Impedance based damage detection under varying temperature and loading conditions

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Abstract

The impedance based damage detection technique utilizing piezoelectric materials has become a promising and attractive tool for structural health monitoring due to its high sensitivity to small local damage. However, impedance signals are also sensitive to time-varying environmental and operational conditions, and these ambient variations can often cause false-alarms. In this study, a data normalization technique using Kernel principal component analysis (KPCA) is developed to improve damage detectability under varying temperature and external loading conditions and to minimize false-alarms due to these variations. The proposed technique is used to detect bolt loosening within a metal fitting lug, which connects a composite aircraft wing to a fuselage. Model and full-scale tests are performed under realistic temperature and loading variations to validate the proposed technique. The uniqueness of this paper lies in that (1) a data normalization technique tailored for impedance based damage detection has been developed, (2) multiple environmental parameters, such as temperature and static/dynamic loading are considered simultaneously for data normalization and (3) the effectiveness of the proposed technique is examined using data collected from a full-scale composite wing specimen with a complex geometry.

1. Introduction

The impedance based damage detection technique is recognized as a promising tool for structural health monitoring (SHM) [1] because of its sensitivity to incipient damage. The impedance technique measures the electrical impedance across the piezoelectric (PZT) transducer attached on a target structure, and it can be shown that this electrical impedance of the PZT is coupled with the mechanical impedance of the host structure. Therefore, damage in the host structure can be detected by monitoring the change of the measured impedance signal [2-4]. However, it has been reported that the impedance signal is also altered by other non-damage related changes such as temperature and loading variations, making it difficult to perform reliable SHM for in-flight and in-situ structures [5-7].

To address this issue, several signal processing, pattern recognition and soft computing techniques were developed, and these techniques are collectively referred to as data normalization techniques [8]. The objective of data normalization is to separate the signal changes caused by structural damage from those caused by operational and environmental variations of the system. Data normalization is previously applied to vibration and guided wave based damage detection techniques [9-11]. However, its applications to impedance based techniques are limited. To name a few, Krishnamurthy et al. developed a correction technique by establishing a temperature coefficient describing the effect of temperature on an impedance signal in order to minimize the variation of the impedance signal due to temperature changes [12]. Temperature is known often to cause horizontal shifting of an impedance signal, and a cross-correlation between the reference data and test data is computed to compensate this shifting by temperature variations [13,14].

In this study, a data normalization technique is developed specifically for impedance based damage detection. The proposed data normalization technique utilizes Kernel principal component analysis (KPCA) to minimize false-alarms due to variations of surrounding environments. In particular, the proposed data normalization technique takes into account three specific variations, temperature, dynamic and static loading. The detectability of bolt loosening in the metal fitting lug connecting a composite aircraft wing to a main fuselage is examined using the proposed impedance technique at varying temperature and loading conditions. The uniqueness of this paper lies in that (1) a data normalization technique specifically tailored for impedance based damage detection has been developed, (2) multiple environmental parameters, such as temperature and static/dynamic loading are...
considered for data normalization, and (3) the effectiveness of the proposed technique is examined using data collected from a full-scale composite wing specimen with a complex geometry.

This paper is organized as follows. In Section 2, basic principles of the piezoelectric active sensor, impedance based damage detection, and the root mean square deviation (RMSD) damage index are briefly reviewed for the completeness of the paper. Section 3 describes the development of a data normalization procedure. Then, outlier analysis with the generalized extreme value (GEV) statistics is introduced in Section 4. In Sections 5 and 6, model and full-scale tests are performed to demonstrate that bolt loosening in the metal fitting lug connecting a composite aircraft wing to a main fuselage can be detected under realistic external temperature and loading variations. In addition, the performance of the proposed KPCA technique is compared with other PCA and conventional impedance techniques. Finally, the conclusion and discussions are provided in Section 7.

### 2. Impedance based damage detection

Piezoelectric materials produce an electrical charge when it is mechanically stressed, and conversely a mechanical strain is produced when an electrical field is applied to the materials. Because of this unique piezoelectric nature, the piezoelectric materials are commonly in use for various actuation and sensing applications [15].

