Structural integrity monitoring by vibration measurements

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Abstract

This paper presents a comparative study on several approaches of structural damage diagnosis based on vibration measurements. Stochastic subspace identification method is used to identify modal parameters and to generate a Kalman prediction model, which are taken as damage-sensitive features for structural damage detection. A statistical process control technique based on principal component analysis (PCA) is also presented. An improvement and enhancement of PCA are proposed. It is assumed that without damage, structural responses should remain approximately in a hyperplane defined by the principal directions of data. Damage localization is explored with these methods. As only the measured output signals are needed, the methods are convenient for an on-line monitoring. The efficiency and limitation of the proposed methods are illustrated by a practical application.

Keywords: damage diagnosis; stochastic subspace identification; modal analysis Kalman model; PCA.

1. Introduction

Structural damage detection via vibration measurements involves the extraction of features from periodically spaced measurements, and the analysis of these features to determine the current state of integrity of the system. In this process, the extraction of damage-sensitive features is of primary importance. As structural constitutive matrices change with damages, model updating of finite elements (FE) may be applied [1]. On the other hand, it is well known that damage may be characterized by changes in the modal parameters, i.e., natural frequencies, mode shapes and modal damping values [2]. Therefore an effective identification of modal parameters is significant. For this sake, a stochastic subspace identification (SSI) technique [3] is adopted in this work.

Damage diagnosis may be realized without need of identification of modal parameters and/or construction of a FE model, see [4-5] for example. In this work, two stochastic process techniques are proposed, which tackle the damage detection problems by a statistical analysis. The first approach [6] is linked to SSI, with which a so-called Kalman model is extracted from the time responses of the structure in normal conditions. The subsequent data are then examined to detect if the features deviate significantly from the norm. A similar idea is adopted in the presented second approach based on principal component analysis (PCA) [7-8]. An improvement or enhancement of PCA is proposed to increase its application efficiency. The aim of this paper is to provide an introduction of these methods with application examples. More details are referred to the related literature.

2. Model identification and damage diagnosis by SSI

The dynamic behaviour of an ambient excited multi-variate linear system is described by the dynamic equilibrium equation:

$$\mathbf{M}\ \ddot{\mathbf{z}}(t) + \mathbf{D}\ \dot{\mathbf{z}}(t) + \mathbf{K}\ \mathbf{z}(t) = \mathbf{f}(t) \qquad (1)$$

where **M**, **D** and **K** are the mass, damping and stiffness matrices respectively; **f**(t) represents the ambient excitation vector and **z**(t) the displacement vector. Eq. (1) may be transformed into the following state equation

$$\dot{\mathbf{x}}(t) = \mathbf{A}_c\ \mathbf{x}(t) + \mathbf{B}_c\ \mathbf{w}(t) \qquad (2)$$

with $\mathbf{x}(t) = \begin{Bmatrix} \dot{\mathbf{z}}(t) \\ \mathbf{z}(t) \end{Bmatrix}$, $\mathbf{w}(t) = \begin{Bmatrix} \mathbf{f}(t) \\ \mathbf{0} \end{Bmatrix}$,

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$$\mathbf{A}_c = \begin{bmatrix} -\mathbf{M}^{-1}\mathbf{D} & -\mathbf{M}^{-1}\mathbf{K} \\ \mathbf{I} & \mathbf{0} \end{bmatrix}, \ \mathbf{B}_c = \begin{bmatrix} \mathbf{M}^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}.$$

