Sensor fault diagnosis coupling deep learning and wavelet transforms

J.J. PERALTA ABADÍA, H. FRITZ, K. DRAGOS and K. SMARSLY

ABSTRACT

Sensor networks facilitate collecting measurement data necessary for decision making regarding structural maintenance and rehabilitation in structural health monitoring (SHM) systems. Nevertheless, the reliability of decision making in SHM systems depends on the proper operation of the sensors. Sensors may exhibit faults, entailing faulty data and incorrect judgment of structural conditions. Therefore, fault diagnosis (FD), comprising detection, isolation, identification, and accommodation of sensor faults, has been introduced in SHM systems, enabling timely detection of faulty data while advancing reliable operation of SHM systems. Traditional FD approaches based on “analytical redundancy” take advantage of correlated sensor data inherent to the SHM system, sometimes neglecting the fault identification step, and are implemented for specific sensor data. In this paper, an analytical redundancy FD approach for SHM systems, coupled with machine learning algorithms and wavelet transforms, capable of processing any type of sensor data is presented. A machine learning (ML) regression algorithm is proposed for fault detection, fault isolation, and fault accommodation, and an ML classification algorithm is proposed for fault identification. Continuous wavelet transform (CWT) is used as a preprocessing step of fault identification, exposing fault patterns in the data. The ML-CWT-FD approach is validated using data from a real-world SHM system in operation at a railway bridge implementing a deep neural network as ML regression algorithm and a convolutional neural network as ML classification algorithm. As a result of this paper, the ML-CWT-FD approach is demonstrated to be capable of ensuring reliable SHM systems.
INTRODUCTION

Long-term structural health monitoring (SHM) strategies rely on the unobstructed operation of sensors over extensive periods of time. Therefore, it is imperative to maintain the reliable and accurate operation of sensors against sensor faults. Sources of sensor faults are manifold: Hardware damage as a result of ageing equipment, power supply disruptions, and interference from external factors (e.g. radio circuits, adverse environmental conditions) are examples of causes of faulty sensor operation [1]. Sensor faults manifest as measurement errors that lead to SHM system failures and can be detected in the sensor data [2]. The severe impact of sensor faults on SHM objectives has fueled research on eradicating faults from sensor data, referred to as “fault diagnosis” (FD), typically comprising four steps, (i) fault detection, (ii) fault isolation, (iii) fault identification, and (iv) fault accommodation.

Detecting, isolating, and accommodating faults requires “benchmark” data to be juxtaposed against actual sensor data. For obtaining benchmark data, the concept of “redundancy” in engineering, i.e. duplication of system components to ensure fail-safe operation, has been utilized [3]. In SHM practice, redundancy is achieved either physically, i.e. via back-up sensors in each location, or analytically (virtually) by approximating sensor data, representing structural responses, using physics-based or data-driven models [4]. In long-term SHM systems, the abundance of sensor data has enabled leveraging machine learning (ML) “big data” techniques for building data-driven models [5]. Approaches towards FD using ML have been reported in several engineering fields, such as wind engineering and aviation [6, 7]. The ML techniques used for FD frequently encompass artificial neural networks, recurrent neural networks, and support vector machines [8-10].

However effective, most ML approaches for FD have focused on fault detection, isolation, and accommodation. This paper aims at exploiting the classification capabilities of ML algorithms in an attempt to provide an integrated ML-FD approach, including all four FD steps. Specifically, the FD approach presented in [2], which covers fault detection, isolation and accommodation using an artificial neural network (ANN), is extended to a full FD approach by including a fault identification step realized via a convolutional neural network (CNN). For applying the CNN, patterns in the sensor data indicative of sensor faults must be exposed; to this end, a preliminary step comprising continuous wavelet transform (CWT) is performed. The ML-CWT-FD approach is validated through tests on field sensor data obtained from a railway bridge, with sensor faults being artificially injected into the data. The remainder of the paper is organized as follows: Section 2 describes the preliminary step for exposing sensor fault patterns, followed by the step-wise explanation of the ML-CWT-FD approach in Section 3. Next, the validation tests are presented in Section 4. The paper ends with a summary and conclusions, and with an outlook on future research.

