

PCA-Data Compression for Impedance-Based Wireless Structural Health Monitoring Framework

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ABSTRACT:

This paper presents a practical method for an electro-mechanical impedance-based wireless structural health monitoring (SHM) framework, which employs the principal component analysis (PCA)-based data compression. An on-board active sensor system, which consists of a miniaturized impedance measuring chip (AD5933) and a self-sensing macro-fiber composite (MFC) patch, is utilized as a next-generation toolkit of the electro-mechanical impedance-based SHM system. The PCA algorithm is applied to the raw impedance data obtained from the MFC patch to enhance a local data analysis-capability of the on-board active sensor system, maintaining the essential vibration characteristics and eliminating the unwanted noises through the data compression. Then, the root-mean square-deviation (RMSD)-based damage detection result using the PCA-compressed impedances is compared with the result obtained from the raw impedance data without the PCA preprocessing. The effectiveness of the proposed methods for a practical use of the electro-mechanical impedance-based wireless SHM was verified through an experimental study inspecting loose bolts in a bolt-jointed aluminum structure.

Introduction

Damage in civil infrastructures may come from fatigues or excessive external loads such as strong winds, earthquakes, explosions, and vehicle impacts. Early detection of the damage or structural degradation prior to local failure can prevent catastrophic collapse of the civil infrastructures. The large physical size of the civil infrastructures may require an intensive array of different sensors and appropriate technologies for data acquisition/reduction for rational structural health monitoring (SHM) applications. At its simplest application, a risk alarm can be provided when the continuously measured responses at the specific locations of the civil infrastructures exceed the pre-set threshold level. In this sense, an automated electro-mechanical impedance-based SHM technique is being investigated with keen interest as a powerful and innovative tool for local damage detection of the civil infrastructures (Giurgiutiu and Rogers, 1997; Park, G. *et al.*, 2000; Tseng *et al.*, 2000; Zagrai and Giurgiutiu, 2001; Park, G. *et al.*, 2003; Park, S. *et al.*, 2006a; Park, S. *et al.*, 2006b). In general, the electro-mechanical impedance-based

SHM technique utilizes small piezoelectric ceramic (PZT) patches attached to a structure as self-sensing actuators to simultaneously excite the structure with high-frequency excitations, and monitor changes in the patch electrical impedance signature. With the current trend of structural health monitoring heading towards unobtrusive self-contained sensors, the first step in meeting the low-cost, portable, and readily combined with a wireless telemetry requirements resulted in an on-board active sensor system which consists of a miniaturized impedance measuring chip (AD5933) and a self-sensing macro-fiber composite (MFC) patch, as displayed in Figure 1 (Mascarenas *et al.*, 2006; Park, S. *et al.*, 2006c). The on-board active sensor system interrogates a structure utilizing a self-sensing MFC patch and the low-cost impedance method, and all the structural interrogation and data analysis is pursued in near real-time at the sensor location. Moreover, a wireless telemetry that alerts the end user to any harmful changes in the structure can be readily installed. At this point, an adequate pre-processing module to enhance a local data analysis-capability of the on-board active sensor system is strongly required. If only using extremely selected partial frequency range of the raw impedance data, improper selection of data points from frequency windows may result in the loss of important structural dynamic information. Also, changes in the ambient noises including environmental conditions such as temperature, humidity, etc., boundary conditions, and impact loading conditions are known to provide considerable effects on impedance-based damage features (Park, G. *et al.*, 1999). In order to circumvent the above difficulties, a novel method to compress the raw impedance data by the principal component analysis (PCA) algorithm is proposed within the framework of the on-board active sensor system for the electro-mechanical impedance-based wireless SHM.

Principal Component Analysis (PCA)

PCA is a statistical technique that linearly transforms an original set of variables into a substantially smaller set of uncorrelated variables that represents most of the information in the original set of variables (Jlooffe, 1986; Dunteman, 1989). It can be viewed as a classical method of multivariate statistical analysis for achieving a dimensionality reduction, also known as Karhunen-Loeve (KL) transform (Krzanowski, 2000). Based on the fact that a small set of uncorrelated variables is much easier to understand and use in further analysis than a larger set of correlated variables, this data compression technique has been widely applied to virtually every substantive area including engineering, biology, medicine, chemistry, meteorology, geology, as well as the behavioral and social sciences. In the present study, it will be shown that the PCA is also very useful for data compression and noise elimination for the electro-mechanical impedance-based SHM technique.

