Damage Size Estimation with Active Piezosensor Network

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ABSTRACT

In this paper an approach to damage size estimation based on algorithms adjusted to the damage location is presented. In particular we propose the so called averaged damage indices based on selected signal characteristics. Covariates for damage size estimation models are derived from them via dimensional reduction methods like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) scaling. The indices proposed are designed to be less dependent on the damage localization and thus can be used in damage size assessment. Based on the emerged damage indices a model of system self diagnostics and several damage size estimation models are presented. The efficiency of those models is verified with cross-validation technique and data collected from fatigue tests of helicopter main rotor blade spar.

INTRODUCTION

The issue of *in situ* damage growth monitoring is one of the main area of research concerning aircraft operation safety. One of the approach to that issue is to use elastic wave excitation in a given medium [1-5]. Basic information concerning the health of the structure can be provided by the so called Damage Indices (DI's). Denoting as f_{gs} the signal generated in transducer g and received in sensor s and as $f_{gs,b}$ its baseline, some basic DI's can be defined using the following simple signal characteristics:

L^1 symmetric characteristic – $$DI_1(g,s) = \frac{\left| \int |f_{gs}| - |f_{gs,b}| \, dt \right|}{\int \left| f_{gs,b} \right| dt},$$

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L^2 symmetric characteristic – $DI_2(g,s) = \dfrac{\int \left(f_{gs}\right)^2 - \left(f_{gs,b}\right)^2 dt}{\int \left(f_{gs,b}\right)^2 dt}$, (1)

correlation with the baseline – $DI_3(g,s) = cor(g,s)$.

Similar DI's can be obtained using Fourier filtered signals, their envelopes or other signal transformations. There are remarkable examples of applications of analogous DI's to determine localization of a damage [6–8]. In these methods two stage algorithms are used. First for each sensing path $g \to s$, i.e. a signal received in sensor s originated from generator g, the structure is quantified into a damaged or undamaged state. This quantitative assessment can be performed using certain threshold level of one or multiple DI's. Then if the structure is considered as damaged a probability density of a damage localization in a given network cell is calculated. This density depends on DI's values and properly defined distance of a given point from a sensing path $g \to s$. Finally joint probability for a damage localization is provided using probability maps obtained for all possible sensing paths in the network cell.

There are several limitations of described SHM method. In particular in order to obtain accurate damage location probability map there is necessity to consider sensing paths for many transducers what influence on computational and system implementation costs. Furthermore improper functioning of a single sensor in the network decrease number of reliable sensing paths which can disturb this probability density. Another obstacle in this approach is system sensitivity adjustment. In complex structures, which contain many wave reflectors, e.g. edges, joints, welds, rivets, etc. resulting map for sensitive algorithms can be noised [9], whereas weakening susceptibility of sensing paths cause risk of damage missing. However the main disadvantage of that method is the difficulty in estimating damage size. Since damage indices $DI_j(g,s)$ (1) used for structure quantification in these algorithms depends strongly on damage localization with respect to given sensing path $g \to s$ it is very difficult to use regression or classification models in estimating size of a damage.

AVERAGED DAMAGE INDICES

Reliable damage size assessment needs to develop methods independent or adjusted to the damage location. Therefore for a given damage index $DI_j(g,s)$ (1) the averaged damage index can be defined [10, 11]:

$$ADI_j := \frac{1}{n(n-1)} \sum_{\substack{g,s: \\ g \neq s}} DI_j(g,s),$$

where n is the number of transducers in the sensor network cell. Averaged damage indices (ADI's) are less dependent on the damage localization which makes them better suited for damage size estimation. These indices remain structure quantification possibility also in case of improper functioning of several transducers in the network.

The efficiency of the proposed signal characteristics (1) can be evaluated using ADI's and Principal Component Analysis (PCA) [12]. PCA is an effective feature extraction algorithm and can be used in predictive models development. This method was frequently used for the SHM purposes [13–17].