As measurements are available at discrete time instants $k\Delta t$, with Δt the sample period, the state-space model looks like [3]

$$\mathbf{x}_{k+1} = \mathbf{A}\ \mathbf{x}_k + \mathbf{w}_k \tag{3}$$

$$\mathbf{y}_k = \mathbf{C}\ \mathbf{x}_k + \mathbf{v}_k \tag{4}$$

where $\mathbf{A}\in\Re^{n\times n}$ and $\mathbf{C}\in\Re^{l\times n}$ are, respectively, the state space matrix and the output matrix; $\mathbf{x}_k$ is the state vector of dimension n (the system order to be determined) and $\mathbf{y}_k$ is the output vector of dimension l (the number of output sensors). $\mathbf{w}_k$ and $\mathbf{v}_k$ denote the process and the measurement noises respectively. Note that the unknown excitation is implicitly taken into account through the noise terms, which are assumed to be zero-mean Gaussian white noise processes

$$\mathbf{E}\left[\begin{pmatrix} \mathbf{w}_k \\ \mathbf{v}_k \end{pmatrix} \begin{pmatrix} \mathbf{w}_{k+t}^{\mathrm{T}} & \mathbf{v}_{k+t}^{\mathrm{T}} \end{pmatrix}\right] = \begin{pmatrix} \mathbf{Q} & \mathbf{S} \\ \mathbf{S}^{\mathrm{T}} & \mathbf{R} \end{pmatrix}\delta(t) \tag{5}$$

where $\mathbf{E}$ is the expectation operator and $\delta(t)$ is the Kronecker delta. The i-step output covariance matrices Λ_i are defined:

$$\Lambda_i = \mathbf{E}\left[\mathbf{y}_{k+i}\ \mathbf{y}_k^{\mathrm{T}}\right],\ \Lambda_0 = \mathbf{E}\left[\mathbf{y}_k\ \mathbf{y}_k^{\mathrm{T}}\right] \tag{6}$$

As $\mathbf{w}_k$ and $\mathbf{v}_k$ are independent of the actual state $\mathbf{x}_k$ which is assumed to be a stationary stochastic process with zero-mean, the following properties can be established from Eqs. (4-6):

$$\mathbf{E}\left[\mathbf{x}_k\ \mathbf{x}_k^{\mathrm{T}}\right] = \Sigma_0 = \mathbf{A}\Sigma_0\mathbf{A}^{\mathrm{T}} + \mathbf{Q} \tag{7}$$

$$\mathbf{E}\left[\mathbf{x}_{k+1}^{\mathrm{T}}\ \mathbf{y}_k^{\mathrm{T}}\right] = \mathbf{G} = \mathbf{A}\Sigma_0\mathbf{C}^{\mathrm{T}} + \mathbf{S} \tag{8}$$

$$\Lambda_0 = \mathbf{C}\Sigma_0\mathbf{C}^{\mathrm{T}} + \mathbf{R} \tag{9}$$

$$\Lambda_i = \mathbf{C}\mathbf{A}^{i-1}\mathbf{G} \tag{10}$$

where $\mathbf{\Sigma}_0$ is called the state covariance matrix; $\mathbf{G}$ the next state-output covariance matrix. The above equations provide the starting point of SSI method.

SSI is applied to identify the defined matrices ($\mathbf{A}$, $\mathbf{C}$, Λ_0, $\mathbf{G}$ etc.), starting from only the output time history $\mathbf{y}_k$ measured by l sensors. The output may be displacement, velocity or acceleration. The details of SSI are referred to [3]. Here, we give only a simple illustration, concerning two kinds of SSI algorithms.

2.1. Covariance-driven SSI

Let $\mathbf{H}_{p,q}$ be the Hankel matrix filled up with p block rows and q block columns of the output covariance matrix Λ_i ($p\le q$)

$$\mathbf{H}_{p,q} = \begin{bmatrix} \Lambda_1 & \Lambda_2 & \dots & \dots & \Lambda_q \\ \Lambda_2 & \Lambda_3 & \dots & \dots & \Lambda_{q+1} \\ \dots & \dots & \dots & \dots & \dots \\ \Lambda_p & \Lambda_{p+1} & \dots & \dots & \Lambda_{p+q-1} \end{bmatrix} \tag{11}$$

with $\Lambda_i \approx \dfrac{1}{N-i}\sum_{k=1}^{N-i} \mathbf{y}_{k+i}\,\mathbf{y}_k^{\mathrm{T}}$

