Innovative Method for Damage Identification and Structural Health Monitoring based on Vibration Measurements

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Abstract. The purpose of this paper is to present an innovative application within the Non Destructive Testing field based upon vibration measurements developed by the authors during these past four years at the Department of Aeronautical Engineering of the University of Naples "Federico II" (Italy). This proposed new method is based upon the acquisition and comparison of the Frequency Response Functions (FRFs) of the monitored structure before and after damage occurs. Structural damage modifies the dynamic behaviour of a structure affecting its mass, stiffness and damping, and consequently the FRFs of a damaged structure, when compared with the FRFs of a sound structure, makes the identification, localization and quantification of structural damage possible.

The activities presented in this paper focus mainly on a new FRFs processing technique based upon the determination of a representative "Damage Index" for identifying and analysing damage on real-scale aeronautical structural components such as large-scale fuselage reinforced panels, and on aluminium and composite panels. Furthermore, a dedicated neural network algorithm has been elaborated aimed at obtaining a "recognition-based learning" method. This kind of learning methodology permits us to train the neural network in order to enable it to recognise only "positive" examples and consequently discarding "negative" ones. Within the structural NDT a "positive" example means a "healthy" state of the analysed structural component and, obviously, a "negative" example means a "damaged" or perturbed state.

From an architectural standpoint, piezoceramic patches have been tested as both actuators and sensors, both in embedded and bonded configuration. Experimental tests have also been performed using a laser-scanning vibrometer as sensor device. Results of typical applications (in terms of structure peculiarities and imposed damage) will be herein presented and discussed.

Most of these results promise to bring us a step forward in the implementation of an automatic "health monitoring" system which will be able to identify structural damage in real time thereby improving safety and reducing maintenance costs.

Introduction

Purpose of the paper is to present an innovative application inside the Non Destructive Testing field based on vibrations measurements, developed, at the Department of Aeronautical Engineering of the University of Naples "Federico II" (Italy), by the authors during the last four years, and already tested for analysing damage of many structural elements. The aim has been the development of a Non Destructive Test (NDT) which meet to most of the mandatory requirements for effective health monitoring systems, simultaneously reducing as much as possible the complexity of the data analysis algorithm and of the experimental acquisition instrumentation; these peculiarities may, in fact, not be neglected for an operative implementation of such a system. The proposed new method is based on the acquisition and comparison of Frequency Response Functions (FRFs) of the monitored structure before and after an occurred damage. Structural damage modify the dynamical behaviour of the structure such as mass, stiffened and damping, and consequently the FRFs of the damaged structure in comparison with the FRFs of the sound structure, making possible to identify, to localize and quantify a structural damage [1,2,3]. The activities, presented in the paper, mostly focused on a new FRFs processing technique based on the determining of a representative "Damage Index" for identifying and analysing damage on aeronautical composite panels. Besides it has been carried out a dedicated neural network algorithm aiming at obtaining a "recognition-based learning"; this kind of learning methodology permits to train the neural network in order to let it recognises only "positive" examples discarding as a consequence the "negative" ones. Within the structural NDT a "positive" example means "healthy" state of the analysed structural component and, obviously, a "negative" one means a "damaged" or perturbed state. With this object in view the neural network has been trained making use of the same FRFs of the healthy structure used for the determining of the Damage Index, as positive examples. From an architectural point of view piezoceramic patches have been tested as actuators and sensors [4,5]. These techniques promise to bring a step forward for the implementation of an automatic "health monitoring" system which will be able to identify a structural damage in real time, improving the safety and reducing maintenance costs.

Damage Index Method

It is common knowledge that structural damage modify the dynamical behaviour of the structure such as mass, stiffened and damping. It has evaluated the variations occurred by means of FRF, which is the ratio between the Fourier transform of the signal used to excite the structure at a point and the Fourier transform of the signal response acquired by a sensor at another point. In fact the FRFs of the sound structure are different from FRFs of the damaged structure. It has determined a damage index to evaluate the variations of FRFs of the monitored structure owing to an occurred damage. The index gives, directly, the measurements of the damage:

$$Index = \frac{\sum_{i=1}^{n} \left| FI_i - FD_i \right|}{\sum_{i=1}^{n} FI_i} \qquad (1)$$

FI_i and FD_i are the amplitude of the FRFs of the sound and damaged structure at the "i" frequency. The index is the ratio between the absolute value of the arithmetic mean of the deviation between FRFs of the sound and damaged structure and the arithmetic mean of the FRFs of the sound structure.