Subsequent principal components λ_i are linear combinations of all ADI's used:

$$\lambda_i = \sum_{j=1}^{D} n_i^j ADI_j, \qquad i = 1, \ldots, D,$$

where D is the number of indices considered. Coefficients n_i^j are components of orthonormal basis n_i, $i = 1, \ldots, D$ diagonalizing sample covariance Σ, i.e.:

$$\Sigma = \sum_{i=1}^{D} \sigma_i n_i n_i^T . \tag{2}$$

Typically values of these coefficients corresponding to different ADI's significantly differs, which provides a measure of effectiveness of the characteristics used in (1). Denoting as $\tilde{n}_i^a$ dominating components of subsequent principal directions corresponding to averaged damage index ADI_a one can consider effective averaged damage indices (eADI's):

$$eADI_i = \sum_a \tilde{n}_i^a ADI_a . \tag{3}$$

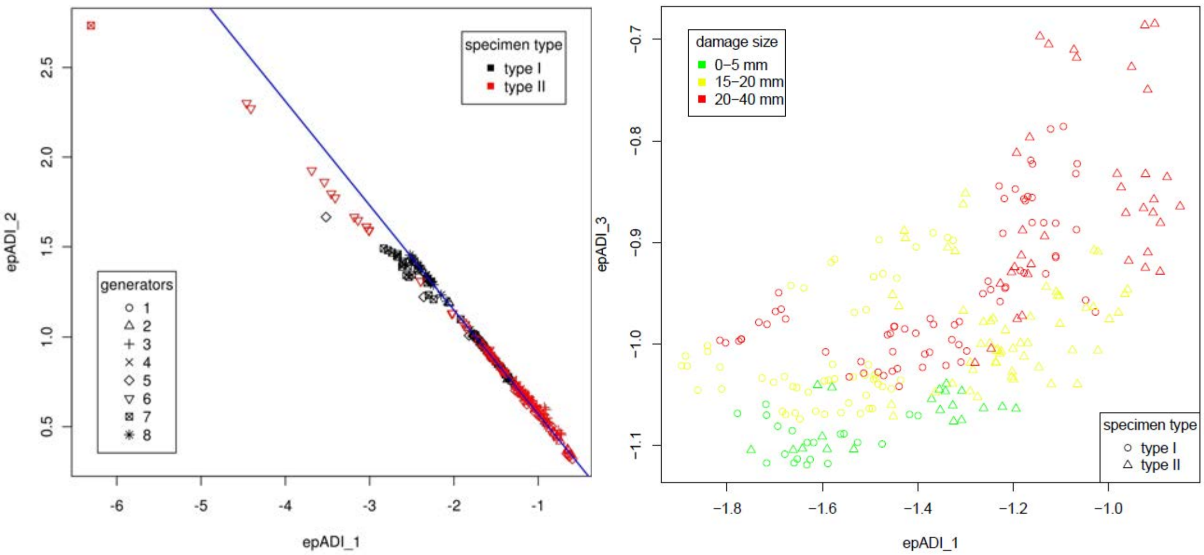
Since eADI's correspond to few signal characteristics they are easier to interpret comparing to principal components λ_i while still preserve data separation property.

Some of the proposed ADI's are defined by linear signal transformations therefore some of the effective averaged damage indices eADI's given above can be highly correlated. In this case they usually correspond to the same signal characteristic but with different weights $\tilde{n}_i^a$ assigned to signal transformation, e.g. Fourier filtering. Observations distorted by noise or originated from faulty generators resulting in particular in different spectrum of the received signal are outlying from the correlation line and therefore can be dropped out providing a sensor network self diagnostic tool.

Using the matrix

$$\Sigma^{-\frac{1}{2}} \Sigma_b \Sigma^{-\frac{1}{2}}$$

instead of (2) in the above consideration, where Σ_b is between class covariance (e.g. damage size intervals), leads to Fisher's linear discriminant (LDA) scaled [12] eADI's. In this method subsequent n_i, $i = 1, \ldots, D$ are directions maximizing class separation S, defined for $v \in \mathbb{R}^D$ as follows:



(a) correlated epADI's ***(b) uncorrelated epADI's***

Figure 1. PCA based effective partially averaged damage indices.

$$S(v) = \frac{v^T \Sigma_b v}{v^T \Sigma v}.$$

The most efficient uncorrelated eADI's can be used to develop parametric (e.g. LDA, QDA, Bayesian) or nonparametric (k-nn, SVM) classification as well as regression models [12] for damage size estimation.

