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Damage detection in a reinforced concrete slab using outlier analysis

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Abstract

Detecting damages from a global perspective, although still a topic of active research, has been resolved with reasonable success by adapting approaches from the fields of statistical pattern recognition and machine learning. As a result, substantial attention is now addressed to bridging the gap between research and industrial use, and numerous successful application studies have been reported for different types of engineering structures. The present paper follows along this path and contributes with an experimental study concerning damage detection in a reinforced concrete slab based on conventional outlier analysis of captured vibration response. The concrete slab is investigated in five measurement setups; one reference, with an initial dent, and four damaged states in which the dent is extended by blank shots fired into the surface. In each state, the structure is subjected to controlled impulse excitation from an installed electro-mechanical actuator, and the response is captured by 14 accelerometers distributed evenly over the concrete slab. The unique entries in the covariance matrix of these accelerations are employed as the feature in the outlier analysis, where the damage index is the Mahalanobis metric.

1. Introduction

Concrete structures are designed to sustain adequate reliability through their life cycle, but due to different environmental and operational effects, the structural integrity is often compromised during the life time. This obviously calls for a need to inspect the structures on a regular basis (1), which, at present, is typically resolved by visual investigations. An inherent deficiency of this visual approach is that some structural areas to be inspected are inaccessible; exemplified by the interior of wind turbine blades and nuclear power plants that are declared safety-critical facilities (2). An inspection alternative is to monitor the structural integrity by means of vibrations measurements, which has been exploited extensively in the Structural Health Monitoring (SHM) research society (2-6). As an application example, wind turbines have been examined with promising results (8-10).

The contribution of the present paper is to investigate the applicability of an existing damage detection scheme, which has shown promising results for wind turbine systems (8-10), in the context of another type of structure, namely, a concrete slab. The concrete slab is treated in an experimental setup, and the damage detection scheme is based on a damage index composed of the Mahalanobis distance (MD).

The paper is built as follows; the experimental setup is described in section 2, followed by a theoretical description of the damage detection method and the detection results. Finally, a conclusion is presented to summarize the content of the paper.

2. Experimental work

A. Instrumentation

The concrete slab has been used as a test specimen by different researchers in order to detect and locate damages by exploring new methods. For instance, Fröjd and Ulriksen (11) demonstrate an approach for detecting and locating the damage in the concrete slab by using wave transmissions. The reader is referred to (11) for a detailed overview of the concrete slab.

In the present study, the concrete slab is investigated with an initial dent. A HILTI DX2 bolt gun is used to increase the dent gradually by shooting several blank shots. The concrete structure and the damages are shown in figure 1.