For impedance based damage detection, a PZT (lead zirconate titanate) transducer, which is one type of piezoceramics, is mounted on a target structure as shown in Fig. 1. Then, an input voltage is applied to the PZT and the output current is measured. The ratio of the input voltage to the output current is defined as the electrical impedance measured by the PZT transducer, and the mechanical impedance of the PZT itself and the host structure are coupled together in the electrical impedance measured by the PZT transducer as follows [16]:

\[
Z(\omega) = \frac{i \omega C \left(1 - k_{31}^2 \frac{Z_e(\omega)}{Z_a(\omega)} + Z_d(\omega)\right)}{1 - k_{31}^2 \frac{Z_e(\omega)}{Z_a(\omega)}}
\]

(1)

where \(C\) is the zero-load capacitance of the PZT, \(k_{31}\) is the electromechanical coupling coefficient of the PZT. \(Z\) is the electrical impedances measured by PZT, \(Z_e\) is the mechanical impedances of the host structure, and \(Z_d\) is the mechanical impedances of the PZT. Assuming that the PZT impedance is invariant, any changes in the measured electrical impedance by PZT can be traced back to the change of the host structure’s mechanical properties, allowing monitoring of defects within the host structure using the measured electrical impedance.

The change of the impedance signal can be quantified by several measures. Root Mean Square Deviation (RMSD) is one of the most frequently used indices and defined as [17]

\[
\text{RMSD} = \sqrt{\frac{\sum_{i=1}^{N} (\text{Re}(Z_{i,o}) - \text{Re}(Z_{i,t}))^2}{\sum_{i=1}^{N} (\text{Re}(Z_{i,t}))^2}}
\]

(2)

where \(\text{Re}(Z_{i,o})\) and \(\text{Re}(Z_{i,t})\) are the real parts of the test and the baseline impedances measured at the \(i\)th frequency interval, respectively. This index is used to detect damage in several applications [18–20]. However, no certain assertion is made in Eq. (2) that only damage causes the change of the RMSD index. In fact, other variations such as surrounding temperature and external loading of an operating aircraft can also produce changes of the RMSD index, and these variations can mask the impedance changes caused by damage.

### 3. Data normalization

#### 3.1. Formulation of the data normalization procedure

To minimize false-alarms that can be produced by variations of surrounding environmental and operational conditions, a data normalization technique using KPCA is developed in this section specifically for impedance based damage detection. Fig. 2 shows the overview of the proposed data normalization procedure: (1) multiple training impedance signals are collected from various operational and environmental conditions of the intact structure. To minimize false-alarms, it is important to collect training data from a wide range of operational and environmental conditions; (2) damage-sensitive features are extracted from the raw impedance signals. The feature extraction should be designed so that the extracted features could be more sensitive to the target damage than environmental variations and the subsequent KPCA could be performed on a reduced dimension; (3) the optimal width of the Kernel function, which is necessary for the following KPCA, is determined in an iterative manner so that the variance of the original features is captured in the first few principal components; (4) the original damage sensitive features are implicitly projected onto the principal axes in a higher dimensional space using KPCA. In fact, the projection onto the higher dimensional space is replaced by a Kernel function in actual implementation. More detail on KPCA is provided in Section 3.3; (5) once a new impedance signal from an unknown condition of the structure is recorded, steps 2 and 4 are repeated using this test impedance signal; (6) the damage index, which is defined as the closest distance between the principal components of the test data and those of the training data, is computed for the subsequent damage diagnosis; (7) outlier analysis is performed on the previously defined damage index by comparing the damage index with a threshold value. Here, the threshold value is determined by fitting an extreme value distribution to the damage indices obtained from the training data. In the next section, linear principal component analysis (LPCA) is first described as a necessary step for introducing KPCA. Then, KPCA is explained in Section 3.3.

#### 3.2. Linear principal component analysis

Linear principal component analysis (LPCA) searches for a linearly transformed coordinate in which the variance of the original data can be maximized [21]. The transformed coordinate and the projection of the original data onto the transformed coordinate can be found by solving an eigenvalue problem of the original data’s covariance matrix. Let \(x_j \in \mathbb{R}^{m \times 1}\), \(j = 1, \ldots, N\), denote a set of \(N\) number of centered, i.e., \(\sum x_j = 0\), \(m\)-dimensional feature vectors extracted from impedance measurements. Then, LPCA is
performed by constructing of the covariance matrix \( C^t \in \mathbb{R}^{m \times m} \)

\[
C^t = \frac{1}{N} \sum_{j=1}^{N} x_j x_j^T
\]  

(3)

which leads to the following eigenvalue problem:

\[
\lambda^* \omega = C^t \omega
\]  

(4)

where \( \omega \) and \( \lambda^* \) are eigenvectors and corresponding eigenvalues, respectively, and \( m \) number of eigenvalues and eigenvectors are available. From LPCA's point of view, \( \omega \) and \( \lambda^* \) are regarded as the principal axes and the variance (information) of the original features projected onto these principal axes.

