHz ARM main processor, 1 MB RAM, 8 MB flash memory storage, and a tri-axial accelerometer. The experimental setup is shown in Figure 2.

![Test structure and wireless SHM system.](image)

The software for implementing the FD-SVR approach consists of two applications written in Java, one “node-application”, deployed on the sensor nodes, and one “host-application”, running on the host computer. The node-application includes classes managing the sensor nodes operation (e.g. calibration, synchronization, data collection) as well as classes for performing fault detection during the testing phase. The host application classes are assigned with calculating the approximation function for each sensor node upon receiving sets of structural response data (training data) from all sensor nodes, as part of the training phase. The approximation functions are implemented into the corresponding sensor nodes during the implementation phase.

### 3.2 Validation tests

The validation tests are performed by deflecting the top story from the equilibrium position and by letting the structure vibrate freely. Since the test structure is a shear frame structure, it is expected that the structural response to free vibration is predominantly governed by the fundamental mode of vibration, in which all stories are in phase with each other, and the corresponding harmonic functions are therefore fully correlated. However, in practice the combined contribution of several modes, in which the measured locations of structures may be either in phase or out of phase, may compromise the accuracy of the FD-SVR approach. Therefore, the applicability of the FD-SVR approach needs to be case-specifically assessed based on the expected structural dynamic behavior. Despite the prevalence of the fundamental mode in the validation tests, non-negligible discrepancies of the correlation coefficient from unity are observed for some combinations of structural response data. For the sake of brevity, the focus is placed on the fault detection outcome of the sensor node on the third story, which shows the highest correlation to the rest of the sensor nodes. To determine the size of the training data, several trials are conducted for sizes ranging from 200 to 2000 data sets. It is observed that while increasing the size of training data improves the approximation accuracy, large data sizes may induce overfitting problems and
prohibitively increase the computational cost, which may be detrimental to the efficiency of the testing phase as well. From the trials, a trade-off between accuracy and computational efficiency at \( n = 700 \) data points for the training data is established. The training phase ends with the calculation of \( R^2 = 0.98 \), which is validated by additional 2000 training data.

As mentioned previously, sensor faults are classified in different types. It is, therefore, of interest, to observe the ability of the embedded SVR algorithm to detect different types of faults. To this end, two different fault types are simulated: bias and gain, as shown in Figure 3. Bias is simulated by shifting data by a constant value. The comparison between virtual sensor outputs obtained by the embedded SVR algorithm and the actual sensor outputs yields \( R^2 = 0.96 \) and \( R^2 = 0.86 \) for bias values of \(+0.13g\) and \(+0.26g\), respectively. Gain is simulated by introducing a scaling factor to the data. Two gain factors are introduced, 125% and 150% returning \( R^2 \) values of 0.99 and 0.95, respectively. Evidently, the FD-SVR approach is capable of detecting even small faults; however, the computational efficiency of the approach depends on the severity of the fault, with larger faults being more easily detectable.

Fig. 3: Acceleration response data overlapped with different gain values.

4 Summary and conclusions

In wireless SHM systems, fault diagnosis is of increasing importance due to the frequent unavailability of raw data, as a result of wireless sensor nodes processing data on board and communicating only the results of SHM tasks. In this paper, a decentralized analytical redundancy approach based on support vector regression, referred to as “FD-SVR approach”, for autonomous sensor fault detection and isolation in wireless SHM systems has been presented. Specifically, fault detection is performed on board wireless sensor nodes based on information inherently redundant in SHM systems, which is utilized to produce virtual sensor outputs that are compared to actual sensor outputs. The FD-SVR approach has been implemented into a prototype wireless SHM system, comprising wireless sensor nodes, a base station and a host computer, and it has been validated through laboratory tests on a four-story shear frame structure. Upon training the SVR algorithm with structural response data, which is assumed being non-faulty data, the SVR algorithm has been embedded into the sensor nodes. Subsequently, the SVR algorithm has been validated with two simulated sensor faults. The test results have demonstrated that the FD-SVR approach presented in this paper enables computationally efficient and accurate fault detection and isolation, for the fault types bias and gain even for small faults, which are hard to be detected. Further research will focus on the influence of other sensor faults on the FD-SVR approach and on other stages of fault diagnosis, such as fault identification.
References