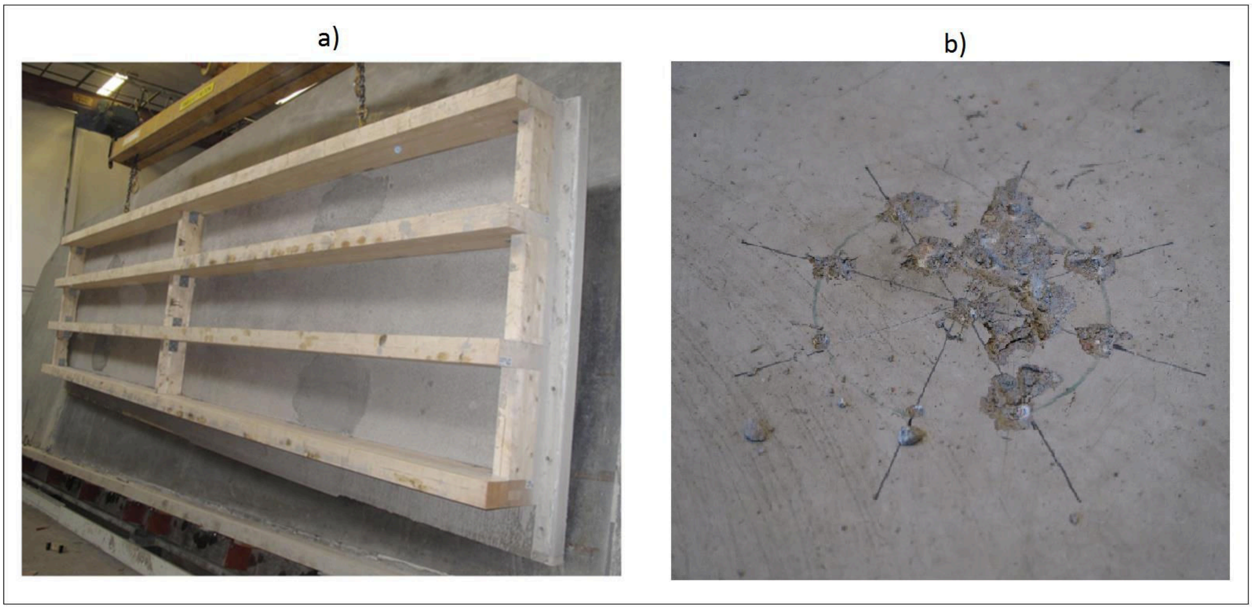

Figure 1. Pictures of the concrete slab, with (a) showing the structure from below and (b) showing an introduced damage (11). Permission under creative commons license (https://creativecommons.org/licenses/by/3.0/.

The concrete slab is 8000 × 2110 × 80 mm in dimensions and is supported horizontally by four equidistant large wooden beams; one beam is supported parallel along the edge and a second beam is shifted in from the opposite edge. The two remaining beams are evenly distributed in between. The concrete slab is instrumented with 14 piezoelectric accelerometers and an electro-mechanical actuator, as shown in figure 2(a). The figure also shows the damage location marked with a black circle.

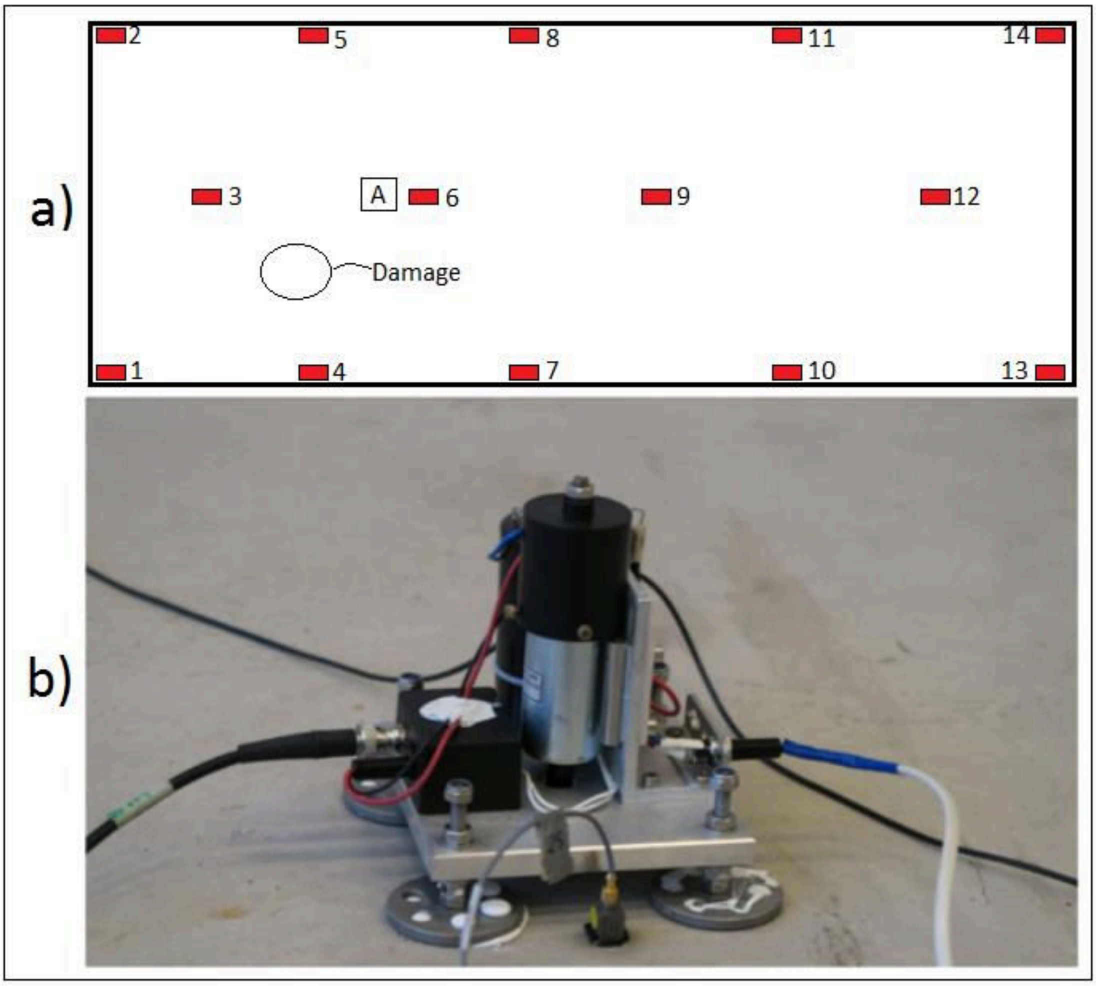

Figure 2. (a) Sensor distribution, damage location marked with black circle and the actuator position marked with the letter A. (b) Electro-mechanical Actuator.