The \( k \)th principal component of a feature vector \( x_j \) is defined as an inner product between \( x_j \) and the corresponding \( k \)th eigenvector (principal axis) \( \omega_k^* \):

\[
Z_{kj} = \omega_k^* x_j
\]  

(5)

where \( Z_{kj} \) represents the \( k \)th linear principal component of the feature vector \( x_j \).

The LPCA operates with an assumption that the original features are linear. However, the relationship among the original features could be nonlinear. In such case, the concept of the LPCA can be extended to the nonlinear principal component analysis (NLPCA) to reveal nonlinear correlations immanent in the original variables. In this study, the NLPCA is realized by using KPCA, also known as unsupervised least-square support vector machine, which employs a Kernel method and solves a simple eigenvalue problem in a nonlinearly transformed high dimensional space [22,23].

3.3. Kernel principal component analysis (KPCA)

In KPCA, the original input features are first transformed into a higher, possibly infinite, dimensional space using a nonlinear mapping, \( \varphi(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^h \) where \( m \leq h \), and then the LPCA can be performed in this higher dimensional space. Here, \( \varphi(x_j) \) represents the nonlinearly transformed feature vector of QUOTE satisfying a centering constraint, that is, \( \sum \varphi(x_j) = 0 \). The eigenvalue problem is formed in this higher dimensional space in the same way as the LPCA.

\[
\lambda^* \omega^* = C^h \omega^*
\]  

(6)

where

\[
C^h = \frac{1}{N} \sum_{j=1}^{N} \varphi(x_j) \varphi(x_j)^T
\]  

(7)
and λ and v are eigenvalues and corresponding eigenvectors, respectively. Here, v can be expressed as a weighted linear summation of φ(x_i), i = 1,...,N [21]

\[ v = \sum_{i=1}^{N} \lambda_i \phi(x_i) \] (8)

where \( \lambda_i \) are unknown coefficients. Multiplying both sides of Eq. (6) with \( \phi(x_j)^T \) results in another eigenvalue problem [21]:

\[ N \lambda x = K \lambda x \] (9)

where \( x = [x_1, x_2, ..., x_N]^T \in \mathbb{R}^{N \times 1} \). From Eq. (9), N number of \( \lambda_k \) and \( x_k \), k = 1,...,N are obtained. Here, the \( k \)th entity of \( K \in \mathbb{R}^{N \times N}, K_{ij} \) is defined as \( K_{ij} = \phi(x_i)^T \phi(x_j) \), and it can be computed using a Kernel function, \( k(x_i,x_j) \), based on the Mercer’s theorem [22]:

\[ K_{ij} = \phi(x_i)^T \phi(x_j) = k(x_i,x_j) \] (10)

The significance of the Mercer’s theorem is that the inner products of two nonlinearly transformed features, \( \phi(x_i)^T \phi(x_j) \), in the higher dimension space can be replaced by \( k(x_i,x_j) \) without involving the actual nonlinear transformation \( \phi(\cdot) \). Some kinds of Kernels such as polynomial, radial basis function, and sigmoid Kernels are widely used. In this study, a Gaussian Kernel \( k(x_i,x_j) = \exp(-|x_i-x_j|^2/\rho^2) \) is utilized. Here, \( \rho \) is a Gaussian width parameter. The Gaussian width parameter is obtained in an iterative manner by maximizing the difference between the first and the next eigenvalue. In this way, the eigenvalue (information) contained in the first principal component is maximized.