Using an orthogonal projection, the original set of variables in an N -dimensional space is transformed into a new set of uncorrelated variables, the so-called principal components (PCs), in a P -dimensional space such that $P < N$. In other words, it seeks to project the high-dimensional data into a new low-dimensional set of Cartesian coordinates (z_1, z_2, \dots, z_P) . The new coordinates have the following property: z_1 is the linear combination of the original coordinates x_i ($i = 1, 2, \dots, N$) with maximal variance, z_2 is the linear combination which explains most of the remaining variance and so on. If exist P -coordinates which are actually a linear combination of N ($> P$) variables, then the first P principal components will completely characterize the data and the remaining $N - P$ will be zero. The calculation is described as follows. Given the measurement data sets

$\{x\}_j = \{x_{j1}, x_{j2}, \dots, x_{jN}\}^T$ ($j = 1, 2, \dots, M$), where T denotes transposition and M is the total number of measurements, we form the $N \times N$ -dimension covariance matrix $[C]$ as

$$[C] = \sum_{j=1}^M \{x\}_j \{x\}_j^T \quad (1)$$

and perform singular value decomposition of $[C]$ as

$$[C] = [A][\Lambda][A]^T \quad (2)$$

where $[\Lambda]$ is a diagonal matrix. The transformation to principal components is then accomplished as

$$\{z\}_j = [A]^T (\{x\}_j - \{\bar{x}\}) \quad (3)$$

where $\{\bar{x}\}$ is the vector of means of the x-data. From the point of view of dimensionality reduction, PCA works by discarding those linear combinations of the data which contribute least to the overall variance or range of the data set.

In the present study, PCA is used to reduce the dimensionality and eliminate the unwanted noises of the raw impedance data obtained from the MFC patch. With the measured impedance vectors $\{x\}_j$ ($j = 1, 2, \dots, M$), it is easy to calculate the principal component matrix $[A]$ and their transformations $\{z\}_j$ ($j = 1, 2, \dots, M$) by using the above formulae. In order to determine how many principal components are enough for reserving most information of the original impedance data, impedance reconstruction using only a few principal components will be conducted firstly. The projection of the original impedance matrix $[H(\omega)]_{M \times N}$ which consists of M impedances and has N frequency points for each impedance, on the N principal components, is given by

$$[B]_{M \times N} = [H(\omega)]_{M \times N} [A]_{N \times N} \quad (4)$$

The projection matrix $[B]$ and the principal component matrix $[A]$ can be portioned into two sub-matrices with P significant principal components and $(N - P)$ insignificant principal components (which actually are trivial and thus not really principal) as

$$[B]_{M \times N} = \left[[B_1]_{M \times P} \ ; \ [B_2]_{M \times (N-P)} \right] \quad (5a)$$

$$[A]_{N \times N} = \left[[A_1]_{N \times P} \ ; \ [A_2]_{N \times (N-P)} \right] \quad (5b)$$

The impedance matrix can therefore be reconstructed for only P principal components as

$$\begin{aligned} [H_R] &= [B][A]^T \\ &= \left[[B_1]_{M \times P} \ ; \ [B_2]_{M \times (N-P)} \right] \left[[A_1]_{N \times P} \ ; \ [A_2]_{N \times (N-P)} \right]^T \\ &\cong [B_1]_{M \times P} [A_1]_{P \times N}^T \end{aligned} \quad (6)$$

By using different number of principal components, impedances are reconstructed. For this study, only two principal components the most sensitive due to damage can be utilized for the subsequent damage pattern recognition.

Verification of the proposed methods

Experimental Study

In order to verify the effectiveness of the proposed approaches for the electro-mechanical impedance-based wireless SHM, an experimental study inspecting loose bolts in a bolt-jointed aluminum structure was performed. As shown in Figure 2, the MFC patch of $4 \times 2.54 \times 0.0267 \text{ cm}^3$ associated with AD5933 was surface mounted to the specimen that consists of two aluminum beam of dimensions $61.5 \times 5 \times 0.4 \text{ cm}^3$ jointed together with four pairs of bolts and nuts of diameter 8mm. The MFC patch was placed at 16 cm apart from the middle of the joint section of the specimen. Firstly, electro-mechanical impedances for healthy and damage states were measured at a frequency range of 60-70 kHz from the self-sensing MFC patch, as shown in Figure 3. The impedances contain 501 data points.