Neural Networks for Health Monitoring

A critical point for the validation of the developed damage analysis approach, based on the comparison of the amplitudes of (FRFs), consists in a "statistical test" assessing the confidence level relatively to the mentioned amplitude differences in order to verify that FRFs variations were effectively due to structural perturbations instead of environmental

influences (noise, temperature, humidity, vibrations, etc…) which excite not linear behaviour of the experimental set-up. That statistical test permits to identify the threshold dividing healthy configurations from damaged ones. Furthermore, to quantify the amplitudes of FRFs differences, it has been developed a dedicated neural network algorithm.
The damage identification problem can be classified as a typical example of binary learning (“healthy” or “damaged”). A neural network able to implement binary learning can be modelled following two approaches: the “discrimination-based learning” and the “recognition-based learning”. In the first approach the network is trained using both “positive” and “negative” samples in order to learn how to discriminate among them; in the second one the network is trained using only “positive” samples and it is able to recognise only these. Within this work has been implemented a system based on the latter approach.
The engine of the damage analysis system is represented by an “autoassociative” neural network (or “auto-encoder”) made of three layers: an input one, an hidden one and obviously the output one, fully connected one each other [6,7].
An auto-associative neural network is a feed forward type network trained only by positive samples in order to rebuild the input on the output layer. If the training phase is successful the network is able to find the common features that samples present in order to extract few general laws permitting to recognise positive unknown examples. The positive samples are represented by the “healthy” configuration’ FRFs. Following the training phase, the auto-encoder will be able to reconstruct more or less accurately on the output layer the positive samples, while it will always reconstruct wrongly the negative samples. So, a bad reconstruction of the input layer on the output one is a clear symptom of an anomalous dynamic behaviour of the monitored structure.
Once the auto-encoder has been implemented and trained, in order to use it as a “classifier” for the health status of a structural component, it is necessary to complete the system using a threshold to divide operatively the two samples classes (positive or “healthy” and negative or “damaged”). To do so it will be preliminary necessary to create an index quantifying the reconstruction level of the input layer on the output one; it is obviously directly related to the reconstruction error that the network presents when trying to recreate the input on its output layer. The error, on its side, will be bigger about negative samples then positive ones [8].

The Experimental Set-Up

A typical fuselage stiffened panel available in the labs of the Department of Aeronautical Engineering was chosen as first test-article. It is an MD11 fuselage panel made of:

- a 2024 aluminium alloy skin (1350mm x 1700mm);
- a 7075 aluminium alloy for the remainder of the structure;
- aluminium alloy rivets and titanium alloy hi-lock rivets.

On this test-article 8 piezoelectric patches have been bonded in order to create an array of actuators/sensors.
The panel has been constraint to the wall by means of stiffeners. Following several tests which have been carried out in order to set up the frequency range, only 4 piezoelectric patches have been used, since 4 are enough to demonstrate the capability of the techniques to identify and quantify the damage.

The second test-article is an aeronautical composite panel made by means of RFI tecnology:

- 14 plies made of multiaxial HTA 3/6 K (520mm x 520mm x 2mm);
- epoxy resin 977-2 by Cytec;
- panel lay-up: [(90/0/+/–)(+/0/–)]s.

The panel has been constrained to a frame by means of four iron springs. The place where the experimental tests have been done about the second test-article was the laboratory of the department.