EXPOSING FAULT PATTERNS USING WAVELET TRANSFORM

Fault patterns are essentially “footprints” left by sensor faults in the sensor data. Considering an $N$-sized array of measurements $\tilde{u}$ from a single location, hereinafter referred to as “data point” in the statistical sense, the CWT of $\tilde{u}$ is [11]:

\[ \text{CWT}(\tilde{u})(t, f) = \frac{1}{\sqrt{t}} \int_{-\infty}^{\infty} \tilde{u}(\tau) \tilde{\psi}^{*} \left( \frac{\tau - t}{t} \right) d\tau \]
where, \( \psi(t) \) is the “mother wavelet”, i.e. a wave-like function which is convoluted with data point \( \hat{u} \). Since the aforementioned convolution only yields information about the similarity between the mother wavelet and data point \( \hat{u} \), the parameters \( a \) and \( b \) are introduced to alter the shape and location, respectively, of the wavelet, thus producing so-called “daughter wavelets”, which obtain a broad picture of the frequency content across the entire duration of data point \( \hat{u} \). Essentially, each daughter wavelet is “run” through a specific location of data point \( \hat{u} \), controlled by parameter \( b \), and for each location of data point \( \hat{u} \), a number of daughter wavelets with different scales, controlled by parameter \( a \), are examined. In this context, the scale parameter \( a \) may be viewed as an indicator of the frequency content of data point \( \hat{u} \) for each time point \( \Delta t \). Several wave-like functions have been used in literature as “mother wavelets”, such as the “Mexican hat”, the “Morlet” wavelet, and the “Shannon” wavelet [11]. The CWT of a typical SHM data point is usually depicted as a color-scaled image. Figure 1 shows fault patterns of sensor faults typically encountered in SHM, namely “bias”, “drift”, “precision degradation”, “complete failure”, “gain”, and “outliers”, along with the manifestation of each sensor fault in the raw sensor data.

![Figure 1. Fault patterns of typical sensor faults.](image-url)
The ML-CWT-FD approach builds upon previous work presented in [2] and extended information of the approach may be found in [12]. The steps towards performing all four stages of FD are listed below and illustrated in Figure 2.

- **Fault detection** is achieved using analytical redundancy. Specifically, for each data point, virtual (expected) values \( \tilde{u} \) are approximated with an ANN to which data points from neighboring measurement locations are fed as input data. For successfully training the ANN, input data points need to be correlated with the output data point. The detection is based upon the coefficient of determination \( R^2 \) being lower than a predefined threshold \( \varepsilon \).

- **Fault isolation** is performed by selecting suitable ANN architectures. In particular, by devising one ANN for each data point, fault isolation is achieved implicitly since each ANN is dedicated to a specific data point.

- **Fault identification** is the outcome of a convolutional neural network, trained to identify fault patterns exposed by CWT. Following the detection and isolation of a sensor fault, CWT is applied to the faulty data point and the CWT image is fed to the CNN, which identifies the fault based on its pattern.

- **Fault accommodation** is accomplished by substituting faulty segments from faulty data points with the corresponding virtual values that are produced by the artificial neural networks.

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (\tilde{u}_{i,n} - \hat{u}_{i,n})^2}{\sum_{i=1}^{N} (\tilde{u}_{i} - \hat{u}_{i})^2} < \varepsilon, \quad \tilde{u}_{i} = \frac{1}{N} \sum_{n=1}^{N} \tilde{u}_{i,n}
\]

Figure 2. Steps of the ML-FD approach.

**VALIDATION TESTS**

The capability of the proposed ML-FD approach to diagnose sensor faults is validated through field tests using long-term SHM data from a 10-span reinforced concrete railway bridge. Each bridge deck is supported by four cylindrical piers, with deck-to-pier connections being monolithic. The data acquisition unit of the SHM systems installed on the bridge includes 8 strain gauges and 3 temperature sensors attached to the pile head beams of bored piles, on which the piers are resting, as shown in Figure 3.
The dataset used for the validation tests contains measurements collected over a period of one year at a sampling rate of 1.7 mHz, i.e. every 10 minutes. As a result, the input data for the ANN consists of 11 data points, each containing \( n = 52,560 \) measurements. All sensor faults depicted in Figure 1 are sequentially injected in the data points, except for the “outlier” fault, which has exhibited no discernible fault pattern, thus rendering the proposed approach unsuitable for detecting outliers. With respect to CWT, the “Mexican hat” mother wavelet is chosen, as shown in Equation 2.