Since \( K \) is a positive semi-definite matrix, all eigenvalues \( \lambda_k, k = 1,...,N \), are non-negative [21]. Then, for the first \( p \leq N \) nonzero eigenvalues, the corresponding eigenvectors are normalized.

\[ v_k = v_k/\|v_k\| = 1/N \lambda_k(x_k^T x_k) = 1, k = 1,...,p \] (11)

where \( \lambda_k \) and \( x_k \) are the \( k \)th eigenvalue and eigenvector obtained from Eq. (9), respectively. Finally, the \( k \)th nonlinear principal component of the feature vector \( x_j \) can be computed as the projection of the feature vector \( x_j \) onto the corresponding \( k \)th eigenvector

\[ Z_{kj} = v_k^T \phi(x_j) = \sum_{i=1}^{N} x_i (k(x_i,x_j)) \] (12)

where \( Z_{kj} \) are nonlinear principal components of the feature vector \( x_j \) obtained by KPCA, the \( i \)th component of the \( k \)th eigenvector \( x_k \), and \( k(x_i,x_j) \) respectively, and \( k(x_i,x_j) \) is the chosen Kernel.

Note that imposing a centering constraint, \( \sum \phi(x_i) = 0 \), in Eq. (9) is not a trivial matter, since the nonlinear mapping \( \phi(\cdot) \) is not explicitly computed. To overcome this difficulty, a centered Kernel matrix \( K^* \) is employed instead of the \( K \) matrix in Eq. (10) as follows:

\[ K^*_i = \left[ \phi(x_i) - \frac{1}{N} \sum_{i=1}^{N} \phi(x_i) \right]^T \left[ \phi(x_j) - \frac{1}{N} \sum_{k=1}^{N} \phi(x_k) \right] \]

\[ = \phi(x_i)^T \phi(x_j) - \frac{1}{N} \sum_{k=1}^{N} \phi(x_i)^T \phi(x_k) - \frac{1}{N} \sum_{k=1}^{N} \phi(x_k)^T \phi(x_j) \]

\[ + \frac{1}{N^2} \sum_{k=1}^{N} \sum_{l=1}^{N} \phi(x_k)^T \phi(x_l) \]

\[ = k(x_i,x_j) - \frac{1}{N} \sum_{k=1}^{N} k(x_i,x_k) - \frac{1}{N} \sum_{k=1}^{N} k(x_k,x_j) + \frac{1}{N^2} \sum_{k=1}^{N} \sum_{l=1}^{N} k(x_k,x_l) \] (13)

The \( k \)th nonlinear principal components for a feature vector \( x_j \) can be computed easily using this centered Kernel matrix.

4. Outlier analysis using extreme value statistics

4.1. Damage index

The occurrence of abnormality is investigated by comparing the most recent test data obtained from an unknown condition with the test data collected from normal conditions using outlier analysis. Once the principal components of the training and test data are computed, the damage index, DI, is defined as the distance from the test data point to the closest training data point in the projected high dimensional space

\[ DI(j) = \min \|Z_j - Z_i\|, i = 1,2,\ldots,N \]

where \( Z_j = [Z_{1j}, Z_{2j}, \ldots, Z_{nj}]^T \), \( Z_i = [Z_{1i}, Z_{2i}, \ldots, Z_{ni}]^T \) (14)

where \( Z_{nj} \) and \( Z_{ni} \) are the \( j \)th test, and the \( i \)th training data projected onto the \( i \)th principal axis, respectively. If the new test data carry abnormal information, the value of the damage index will increase. This characteristic of the index is utilized in this study to identify damage after the data normalization. The statistical model of the damage indices corresponding normal conditions is estimated using extreme value statistics, and then a threshold value associated with a specific confidence level is determined.

4.2. Extreme value statistics

The features associated with damage are often outliers deviating from the normal conditions. These outliers usually occupy the tails of a distribution. Therefore, proper modeling the tail characteristics of a distribution is important when it comes to outlier analysis. To achieve this goal, extreme value statistics is used to model the tail distribution of the damage indices obtained from various operational and environmental conditions of the intact structure. Suppose that the given data are divided into \( n \) numbers of subsets\( [x_1,x_2,\ldots,x_n] \). Then, the most relevant statistics for the tail distribution is the maximum operator, i.e. max\( (x_1,x_2,\ldots,x_n) \), or the minimum operator, i.e. min\( (x_1,x_2,\ldots,x_n) \), that selects the maximum (or minimum) values from each subset. If a large number of data are generated from a single probability distribution and they are independent and identically distributed, the maximum of each subset can be modeled using a single cumulative density distribution called generalized extreme value (GEV) distribution [24].