Figure 1: First test-article

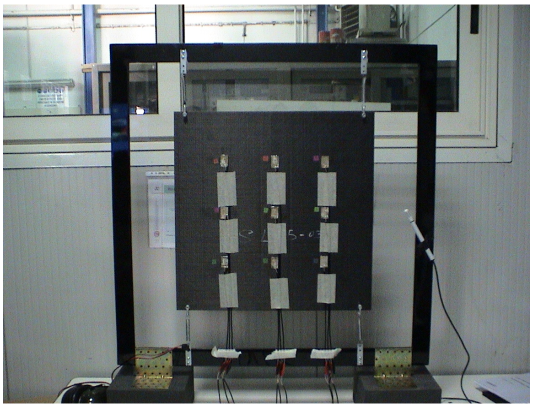

Figure 2: Second test-article

Employing alternately the piezoceramic patches as sensors and as actuators it was possible, for the first test-article, to acquire 12 Frequency Response Functions (3 sensors x 4 actuators), while for the second 72 FRFs have been acquired (8 x 9). Moreover the frequency range of the acquisitions was fixed by taking in account the “coherence function” behaviour: this function, if evaluated between the response and the actuation patch signal presents values very close to 1 if the input and output signal are correlated; these values become much lower at frequencies where the sensor measurements are not correlated with the excitation, or, in other words, where the input mechanical energy does not reach anymore the sensors. Following this analysis, for the first test-article, the operative frequency range was fixed from 1,0 and 19,0 kHz measured through 1422 spectral lines (this last number is related to the signal acquisition device). For the second test-article the chosen frequency range was 1,0 and 8,5 kHz measured through 1201 spectral lines. The acquisition was carried on employing a two-channel spectrum analyser.

Implementation of the Neural Network

As mentioned in the introduction the neural network has been trained making use of the same FRFs of the healthy structure used for the determining of the Damage Index, as positive examples.
It had avoided to implement a single neural network including all the FRFs due to the high number of neurones needed (17064 = 12 x 1422). Also considering to implement a single

network where neurones were associated with FRFs, some problems were forecasted: in such case in fact it could have been possible that for distinct experimental campaigns two FRFs related to different sensor-actuator couples resulted very similar; this would be a symptom of structural modifications but the network could deduce the opposite situation if the actuator-sensor couple is not explicitly declared. In the end it has employed only one kind of network which is trained separately for each actuator-sensor couple. That has resulted in neural networks equal from an architectural point of view but each one trained by FRFs referred to the healthy configuration and measured by a specific actuator-sensor couple.
The neural network algorithm was implemented in MATLAB environment by using Neural Networks Toolbox. The number of "training" FRFs groups were, for the test-articles, respectively five and thirteen.

Reconstruction Index and "Threshold" Evaluation

Once completed the training phase it raised up the problem on how to concretely employ the networks for identifying damage. The idea was to develop a "reconstruction" index representing the ability of the networks in rebuilding (and as a consequence, recognise) the input FRFs received. A good recognition level would have been connected with a "healthy" status of our structure. It has been defined for each network the reconstruction error between input I and output O:

$$E_n = (O_n - I_n)^2 \quad n=1,..,N \tag{2}$$

where n represents the number of neurones (or acquired FRFs spectral lines). Following it has been defined an overall index of reconstruction of the input vector as:

$$R = mean(E_n) + iqr(E_n) \tag{3}$$

where "mean" is the individual error mean and "iqr" represents a measurement of their dispersion in a statistic sense. It is possible to plot a graph S(R) of the output of the neural network obtained. That graph shows, for each value of R, the ratio between the FRFs (used for the post process), which have a reconstruction R value higher then the fixed one, and the total number of FRFs acquired during a single test campaign. The range of S is from 0 to 1. Practically, the curve S(R) is an estimator of the panel healthy status.
Even if no damage has occurred, FRFs, which have been acquired for each actuator-sensor couple on different times, could be not equal between them because of environmental disturbance. Once the FRFs of the sound structure are settled, the more different FRFs are the higher reconstruction error is, even if the damage is not present. For that reason is very important to consider the FRF maximum discrepancy of an actuator-sensor couple such that the neural network is able to reconstruct the input correctly. To do this the FRFs of the sound structure have been perturbed by means of increasing disturbance so much that it has been possible to specify the limit. In order to perturb the reference FRFs it has summed to each FRF a vector having the same dimension. Random values, whose probability distribution is normal with a variable mean and standard deviation, form the vector. Those random values have the same order of magnitude as FRF; to make the number of generated negative values negligible, since FRFs magnitudes are positive quantities, the mean has been restricted to be greater or equal to the standard deviation.
Such vectors have been added to the reference FRFs so as to generate two various families of perturbed FRFs. First family (fig. 3) has been determined assuming the same disturbance, having a mean greater or, at least, equal to the standard deviation, for all

reference FRFs. The relevant curves are characterised by a quick descent of the parameter S from 1 to 0. Second family (fig. 4) has arisen from considering that a real disturb modify the FRFs acquired during a campaign, which represent the healthy status of the panel in a particular instant, with several quantities; with this object in view perturbations having several intensities have been imposed randomly to the reference FRFs. If we take in account the output of the neural network whose input data are the gradually increasing perturbations of the second family FRFs, we note that the reconstruction error increase and the estimator curves shift coherently toward the right.