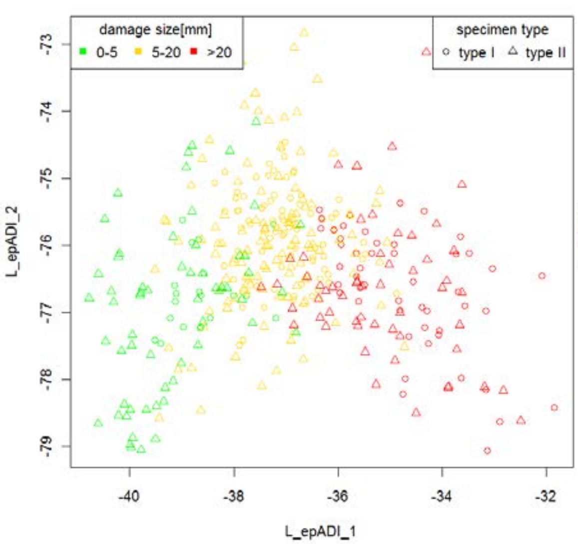
DAMAGE SIZE ESTIMATION

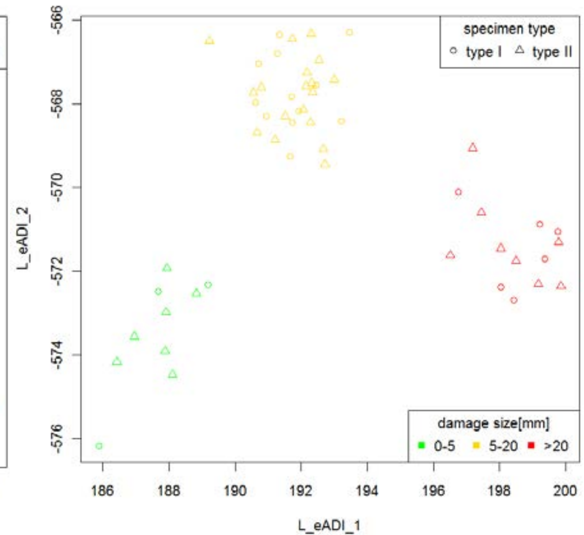
The SHM system scheme outlined in the previous section was verified on back wall of helicopter main rotor blade spar [10]. Three specimens of two different types were prepared and fatigue tests were performed. In order to increase the size of the trial the following partially averaged damage indices (pADI's) were used:

$$pADI_j(g) = \frac{1}{(n-1)} \sum_{\substack{s: \\ s \neq g}} DI_j(g,s)$$

and their effective counterparts (epADI's) defined analogously as in (3).

Two chosen correlated PCA based epADI's: epADI_1, epADI_2 were used to provide a network self diagnostic tool (Fig. 1(a)). Observations originated from generator no. 7 for type I specimen as well as single excitations from generator no. 3 and 5 are outlying from the correlation line and therefore were dropped out. Separation of the two most effective PCA based uncorrelated epADI's: epADI_1, epADI_3 is presented on the figure (Fig. 1(b)). Since the interaction of elastic waves with a structure discontinuity is a local phenomenon epADI's values depend strongly on the localization of a generator, e.g. its distance from a damage which is clearly visible on this plot (Fig. 1(b)).