B. Measurement

The hardware setup contains, as mentioned previously, 14 uniaxial accelerometers (Brüel and Kjær Type 4507-B) distributed on the concrete slab. The actuator is glued onto the concrete slab and releases an impact on the concrete slab for each adjusted time interval caused by a hit from a plunger, mounted inside a coil. After the impact, the plunger retracts back to the initial position by a spring, see figure 2(b). The Brüel and Kjær software is programmed to sample with a frequency of 16384 Hz with a signal length of 10 seconds, see figure 3 for a captured response.

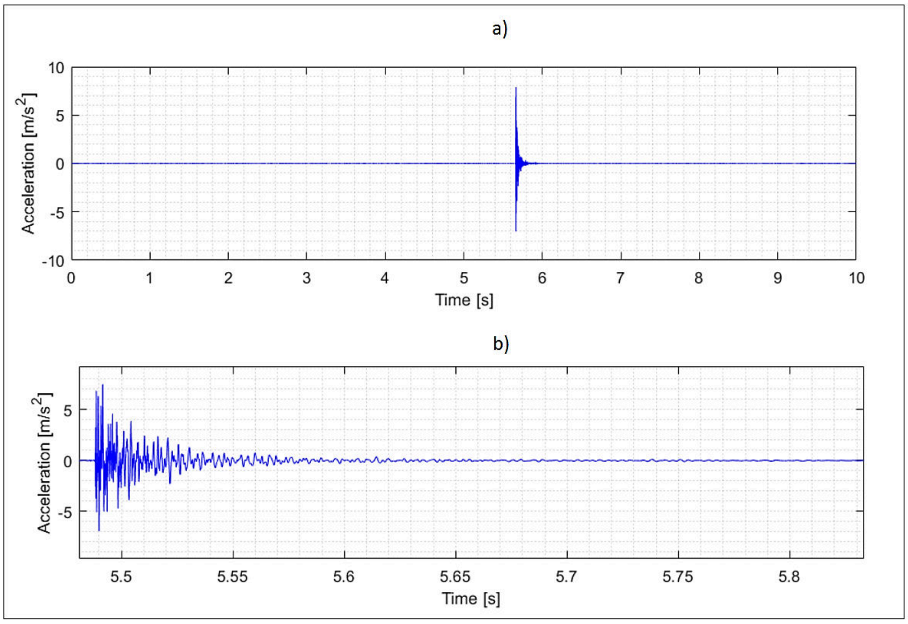

Figure 3. (a) The impulse response and (b) an enlarged visualization of the impulse response.

3. Damage detection

A. Methodology

As described in section 1, the MD-metric is used as a damaged indicator. The MD-metric has, with acceleration measurements as feature, shown promising results for a V27 and an SSP34m wind turbine (8-10). In (8), the MD-metric utilizes a feature composed of principal components of the accelerations, while, in (9), the MD-metric employs the unique entries in the cross-covariance matrix of the captured accelerations.

The present study follows the methodological principle described in (9), but for convenience an explanation of the approach is included in the upcoming description. The cross-covariance matrix is a symmetric matrix that expresses the similarities between the captured response. Assuming a damage is present, the energy propagation, caused by the actuator, will be affected in the concrete slab and the aberration will be captured in the cross-covariance response. Following Tcherniak and Mølgaard (4), the feature vector is obtained by calculating the cross-covariance matrix and reshaping it into a $M = \frac{N(N+1)}{2}$ length vector, which consists of the unique elements in the cross-covariance matrix for N sensors.

In order to establish a baseline for the MD-metric, a training model, representing the reference state of the slab, is constructed by collecting a total of B feature vectors. The feature vectors are subsequently assembled in a matrix $= [x_1, x_2, \dots, x_B] \in \mathbb{R}^{M\times B}$, where $x_1, x_2 \dots, x_B$ are the collected feature vectors that form the baseline. In the current, potentially damaged state, the actuator generates a new sample y_i for every hit, and if the sample deviates significantly from the baseline, the concrete slab is declared damaged. The deviation can be quantified by the MD-metric defined as