PCA-data compression

The present study is a promising work to wirelessly transfer the health-diagnostic information which indicates loose bolts in bolt-jointed structures to end user. Because the size of the raw impedance data is prohibitive for a direct use and the raw impedance data are usually very sensitive to some ambient noise effects, the PCA is applied as a preprocessing module to reduce the data dimensionality and eliminate the unwanted noises. The most significant principal components (PCs) obtained from the raw impedances contain those features which are dominant in most of the frequency responses. In order to determine an adequate number of the PCs which can represent the original impedances well, the reconstruction using a different number of the PCs is investigated. Firstly, a total of seven impedance matrixes corresponding to intact state and all damage states are generated, where each matrix has 501 columns equal to the number of data points in each impedance measurement. Then, by combining the above seven matrices, we yield a 7×501 matrix consisting of seven impedances which represent both three healthy structures and four damaged structures. Subsequently, with the use of Equations (4)-(6), the PCs are calculated and impedances are reconstructed using two, four, and six PCs, respectively. In Figure 4, the results are displayed. It can be observed that when two PCs are used, considerable noises of the original impedance can be effectively eliminated, although the impedances reconstructed using six PCs are almost identical with the original ones as a whole. It is assumed that the fourth, fifth, sixth, and seventh PCs might be noise components. Therefore, only three PCs (the first, second, and third PC) will be investigated for the damage identification supposing that they are enough to represent most of features in the original impedance data.

RMSD-based damage detection

Damage is inflicted on the specimen, and the electro-mechanical impedance is recorded for each damage case. In Figure 5(a), it is observed that the damage not only shifts the resonant frequency,

but also makes appearance of new resonant peaks. PCA is applied to the impedance data. It is seen that the ambient noises in the original impedance data (Figure 5(a)) can be filtered effectively by PCA-data compression (Figure 5(b)). For damage quantification of the electro-mechanical impedance-based damage detection technique, root mean square deviation (RMSD) of the real part of the impedance signatures is utilized as a damage indicator. The RMSD metric is given as

$$RMSD(\%) = \sqrt{\frac{\sum_{i=1}^{i=N} (\text{Re}(Z(\omega_i)) - \text{Re}(Z_0(\omega_i)))^2}{\sum_{i=1}^{i=N} (\text{Re}(Z_0(\omega_i)))^2}} \times 100 \quad (7)$$

where $Z(\omega_i)$ is the post-damage impedance signature at the i -th measurement point and $Z_0(\omega_i)$ is the pre-damage value at the i -th measurement point. Recently, an outlier analysis (novelty detection)-based damage detection method was successfully applied to the impedance methods using the RMSD damage metric (Park, S. *et al.*, 2006b). Through the outlier analysis, an optimal threshold value which provides the damage tolerance of the RMSD metric can be determined. At this point, this study executes a PCA-data compression process between the impedance data-measurement and the RMSD metric-calculation. In other words, the RMSD-based damage detection is performed by using the PCA-compressed impedance data. The RMSD results obtained without PCA-preprocessing (Figure 5(a)) are compared with the RMSD results using the impedances reconstructed from one, two, and three PCs in Figures 5(b), (c), and (d). It is observed that the RMSD results using the impedance reconstructed from only two PCs show the most significant damage detectible capability. This result presents that the RMSD method using only a few PCs, which might be the most sensitive due to damage, extracted from the original impedance data will be able to reduce a false-positive damage call in real-world SHM applications. Even if the impedance signatures contaminated by noises are considered, the present approach will be able to provide a rational SHM solution showing the efficient noise elimination.

Conclusions

An experimental study inspecting loose bolts in a bolt-jointed aluminum structure has been conducted to examine the effectiveness of principal component analysis (PCA)-data compression proposed for a practical use of the electro-mechanical impedance-based wireless structural health monitoring (SHM) system. The key idea of this study is to apply the PCA algorithm to the raw impedance data for better local data analysis-capability of an on-board active sensor system. The PCA algorithm was then applied to the raw impedance data so that reduced the dimensionality of impedance data and eliminated unwanted ambient noises including environmental effects such as temperature, humidity, etc by extracting only essential features. The root-mean square-deviation (RMSD)-based damage detection results using the PCA-compressed impedances showed more significant damage detection capability than the RMSD results obtained from the raw impedance data without the PCA preprocessing. One can envision that the on-board active sensor system with a wireless telemetry, that wirelessly transfers only diagnostic information to end users by embedding the PCA-data compression, is placed on in service civil infrastructures to assess the structural health in real-time.