\[ F_{\text{GEV}}(x|\mu,\sigma,\gamma) = \exp \left\{ -\left[ 1 + \gamma \left( \frac{x-\mu}{\sigma} \right) \right]^{-1/\gamma} \right\}, \quad -\gamma^{-1}(x-\mu) \leq 0, \sigma > 0 \] (15)

where \( \mu, \sigma \) and \( \gamma \) are location, scale and shape parameters of the GEV distribution, respectively. For a given data set, a generalized weighted least square method, which solves a nonlinear optimization problem subject to multiple constrains, is utilized to estimate \( \mu, \sigma \) and \( \gamma \) parameters. More details on the parameter estimation are given in Park et al. [25]. Once the statistical model of the training data is established, a threshold value corresponding to a user specification is readily computed for outlier analysis.

5. Experimental study with a composite aircraft wing segment

5.1. Test set-up

To examine the effectiveness of the proposed data normalization technique, experimental tests were conducted with an aircraft wing segment model shown in Fig. 3. The test article
Consisted of a composite wing segment and two aluminum fitting lugs connected by ten steel bolts. One APC 850 PZT transducer (30 mm diameter and 3 mm thickness) from American Piezo Ceramics Inc. with a feedback electrode was placed on one side of the fitting lug using Loctite 401 (Henkel) adhesive, and the electrical impedance across the PZT was measured to monitor bolt loosening. An onboard impedance unit (4.2 kg) was developed for this study in collaboration with Fiberpro Inc. as shown in Fig. 4(a). An impedance measurement chip, AD5933 developed by Analog Device, was integrated with additional circuits to allow simultaneous impedance measurements from 12-channels (Fig. 4(b)). The impedance chip has a measureable frequency range of up to 100 kHz, and a variable impedance of $100 \Omega$–$1 \text{ M}\Omega$. In this study, the impedance was measured within 60–70 kHz with a 20 Hz frequency resolution. The excitation frequency was selected to be in the range where a higher density
of impedance peaks is observed because more impedance peaks indicate a better coupled behavior between the PZT and the host structure [1]. Furthermore, the driving frequency was limited to be below 100 kHz to minimize the adverse bonding layer effect on impedance signals caused by temperature variation [26].

Impedance signals were measured under varying temperature and static/dynamic loading conditions as shown in Fig. 5. For the temperature experiment, the specimen was placed inside a temperature chamber and a thermocouple was installed on the specimen. Then, temperature was varied from –30 to 50 °C with an incremental value of 10 °C. The temperature of the temperature chamber was maintained within 1–2 °C accuracy while the data from each temperature were collected. Impedance signals obtained under a constant temperature of 10 °C are presented in Fig. 6. It shows that the impedance signal still varies although a constant temperature was maintained with small variation. For the dynamic loading test, random excitations with different peak amplitudes (5, 7 and 10 voltages) and frequency ranges (10–20 Hz, 15–25 Hz and 20–30 Hz) were generated by a shaker and applied to the specimen. For the static loading test, the specimen was loaded using a universal test machine (UTM) from 10,000 to 40,000 kN with an incremental value of 5000 kN. For each loading test, the clamp was repositioned and retightened because the specimen was shifted and the clamp got loose during each loading test. Once the training data were collected from these various temperature and loading conditions, damage was introduced to the specimen by loosening one of ten bolts with a half turn as shown in Fig. 3(b). Then, test data were also collected under temperature and loading variations.

5.2. Damage detection using the proposed data normalization technique

5.2.1. Feature extraction

One of the important steps in successful damage detection is to identify features that are sensitive to the target damage, but less sensitive to varying environmental conditions. Note that understanding of how damage, temperature and loading conditions physically affect the impedance signatures is the key in selecting the features used for KPCA. For the proposed damage detection technique, a measured impedance signal is first divided into real and imaginary parts because it is physically known that temperature and loading mainly affects the imaginary part of the impedance signal while the damage affects the real part of the impedance [6–7,12–14]. Then, the root mean square (RMS), the x coordinate centroid, the maximum and minimum response values and the coefficients of a polynomial function fitted to the impedance signal are computed from the real and imaginary parts of the impedance signal, respectively. Giurgiutiu et al. used polynomial curve fitting for impedance based crack detection in the near field of piezoelectric actuators [27]. These features were selected for representing (1) the horizontal and vertical shifts of the impedance signal due to temperature and loading variations; (2) the amplitude and frequency changes of the impedance peaks due to damage effectively.