The Hankel matrix may be factorised into the p-order observability matrix $\boldsymbol{O}_p$ and q-order controllability matrix $\boldsymbol{C}_q$ of rank n:

$$\mathbf{H}_{p,q} = \boldsymbol{O}_p\ \boldsymbol{C}_q \tag{12}$$

with $\boldsymbol{O}_p = \begin{bmatrix} \mathbf{C} & \mathbf{CA} & \dots & \mathbf{CA}^{p\text{-}1} \end{bmatrix}^{\mathrm{T}}$

$\boldsymbol{C}_q = \begin{bmatrix} \mathbf{G} & \mathbf{AG} & \dots & \mathbf{A}^{q\text{-}1}\mathbf{G} \end{bmatrix}$

Factorisation may also be performed by a very popular mathematical tool called the singular value decomposition (SVD) on the Hankel matrix, which leads to

$$\mathbf{H}_{p,q} = \begin{bmatrix} \mathbf{U}_1 & \mathbf{U}_2 \end{bmatrix} \begin{bmatrix} \mathbf{S}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_2 \end{bmatrix} \begin{bmatrix} \mathbf{V}_1\ \mathbf{V}_2 \end{bmatrix}^{\mathrm{T}} \approx \mathbf{U}_1\mathbf{S}_1\mathbf{V}_1^{\mathrm{T}} \tag{13}$$

where it is assumed that the second part of singular value $\mathbf{S}_2$ (containing the system noises, etc.) are small enough to be neglected, so that the order of system (rank) n is determined by the dimension of $\mathbf{S}_1$. By a comparison between (12) and (13), matrices $\mathbf{A}$,$\mathbf{C}$, $\mathbf{G}$ etc. may be found.

2.2. Data-driven SSI

By this method, the Hankle matrix is formed directly by the measured responses:

$$\mathbf{H}_{1,2i} = \frac{1}{\sqrt{j}}\left[\begin{array}{cccc} \mathbf{y}_1 & \mathbf{y}_2 & \cdots & \mathbf{y}_j \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{y}_i & \mathbf{y}_{i+1} & \cdots & \mathbf{y}_{i+j-1} \\ \hline \mathbf{y}_{i+1} & \mathbf{y}_{i+2} & \cdots & \mathbf{y}_{i+j} \\ \cdots & \cdots & \cdots & \cdots \\ \mathbf{y}_{2i} & \mathbf{y}_{2i+1} & \cdots & \mathbf{y}_{2i+j-1} \end{array}\right] \equiv \left(\frac{\mathbf{H}_{1,i}}{\mathbf{H}_{i+1,2i}}\right) \equiv \left(\frac{\mathbf{Y}_p}{\mathbf{Y}_f}\right) \quad \frac{\text{"past"}}{\text{"future"}} \tag{14}$$

It is split into a "past" and a "future" part of *i* block rows. The identification process is, in certain extent, similar to the first one. The details are refereed to [3]. Specially, the method may identify a so-called Kalman model for damage detection [6].

2.3. Modal parameters

Once the system state matrices ($\mathbf{A}$, $\mathbf{C}$, Λ_0, $\mathbf{G}$ etc) have been found by either of two algorithms above, the modal parameters may be determined. The eigenvalue decomposition of $\mathbf{A}$ leads to

$$\mathbf{A} = \mathbf{\Psi\Lambda\Psi}^{-1} \tag{15}$$

Diagonal matrix Λ contains the discrete eigenvalues τ_r, from which the natural frequencies f_i and damping ratios ζ_i of the system can be extracted

$$\begin{cases} f_i = \dfrac{\omega_i}{2\pi} = \dfrac{|\ln(\tau_r)|}{2\pi\,\Delta t} \\ \zeta_i = -\dfrac{\mathrm{Real}\left(\ln(\tau_r)\right)}{|\ln(\tau_r)|} \end{cases} \tag{16}$$

where i=1,2,...,n/2; r=1,3...,(2i-1) ; ω_i is i-th angle frequency. From the eigenvector matrix ψ, the mode-shapes $\mathbf{\Phi}$ may be obtained in dimension of the measured degrees of freedom (DOF)

$$\mathbf{\Phi} = \mathbf{C\Psi} \tag{17}$$

2.4. Damage detection and localisation

If the identification procedure is performed on the system, respectively, in reference and actual states, damage detection may be realised by comparing the corresponding modal parameters (e.g. natural frequencies). The uncertainties of the identified modal parameters may be estimated so that the probabilistic confidence on the existence of damages may be estimated.