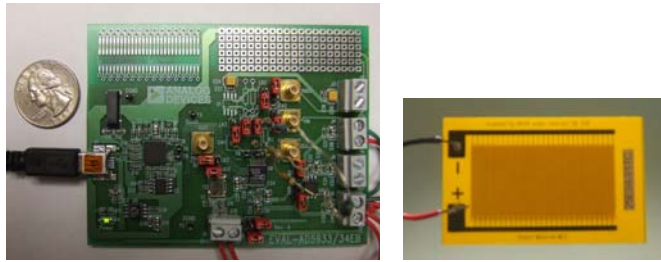


Figure 1. A miniaturized impedance measuring chip (AD5933) and a self-sensing MFC patch

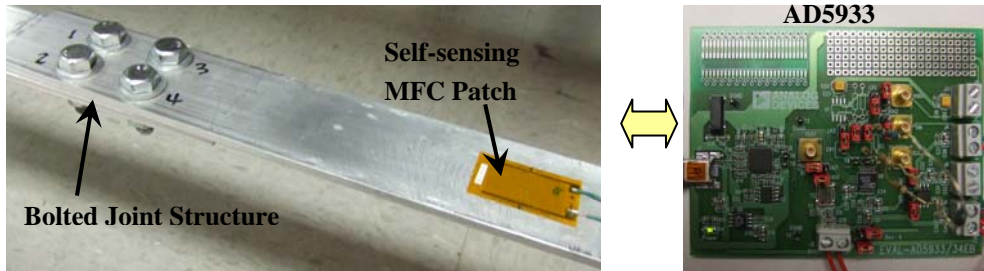


Figure 2. An on-board active sensor system surface mounted on a bolted joint structure

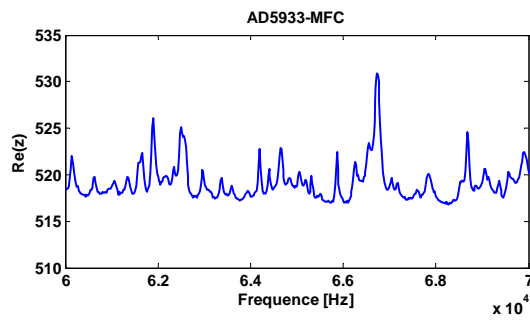


Figure 3. Electro-mechanical impedance data obtained from the AD5933-MFC

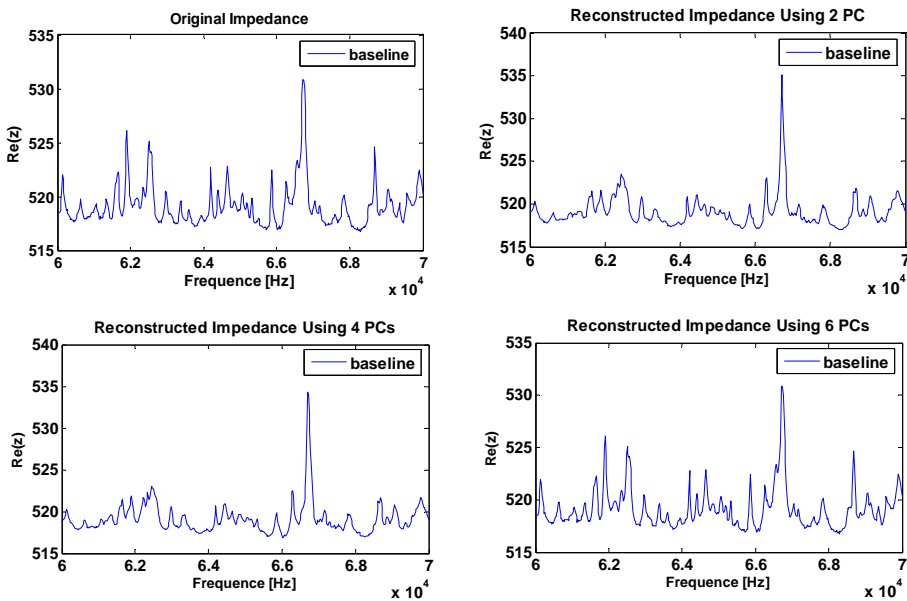
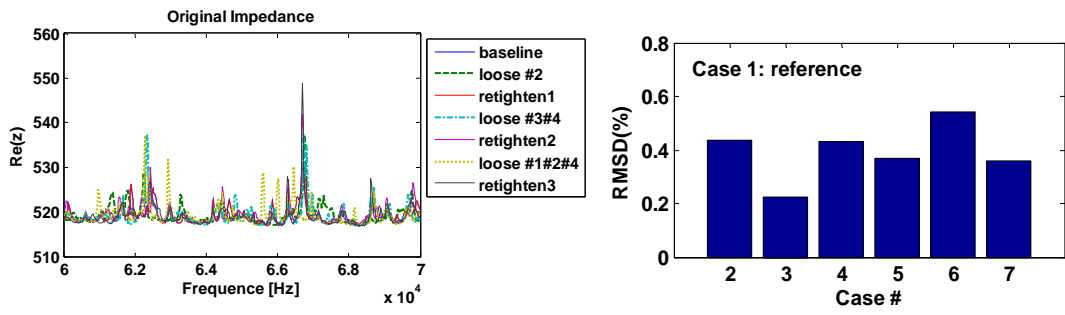
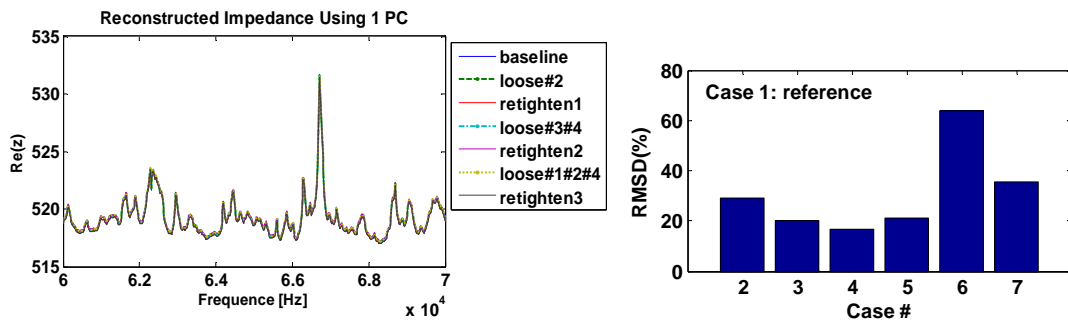