\[
\psi(t) = \frac{2}{\pi^{1/4} \sqrt{3} \sigma} \left[1 - \left(\frac{t}{\sigma}\right)^2\right] e^{-t^2/2\sigma^2}
\]  

(2)

Upon injecting one sensor fault, the data points are fed to the ANN, which detects and (implicitly) isolates the fault. Subsequently, the CWT of the faulty data point is obtained and fed to the CNN, which identifies the fault. Finally, the fault is accommodated using the virtual values from the output of the ANN. The fault detection results expressed as \( R^2 \) values are summarized in Table I, and the results from identifying the faults injected into the data points are shown in Table II in the form of a “confusion” matrix that showcases the performance of the CNN. Figure 4 shows the patterns of the faults injected into the data points for each sensor fault.

As can be seen from Table I, the rate of fault detection is high. Even for sensor faults causing relatively small deviation from the actual values (i.e. 5% of the mean actual value), a considerable deviation of \( R^2 \) from unity is observed. As regards fault identification, the confusion matrix of Table II shows that the rate of false identification is particularly low. The results clearly highlight the ability of the proposed ML-CWT-FD approach to perform full fault diagnosis.
TABLE I. FAULT DETECTION RESULTS

<table>
<thead>
<tr>
<th>Fault type</th>
<th>Fault parameter</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-faulty $\bar{x}(t)$</td>
<td>$b = 0.01 \bar{x}$</td>
<td>0.992</td>
</tr>
<tr>
<td>Bias</td>
<td>$b = 0.05 \bar{x}$</td>
<td>0.985</td>
</tr>
<tr>
<td>Gain</td>
<td>$b = 1.01 \bar{x}$</td>
<td>0.851</td>
</tr>
<tr>
<td>Drift</td>
<td>$b = 1.05 \bar{x}$</td>
<td>0.072</td>
</tr>
<tr>
<td>Precision degradation (PD)</td>
<td>$\sigma^2 = 0.02$</td>
<td>0.473</td>
</tr>
<tr>
<td>Complete failure</td>
<td>$\sigma^2 = 0.1$</td>
<td>0.037</td>
</tr>
<tr>
<td>a. Noise</td>
<td></td>
<td>-1.066</td>
</tr>
<tr>
<td>b. Constant</td>
<td>$b = 0 \bar{x}$</td>
<td>-1.087</td>
</tr>
</tbody>
</table>

TABLE II. CONFUSION MATRIX OF THE CNN

<table>
<thead>
<tr>
<th></th>
<th>Bias</th>
<th>Gain</th>
<th>Drift</th>
<th>PD</th>
<th>CF a.</th>
<th>CF b.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias</td>
<td>394</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Gain</td>
<td>0</td>
<td>383</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Drift</td>
<td>0</td>
<td>0</td>
<td>371</td>
<td>0</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>PD</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>369</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>CF a.</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>403</td>
<td>0</td>
</tr>
<tr>
<td>CF b.</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>376</td>
</tr>
</tbody>
</table>

Figure 4. Fault patterns of sensor faults injected in the data points.

SUMMARY AND CONCLUSIONS

In this paper, a fault diagnosis approach for SHM, based on machine learning, has been presented. The ML-CWT-FD approach builds upon previous work on fault detection and isolation using artificial neural networks. To incorporate all stages of fault diagnosis, i.e. fault detection, isolation, identification and accommodation, the ANN used for fault detection and isolation is combined with a CNN for identifying patterns in sensor data indicative of sensor faults, exposed by continuous wavelet transform. Finally, fault accommodation is achieved by substituting faulty data with virtual values obtained from the artificial neural networks, upon which fault detection has been based.
The ML-FD approach has been validated using data from a long-term SHM system installed in a reinforced concrete railway bridge. In particular, strain as well as temperature data collected over a period of one year has been used for the validation tests. Sensor fault types commonly encountered in SHM have been artificially injected into the sensor data. From the results of the validation tests, it is evident that the majority of sensor faults have been successfully detected and identified. Furthermore, the metric used for detecting the sensor faults has been proven particularly sensitive even for faults with low impact on the sensor data. Future work will involve testing the ML-CWT-FD approach with sensor data collected at high sampling rates (e.g. acceleration response data) and investigating the ability of the ML-CWT-FD approach to detect combinations of sensor faults.

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REFERENCES