$$d(y_i, X) = \sqrt{(y_i - \mu_X)^T \Sigma_X^{-1} (y_i - \mu_X)}\,, \tag{1}$$

where $\mu_X \in \mathbb{R}^{M\times 1}$ is the mean of the feature vectors stored in matrix $\boldsymbol{X}$ and $\boldsymbol{\Sigma_X} \in \mathbb{R}^{M\times M}$ is the covariance matrix of $\boldsymbol{X}$. To distinguish whether a sample is an inlier or an outlier, a conservative choice of a threshold, D, is generated by the maximum value of the undamaged measurements. If a sample exceeds the threshold, the system is declared damaged. The threshold is calculated by

$$D = \max_{\mathrm{i}}\left(d(x_i, X)\right). \tag{2}$$

B. Results

A total of 621 measurements are performed during the whole experiment, where 113 measurements are from the healthy state. 50 measurement sequences are used to construct the training model and 63 are used to test the undamaged state. The experimental campaign is carried out by introducing a damage, collecting measurements for this structural state, and subsequently extending the damage to collect measurements for this state.

Figure 4 shows the obtained detection results, and it is clearly seen how all damages are clearly detected. In the figure, the green crosses represent the first damaged state, the blue circles the second damaged state, and so forth for the magenta diamonds and the red crosses. It is also that there is a clear consistency between the increase in the damage and the damage indicator; the same behaviour was noted in the wind turbine study by Tcherniak and Mølgaard (4).

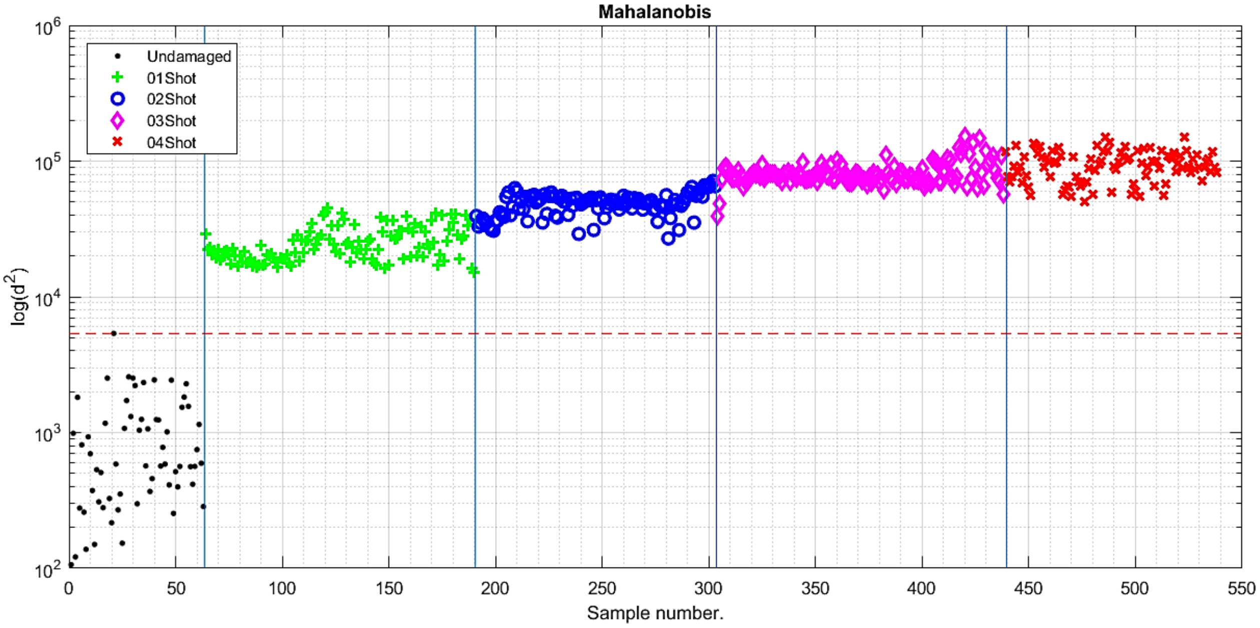

Figure 4. Damage indicators for reference state (1:63), 1st damaged state (64:190), 2nd damaged state (191:303), 3rd damaged state (304:438), and 4th damaged state (439:538). The red horizontal line marks the threshold.

4. Conclusion

This paper presents a damage detection study of a reinforced concrete slab using 14 piezoelectric accelerometers and an electro-mechanical actuator. For the MD-metric, a feature vector, constructed by reshaping the unique elements in the cross-covariance matrix of the accelerations, is generated for each measurement. Four damage states are investigated by gradually increasing the damage with a bolt gun, and it is found that the employed detection scheme enables detection of all the introduced damages.

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