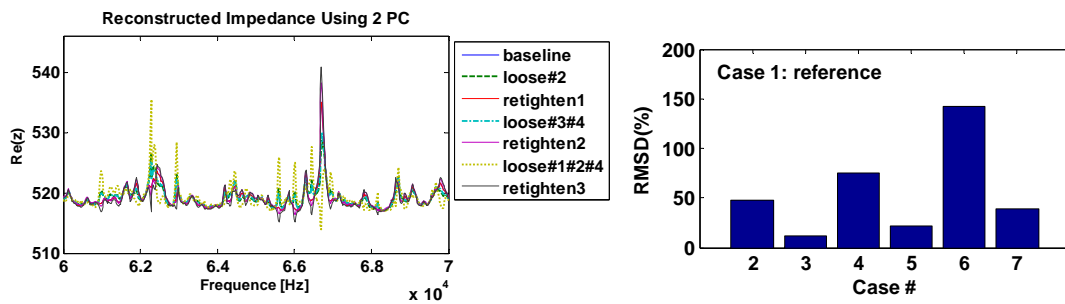
Figure 4. Reconstructed impedances using a different number of principal components



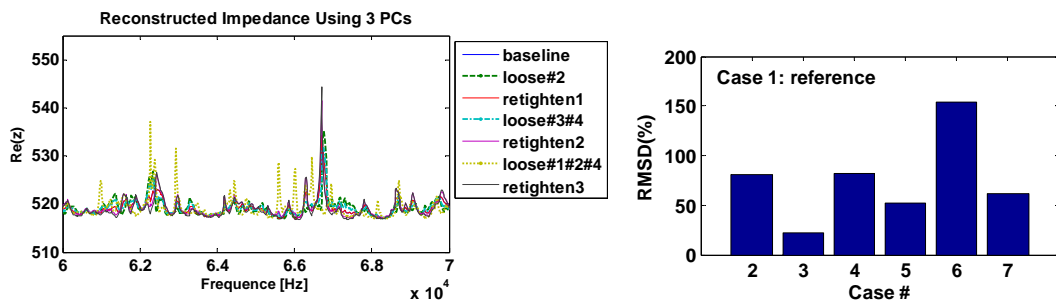
(a) Changes in original impedance due to damage



(b) Changes in reconstructed impedances using one principal component



(c) Changes in reconstructed impedances using two principal components



(d) Changes in reconstructed impedances using three principal components

Figure 5. A comparison between RMSD results with and without PCA-preprocessing

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