Damage localisation may be based on a combined analysis on changes of the measured stiffness and flexibility of the structure, which is estimated by the identified modal parameters. This subject is discussed in details in [9].

3. Damage diagnosis by Kalman model

Note that the Kalman model is a concept of the control theory. By constructing the associated Kalman filter, it is possible to predict, in one-step-ahead way, the responses of a noise-contaminated system. Defining $\hat{\mathbf{x}}_{\mathbf{k}+1}$ the optimal prediction for the state vector $\mathbf{x}_{k+1}$ based on the system matrices of the stochastic state space model (3-4) and on available outputs up to time t_k. Then the response prediction is

$$\hat{\mathbf{y}}_\mathbf{k} = \mathbf{C}\,\hat{\mathbf{x}}_\mathbf{k} \tag{18}$$

The two predictors are related through the so-called Kalman filter [3,6] for a linear-invariant system:

$$\hat{\mathbf{x}}_{\mathbf{k}+1} = \mathbf{A}\,\hat{\mathbf{x}}_\mathbf{k} + \mathbf{K}_\mathbf{k}\,\mathbf{e}_\mathbf{k} \tag{19}$$

$$\mathbf{y}_\mathbf{k} = \mathbf{C}\,\hat{\mathbf{x}}_\mathbf{k} + \mathbf{e}_\mathbf{k} \tag{20}$$

$\mathbf{K}_k \in \Re^{n\times m}$ is called the non-steady state Kalman gain matrix and $\mathbf{e}_k$ the innovation or predicting errors (a zero-mean Gaussian white noise process). At the beginning stage, the Kalman filter will experience a transient phase where the predictor is non-steady. However, if the state matrix $\mathbf{A}$ is stable, the filter will quickly enter a steady state. When this steady state is reached, the covariance matrix of the predicted state vector $\hat{\mathbf{x}}_\mathbf{k}$ becomes constant, which implies that the Kalman gain becomes constant as well, i.e.

$\mathbf{K}_k = \mathbf{K}$ so that the Kalman filter is operating in a steady state. By minimizing the variance of the state prediction error, the Kalman gain in the steady state may be calculated from the so-called Ricatti equation, provide that system matrices ($\mathbf{A}$, $\mathbf{C}$, Λ_0, $\mathbf{G}$ etc.) have been identified by the data-driven SSI [3].

Application of the Kalman model in structural damage diagnosis has been originally proposed in [6]. Starting from an "initial" state $\mathbf{x}_0=\mathbf{0}$ and $\mathbf{e}_0=\mathbf{0}$, the k-step state vector and the corresponding prediction error are calculated as:

$$\hat{\mathbf{x}}_\mathbf{k} = \mathbf{A}\,\hat{\mathbf{x}}_{\mathbf{k}-1} + \mathbf{K}\,\mathbf{e}_{\mathbf{k}-1} \tag{21}$$

$$\mathbf{e}_\mathbf{k} = \mathbf{y}_\mathbf{k} - \hat{\mathbf{y}}_\mathbf{k} = \mathbf{y}_\mathbf{k} - \mathbf{C}\,\hat{\mathbf{x}}_\mathbf{k} \tag{22}$$