When the polynomial function was fitted to the imaginary part of the impedance, the order of the polynomial function was simply fixed to the 5th order because damage diagnosis performance was insensitive to the imaginary part. The order of the polynomial function used for fitting the real component of the impedance was computed so that the features projected onto the higher dimensional space can be well clustered. This well-clustered behavior of the projected features was achieved by minimizing the variance of the projected features with respect to the polynomial order. Fig. 7(a) shows the total variance of the first 5 principal components as a function of the polynomial order. It can be seen that the first local minimum of the variance is achieved when the polynomial order is 5. The impedance signals in Fig. 6 are fitted with the 5th order polynomial curves and shown in Fig. 7(b).

The number of principal components in Eq. (14) was decided to maximize the information (variance) captured within the retained principal components. Fig. 8 shows the variance of the features projected onto the first 6 principal axes, when
the extracted features of training data obtained from different temperature and loading conditions of the intact specimen. It can be shown that the variance drastically decreases for higher principal components, and the majority of variances are captured by the first 5 principal components. Therefore, the first 5 principal components were used for the KPCA based data normalization.

5.2.2. Damage diagnosis with data normalization

Table 1. shows the list of impedance signals obtained under varying temperature conditions. The first 7 data sets (#1–7) obtained from the intact condition of the test article were used to build the KPCA model (for training), and the additional 3 data sets (#8–10) for false-alarm tests. The last 3 data sets (#11–13) were obtained after loosening one of the bolts about 180°, and constituted test data with damage. Note that 15 impedance signals were collected for each data set in Table 1. Fig. 9 (a) shows the damage diagnosis under varying temperature. The threshold value of 0.044 was computed by fitting an extreme value distribution to the damage indices obtained from the training data with 97% confidence interval. Fig. 9(a) demonstrates that bolt loosening is successfully detected under temperature variation while mere temperature changes did not produce false-positive alarms.

Table 2 shows the data sets obtained under dynamic loadings with varying peak-to-peak amplitudes and excitation frequencies. The first 5 data sets (#14–18) were used for training, and the remaining 10 data sets (#19–28) were used for testing. The test data sets consisted of the data from the intact case (#19–23) and the bolt loosening case (#24–28). The other setups were identical to the previous experiment. In Fig. 9(b), bolt loosening is successfully detected under varying dynamic loading without producing false-alarm. The effect of static loading was investigated in Fig. 9(c) using impedance signals listed in Table 3. Successful diagnosis similar to the previous ones is obtained.

Finally, all data obtained from varying temperature and static/dynamic loading are analyzed together. Training was performed using data sets #1–7, #14–18, and #19–32. False-alarm tests were conducted using data sets #8–10, #19–23, and #33–34. Bolt was loosened under varying conditions (data sets #11–13, #24–28, and #35–38) and tested as shown in Fig. 9(d). Note that only the test data are shown in Fig. 9(d) due to the space limit. (Note that data sets # 37 and 38 are not shown in Fig. 9(d)).

Fig. 9 shows that the damage index varies when the bolt is loosened each time. The variation is mainly attributed to two factors: First, when the bolt is loosened each time, it does not necessarily replicate the same damage condition. The friction between the bolt and the specimen, the bolt tension, the gap between the bolt and the specimen all vary every time the bolt is

Table 1

<table>
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<tr>
<th>Data#</th>
<th>State</th>
<th>Temp. (°C)</th>
<th>Data#</th>
<th>State</th>
<th>Temp. (°C)</th>
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*One out of ten bolts in the fitting lug was loosened by a half turn
untightened. Second, the damage index value depends on not only the actual condition of the structure but also the training data used. Since the training data are different for each case presented in Fig. 9, the damage index value inevitably changes each time.