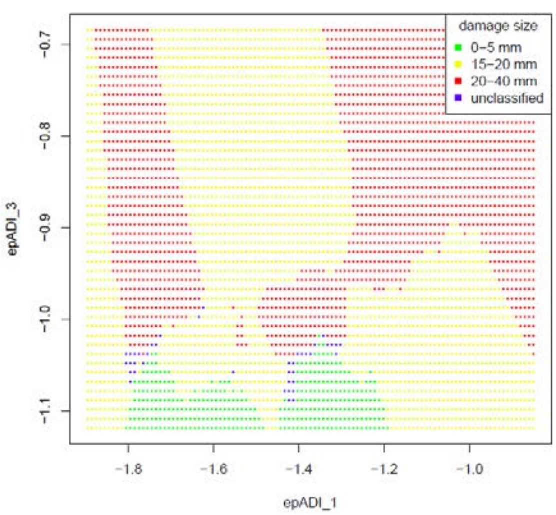


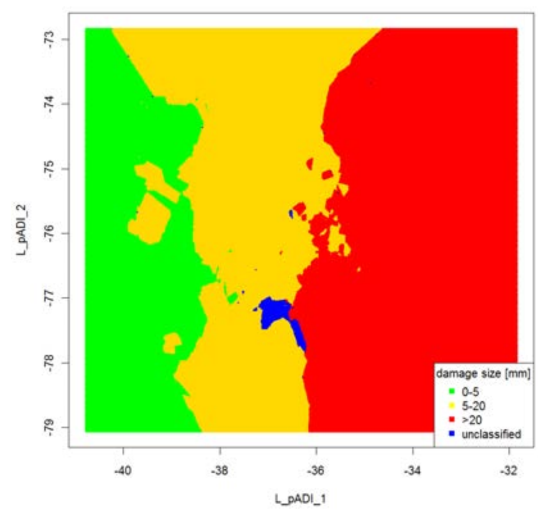


(a) partially averaged ***(b) averaged***

Figure 2. LDA based effective damage indices.

Uncorrelated effective damage indices were also obtained by LDA method. Partially averaged effective damage indices: L_epADI_1, L_epADI_2 separate data for undamaged (0-5 [mm]) and seriously damaged (>20 [mm]) specimens (Fig. 2(a)) as opposed to PCA based epADI's (Fig. 1(b)). LDA based effective damage indices averaged also with respect to generators (3): L_eADI_1, L_eADI_2 separate each group of damage size. PCA and LDA uncorrelated epADI's were used to provide two k nearest neighbor (k-nn) models for damage size estimation. Classification regions for nearest neighbor models are calculated determining the most frequent class of k samples from the training dataset which are the nearest to the given point. Classification regions for 5-nn models based on euclidean metric in the space spanned by two the most effective PCA based epADI's (Fig. 3(a)) and LDA based epADI's (Fig. 3(b)) were obtained.





(a) PCA based epADI's 5-nn model ***(b) LDA epADI's based 5-nn model***

Figure 3. Classification regions of nearest neighbor models .

		Probability of classification into damage size interval		
		0 – 5 [mm]	5 – 20 [mm]	> 20 [mm]
Damage	0 – 5 [mm]	0.66÷0.76	0.24÷0.34	0
	5 – 20 [mm]	0.01÷0.05	0.81÷0.93	0.05÷0.15
	> 20 [mm]	0÷0.02	0.06÷0.30	0.68÷0.94

Table 1. Cross-validation results of PCA based 5-nn model.

The efficiency of these classification models was verified with use of 5-fold cross-validation method [12] (Tab. 1, Tab. 2) obtaining damage size classification probability for different size intervals. Considered models are comparable in sensitivity and specificity. However since epADI's based on LDA method separate undamaged (0-5 [mm]) and seriously damaged (>20 [mm]) specimens (Fig. 2(a), Fig. 3(b)) as opposed to PCA based epADI's, therefore classification model corresponding to them should be preferred from the operational safety perspective.

		Probability of classification into damage size interval		
		0 – 5 [mm]	5 – 20 [mm]	> 20 [mm]
Damage	0 – 5 [mm]	0.57÷0.78	0.22÷0.43	0
	5 – 20 [mm]	0.04÷0.12	0.78÷0.88	0.07÷0.13
	> 20 [mm]	0	0.12÷0.32	0.68÷0.88

Table 2. Cross-validation results of LDA based 5-nn model.

SUMMARY

In this paper certain damage indices appropriate for damage size estimation were presented and a preliminary SHM model based on them was proposed and verified. Further studies are needed to improve their sensitivity on damage growth and confirm validity of the model. In particular different classification and regression models should be tested, which demands larger training data set.

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