A sequence of prediction errors may be obtained by an iterative process. This error sequence is taken as damage-sensitive features of the structure. It is assumed that the Kalman prediction model of the undamaged structure would not be able to reproduce the newly measured responses when damage occurs. Therefore structural damages are indicated by an increase in error level of prediction with respect to the reference state. From the error vector $\mathbf{e}_k$ at any k-th sampling point, the Novelty Index (NI) is defined as the Euclidean norm [4]:

$$NI_k^{\mathrm{E}} = \left\|\mathbf{e}_k\right\| \tag{23}$$

or as the Mahalanobis norm

$$NI_k^{\mathrm{M}} = \sqrt{\mathbf{e}_k \Sigma^{-1} \mathbf{e}_k^{\mathrm{T}}} \tag{24}$$

where $\Sigma = \dfrac{1}{N}\mathbf{Y}\,\mathbf{Y}^{\mathrm{T}}$ is the response covariance matrix, N the number of sampling points, $\mathbf{Y}$ the assembly matrix of $\mathbf{y}_k$, k=1…N. The prediction procedure is performed using data of the structure respectively in reference and actual states. Without structural damage, the level of prediction errors should remain unchanged. Otherwise, an alarm of structural damage will be issued. According to the subspace identification theory, the prediction errors of responses by the Kalman model correspond to a normal Gaussian distribution, so does the Mahalanobis or Euclidean indices. Therefore, it is appropriate to perform a statistical analysis to give a quantitative assessment of damage level. The detailed discussion is referred to [6].

4. Damage diagnosis by enhanced PCA

Principal component analysis (PCA) is an efficient multi-variate statistical method for data analysis. In the field of structural dynamics, it has been applied for dimensionality studies, modal analysis, reduced-order modelling, etc. When a large number of sensors are distributed on a system for controlling and monitoring (for example in chemical engineering community), PCA may be used for sensor validation [5]. This method has been extended for structural health monitoring (SHM) [7-8]. In this section, an improvement or enhancement on classical PCA in SHM is proposed.

Starting from the standard motion equation (1), dynamic responses of a structure may be described by applying the modal transformation:

$$\mathbf{y}(t) = \sum_{i=1}^{m} \alpha_i(t)\,\mathbf{\Phi}_i + \alpha_r(t)\,\mathbf{R} \tag{25}$$

where the complete response $\mathbf{z}$ in Eq. (1) is replaced by the measured response $\mathbf{y}$ of sensors; $\mathbf{\Phi}_i$ is the i-th mode-shape vector, with m first modes adopted; $\mathbf{R}$ is the global residue of the higher frequency modes, $\alpha_i(t)$ and $\alpha_r(t)$ are the modal coordinates. This expression suggests that the responses are approximately located in a geometrical subspace (called hyperplane) covered by some main structural modes $\mathbf{\Phi}_i$ (usually with lower frequencies). The hyperplane is independent of the excitation history if the structure is linear. It changes only when damage occurs. Therefore, damage detection may be realized by monitoring this hyperplane, which, of course, may be captured by using SSI presented in §2.

Instead of performing an exact modal identification to compute the trajectories covered by the measurements, it appears more efficient to identify directly the principal components of responses. Let $\mathbf{Y}$ denotes a matrix of discrete block time-history $\mathbf{y}_k$ with l sensors and N sampling points ($N >> l$)

$$\mathbf{Y} = \begin{bmatrix} y_{11} & \cdots & y_{1N} \\ \vdots & \ddots & \vdots \\ y_{l1} & \cdots & y_{lN} \end{bmatrix} \tag{26}$$

Performing SVD of **Y**, see Eq. (13), gives

$$\mathbf{Y} \approx \mathbf{U}_1 \mathbf{S}_1 \mathbf{V}_1^T \tag{27}$$

where $\mathbf{U}_1 \in \Re^{l \times m}$, is a part of an orthonormal matrix, with chosen m ($<l$) columns, which covers the geometrical subspace generated by the responses. Each column of **U** is associated with N time coefficient containing in matrix **V**. The active singular values, given by diagonal matrix $\mathbf{S}_1$ of ($l \times m$) and sorted in descending order, can be related to the energy associated with the corresponding principal components in $\mathbf{U}_1$. This means that the structure reacts mainly along the directions of the principal components associated with the highest energies. Writing $\mathbf{S}_1 \mathbf{V}_1^T$ into a time series β, (27) may be expressed in the following form which is completely similar to Eq. (25)

$$\mathbf{y}(t) = \sum_{i=1}^{m} \beta_i(t) \mathbf{U}_i + \beta_r(t) \mathbf{R} \tag{28}$$

So we have shown that the hyperplane of responses may be constructed by the principal components instead of the mode shapes. This provides an efficient numerical method.