5.2.3. Comparison with other PCA approaches
The performance of the proposed KPCA based data normalization technique was compared with LPCA based data normalization. Except a fact that the principal components were computed using Eq. (5) instead of Eq. (12), all the other parameters such as extracted features, the order of polynomial fitting, and the number of principal components were kept same as the previous KPCA based approach. Fig. 10 presents damage diagnosis using LPCA. It can be seen that false-alarm is produced when LPCA was employed instead of KPCA, in particular due to temperature variations. However, all damage cases are successfully detected. There are other ways of realizing nonlinear PCA including auto-associative neural network (AANN), principal curve, Samson’s mapping and so on. The performance of KPCA was compared with that of AANN in Oh et al. [13]. The advantages of KPCA over AANN can be summarized as follows:

(1) Simpler computation: While a complex nonlinear optimization needs to be solved for AANN, only a simple eigenvalue problem has to be solved for KPCA. In particular, once the training is completed, only dot product between test and training data is required for damage diagnosis, making it more attractive for onboard implementation.

(2) Existence of a unique and global solution: Although the solution of AANN varies depending on the initial guess used for solving

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**Table 2**

<table>
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<tbody>
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<td>29</td>
<td>Intact (training)</td>
<td>33</td>
</tr>
<tr>
<td>30</td>
<td>Intact (training)</td>
<td>10,000</td>
</tr>
<tr>
<td>31</td>
<td>Intact (training)</td>
<td>20,000</td>
</tr>
<tr>
<td>32</td>
<td>Intact (training)</td>
<td>40,000</td>
</tr>
</tbody>
</table>

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*a* Peak-to-peak voltage of the random input signal  
*b* Frequency range of the random input signal  
*c* One out of ten bolts at the connection was loosened by a half turn.  

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Fig. 9. Damage diagnosis using KPCA based data normalization: (a) Under temperature variations. (b) Under dynamic loading. (c) Under static loading. (d) Under temperature, dynamic and static loading variations (The damage index for each data set was the average of 15 damage indices except case (d). For case (d), only 5 values were averaged).
the nonlinear optimization problem, KPCA guarantees a unique and global solution for fixed Kernels. This makes KPCA more attractive for autonomous diagnosis because unnecessary human intervention can be minimized. 

3) Better generalization: Because AANN approach is susceptible to over-fitting, regularization and early stopping schemes are often employed to improve generalization performance of AANN. On the other hand, KPCA, which is also known as least-square
support vector machine, is known to have better generalization performance than AANN [28].

5.3. Damage diagnosis using a conventional impedance based damage detection technique

The performance of a conventional impedance technique was examined under various environmental conditions as shown in Fig. 11. For all cases shown in Fig. 11, data set #1 obtained from the intact condition at 17°C was used as the reference for computing the RMSD index in Eq. (2). Note that 15 individual impedance signals were obtained for each data set shown in Fig. 11, and the corresponding RMSD index for each data set is the average of 15 individual RMSD indices except case (d). For case (d), the averaged RMSD value was computed from 5 individual values. The threshold value was computed using the same extreme value distribution (GEV) and the confidence interval (97%).

The RMSD index simply computes the difference between two impedance signals without concerning what is actually causing such variation. On the other hand, KPCA intelligently finds a mapping of the original features so that the projected features are more sensitive to damage of interest but less sensitive to undesired variations such as temperature variation. This is accomplished by minimizing the variation of the training data in a projected higher dimensional space. That is, fewer false-alarms are triggered using the proposed technique, substantiating the advantage of the proposed KPCA based technique over the conventional impedance technique.

6. Experimental study with a full-scale real aircraft wing segment

To further examine the effectiveness of the proposed data normalization technique, experimental tests under temperature and static loading variations were conducted on a full-scale real aircraft wing segment. The structure consisted of a carbon fiber reinforced composite wing and two aluminum fitting lugs connected by steel bolts as shown in Fig. 12(a) and (b). One PZT transducer (diameter: 30 mm and thickness: 3 mm) was placed on one of the aluminum fitting lugs, and the impedance across the PZT was measured to monitor bolt loosening within a frequency range of 60–80 kHz with a 20 Hz frequency resolution. To introduce temperature and static loading variations, an infrared heater and a hydraulic actuator were used, respectively. For the temperature experiment, the aluminum fitting lug was locally heated from 20°C to 55°C. For the static loading test, one end of the aircraft wing was fixed and the other free-end was loaded up to 6900 N. Once the training data were collected from these temperature and static loading conditions, bolt loosening was introduced to the test article by loosening one out of ten bolts 360° as shown in Fig. 12(c).