Damage detection is carried out on basis of the fact that the hyperplane of responses changes due to damages. The first way of assessing the change of the hyperplane is to calculate the angle between the hyperplanes of reference and current states. See Fig. 1. for a geometrical explanation. The calculation of the angle is a simple mathematical and geometrical problem, see [7-8] for details.

The second way takes an idea similar to the previous method with the Kalman model: the obtained principal components are taken to construct a prediction model. The prediction error may be estimated as:

$$\mathbf{E} = \mathbf{Y} - \hat{\mathbf{Y}} = \mathbf{Y} - \mathbf{U}_1^T \mathbf{U}_1 \mathbf{Y} \tag{29}$$

Similarly, the Euclidean or Mahalanobis norm is calculated as the novelty index (*NI*), respectively for reference and current states. The increase of *NI* level indicates structural damages.

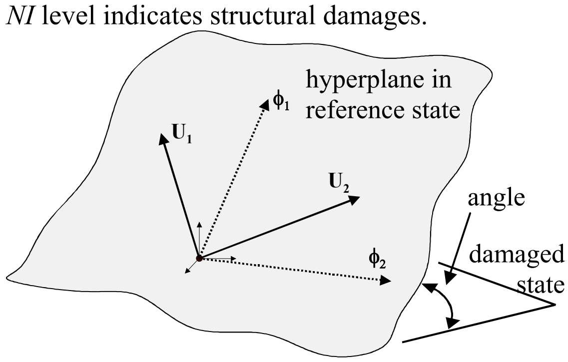

Fig. 1. 3-D interpretation of the angle between hyperplanes of data in two states.

Damage localization with this method has been proposed in [7-8] which are referred to for the details. The basic idea is to identify the sensors with maximum prediction error or largest effect on calculating the angle between the hyperplanes.

It was noticed in our calculating practices that damage diagnosis by PCA poses some limitations mainly in two aspects: a) the number of installed sensors must be enough larger than the number of modes contained in the measured responses; b) sometimes, the calculated *NI* or angle of hyperplanes are not very sensitive to the existence of damages. In order to overcome these difficulties, an improvement of PCA is proposed in this paper leading to an enhanced PCA as follows. The idea is inspired by the SSI method: as complete dynamic information are contained in the Hankle matrix consisting of either output covariance by Eq.(11) or directly by output data by Eq.(14), we propose to use the Hankle matrix, instead of output matrix (26), in PCA-based damage diagnosis. With a close observation, it may be shown that the above two limitations are overcome or reduced.

5. Damage diagnosis with varying environmental conditions

In the above analysis, it is implicitly assumed that environmental conditions (e.g. temperature) do not change during the monitoring, or their effects are small. If it is not the case, the effects due to environmental conditions should be included in SHM process. In general, this issue may be addressed along two directions. The first one is to establish a correlation between the measured features and the corresponding environmental conditions. In consequence, the normal condition may be parameterised to reflect the environmental and operational variation, and structural damages are responsible for the additional changes in features. The second approach does not require measuring environmental parameters which are formulated as embedded variables. The subject is addressed in [10] and it is not reported in this paper.

6. Application examples

The presented methods are illustrated by a laboratory test on an aircraft model made of steel and suspended by means of three springs (See Fig. 2). The fuselage consists of a straight beam of rectangular section with a length of 1.2m. Plate-type beams connected to the fuselage form the wings (1.5m) and tail (0.5×0.275m). The structure is randomly excited on the top left wing by means of an electro-dynamic shaker in the frequency band of 0-130Hz and the dynamic responses are captured by 11 accelerometers distributed on the wing and tail (See Fig. 3). Three levels of damages are created by removing, respectively, one, two or three connecting bolts on the right side of wing as shown in Fig. 2.

The data-driven SSI was used to identify modal parameters of the structure with different levels (0~3) of damages, which are well indicated by comparing the natural frequencies of the damaged model with reference. Fig. 4 gives an example of detection with the frequencies of mode 1.

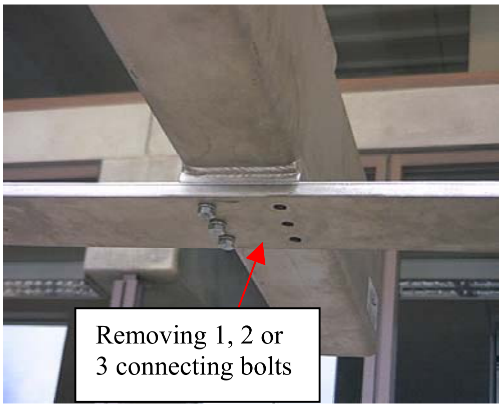

Fig. 2. An experimental aircraft model.

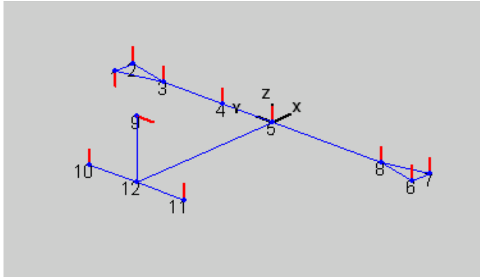

Fig. 3. Distribution of 11 sensors.

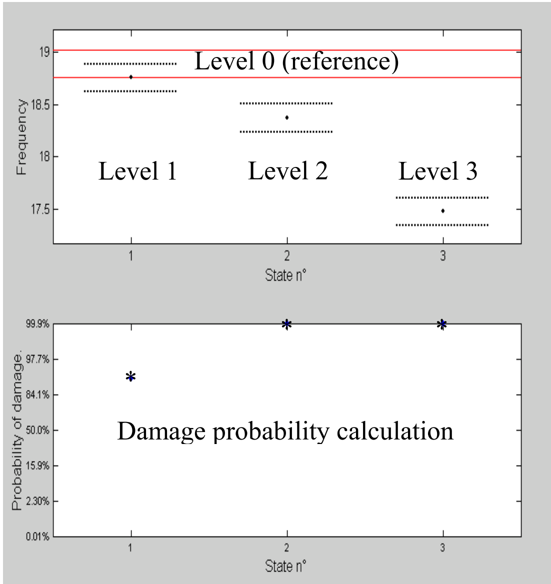

Fig. 4. Damage detection by identified natural frequency of the first mode.

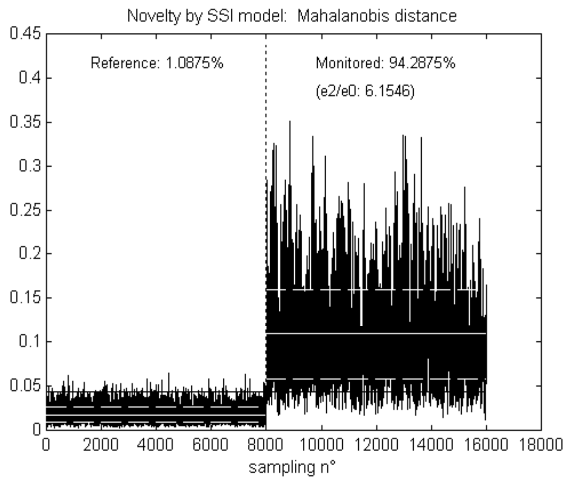

Fig. 5. Damage detection by a statistic analysis based on Kalman model (level 2).

Table 1. Damage detection of experimental aircraft model by the Kalman model.