In this full-scale experiment, a 4th order polynomial function was used and the other setups remained the same as the previous model segment test. Table 4 shows the training and test data sets collected from varying temperature and static loading conditions. Data sets #1–14 were obtained from the undamaged condition of the wing structure, and data sets #15–17 were collected after loosening one out of ten bolts by one turn. False-alarm tests were conducted using data sets #11–14. Note that five impedance signals were collected for each data set.

![Fig. 12. A full-scale composite aircraft wing segment: (a) Overview of the aircraft wing consisted of a composite wing and two aluminum fitting lugs connected by ten bolts. (b) the aluminum fitting lug with a surface mounted PZT. (c) Specification of the fitting lug and the PZT sensor.](image)

<table>
<thead>
<tr>
<th>Data #</th>
<th>State</th>
<th>Loading (Temperature)</th>
<th>Data #</th>
<th>State</th>
<th>Loading (Temperature)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Intact (training)</td>
<td>750 N (19°C)</td>
<td>11</td>
<td>Intact (test)</td>
<td>750 N (41°C)</td>
</tr>
<tr>
<td>2</td>
<td>Intact (training)</td>
<td>750 N (19.5°C)</td>
<td>12</td>
<td>Intact (test)</td>
<td>750 N (51°C)</td>
</tr>
<tr>
<td>3</td>
<td>Intact (training)</td>
<td>750 N (20°C)</td>
<td>13</td>
<td>Intact (test)</td>
<td>Up 1300 N (20°C)</td>
</tr>
<tr>
<td>4</td>
<td>Intact (training)</td>
<td>750 N (32°C)</td>
<td>14</td>
<td>Intact (test)</td>
<td>Down 3000 N (20°C)</td>
</tr>
<tr>
<td>5</td>
<td>Intact (training)</td>
<td>750 N (46°C)</td>
<td>15</td>
<td>Bolt Looseninga (test)</td>
<td>750N (20°C)</td>
</tr>
<tr>
<td>6</td>
<td>Intact (training)</td>
<td>750 N (55°C)</td>
<td>16</td>
<td>Bolt loosening (test)</td>
<td>Up 3900 N (20°C)</td>
</tr>
<tr>
<td>7</td>
<td>Intact (training)</td>
<td>Up 3900 N (20°C)</td>
<td>17</td>
<td>Bolt loosening (test)</td>
<td>Down 3000 N/20°C</td>
</tr>
<tr>
<td>8</td>
<td>Intact (training)</td>
<td>Up 6500 N (20°C)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Intact (training)</td>
<td>Down 1000 N (20°C)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Intact (training)</td>
<td>Down 5000 N (20°C)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* One out of ten bolts at the connection was loosened by 1 cycle turn.
7. Conclusion

In this study, a new impedance damage detection technique using KPCA based data normalization is developed to improve damage detectability and minimize false-alarms caused by non-damage related variations such as temperature and external loading conditions. Bolt loosening within a metal fitting lug, which connects a composite aircraft wing to a fuselage, is successfully detected under changing static/dynamic loading and temperature conditions. Segment and full-scale aircraft wing tests are conducted under realistic temperature and loading variations to examine the effectiveness of the proposed data normalization technique. The uniqueness of this paper lies in that (1) a data normalization technique specifically tailored for impedance based damage detection has been developed and (2) multiple environmental parameters such as temperature and static/dynamic loading are considered for data normalization. Furthermore, it has been experimentally shown that the proposed KPCA based data normalization may outperform other data normalization using LPCA or AANN and the conventional impedance based damage detection tests, respectively. The damage index for each data set was obtained by averaging 5 damage indices from each data set.

Fig. 13 shows the damage diagnosis with the proposed data normalization. Note that the damage index for each data set was obtained by averaging 5 damage index values computed from all impedance signals in each data set. The threshold corresponding to a 97% confidence interval was calculated as 0.001. It shows that all damage indices obtained from the undamaged conditions do not exceed the threshold, while those from bolt loosening exceed the threshold. A successful damage diagnosis was achieved using the proposed data normalization technique.

Acknowledgements

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References