Damage scenario	Ref. state	Level 0	Level 1	Level 2	Level 3
Outlier statistics	1.0875%	2.6625%	14.9125%	94.2875%	97.925%
$\overline{NI}_d / \overline{NI}_r$	1	1.1396	1.6796	6.1546	6.6704
Num. of removed bolts (note)	0 (reference state)	0 (exciting force +50%)	1 (slight damage)	2 (damage detected)	3 (damage detected)

While level-1 damage, as a slight damage case, is not definitively detected, levels 2-3 of damages are clearly indicated (Fig 4).

By the method with the Kalman prediction model, the results are very similar. The statistical monitoring diagram is presented in Fig. 5 for level-2 damage as an example. The diagram is split into two parts. The left part (8000 sampling points) trains the reference data and the right part examines the new data. Difference in outlier statistics (in %), and ratio of the mean *NI* values indicate the existence of damages. Complete results are summarized in Table 1. While a slight damage (Level-1 scenario) is already noticed, damage levels 2-3 are detected with clear damage indicators. The column 3 of Table 1 concerns a false-positive testing: two tests without damage (level 0) but with different excitation levels (1:1.5). It is shown that the damage indicators are small despite a large difference in excitation levels.

Novelty analysis with PCA prediction model is also applied. However, calculating results showed that with classical PCA, the *NI* values are not enough sensitive to damages for this problem. Therefore, the enhanced PCA proposed in 4 was applied. The number of Hankle matrix blocks in (14) is chosen as 3 as an optimum in the sense that the PCA model is sensitive to damages but not to the excitation and noise levels. The results are summarized in Table 2, which are in good agreement with previous analyses with modal parameters or the Kalman model.

Damage detection and localization with enhanced PCA may also be performed by calculating the angle between the hyperplanes as described in 4. The results are presented in Fig. 6 as an example. Damage is indicated by a large angle between the hyperplanes of reference and current states. When removing sensors 6-8 installed in the right wing, the angle reduces most. This indicates that damages occur in the right wing of the aircraft model.

7. Conclusions

This paper summarised several techniques of structural health monitoring (SHM), which were applied and developed recently in our laboratory. The SSI technique was used to provide a precise identification of modal parameters and also the Kalman model, from the output-only measurements. SHM with this last model requires a model identification only on the reference data. Improvement and enhancement on PCA for SHM were proposed in this paper. A significant advantage of the methods (particularly PCA) lies in their simplicity and efficiency in calculation, allowing an on-line implementation. An experimental aircraft model was presented to illustrate and compare the application of the presented methods.

Table 2. Damage detection of an experimental aircraft model by enhanced PCA.

Damage scenario	Ref. state	Level 0	Level 1	Level 2	Level 3
Outlier statistics	0.1221%	1.1355%	11.624%	73.309%	60.232%
$\overline{NI}_d / \overline{NI}_r$	1	1.047	1.188	1.6925	1.6126
Num. of removing bolts (Note)	0 (reference state)	0 (force ratio is 0.5:1.5)	1 (slight damage)	2 (damage detected)	3 (damage detected)

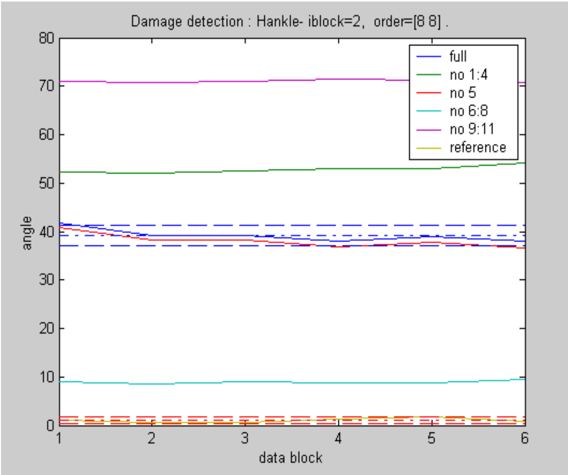

Fig. 6. Damage location by enhanced PCA.

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