After having trained a neural network it is possible to estimate the error which is in its output by means of the linear regression between the network output and the corresponding target (during the training we assume that target coincides with input data). By means of that estimation it is possible to obtain delimiting the "healthy configuration" and the "damaged configuration" zones. In between there is a "doubt zone", a family of curves that can give good or bad reconstruction.

Figure 5 represents the evaluation of the threshold: the curve of the second family intercepting the last blue curve of the first family (limit of good reconstruction) is chosen. The interception between the "variable" perturbation curve and the lower limit of the "doubt zone" is fixed as the healthy status threshold [9].

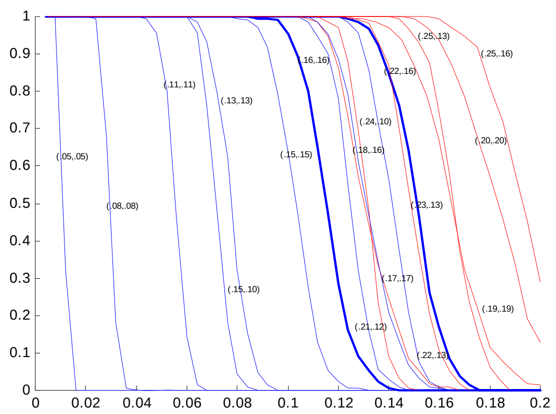

Figure 3: Analytical "constant" perturbations

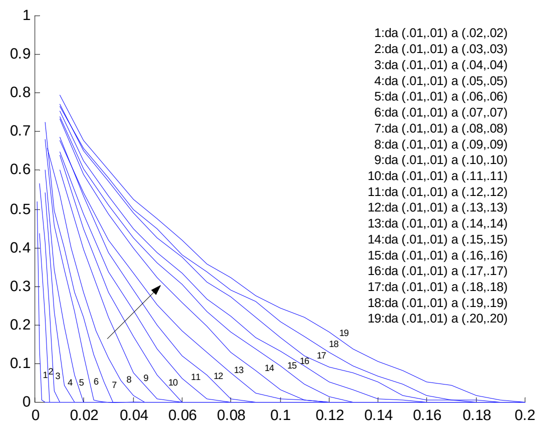

Figure 4: Analytical "variable" perturbations

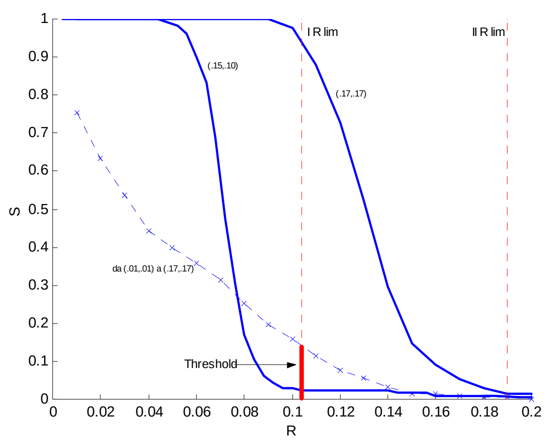

Figure 5: Threshold

Experimental Results

Once the threshold representing the health status of the structure was identified, an experimental test has been carried out in order to test the “Damage Index” method, the neural network and the discrimination approach.
The damage imposed on the first test-article has consisted in a chemical corrosion. It was carried out by means of the hydrochloric acid with a 15% title, whose pH is -0,65. The corroded region measures 8,5 cm2. The corrosion was carried out two times on that region, removing about 0,67 grams at a time.
About the Damage Index method, it is possible to show a graph for each couple of actuator-sensor. To sum up the results, they have been gathered in a graph which contains four groups of bars. Every group represents the sum of indexes of the couple actuator-sensor, in which the actuator is fixed. Moreover each group consists of three bars: the first represent the sensitivity index, which is determined using FRFs of the healthy structure acquired at different times to measure the experimental error and the environmental noise and vibrations which can influence the FRFs; the second and third bars are the indexes obtained after the two corrosion steps.
It can be noted (fig. 6) that the index has identified the damage. In fact DIs are higher than the sensitivity indexes. Besides, the piezoceramic patch #6, which is close to the damaged area, has given the highest index, so it is possible to assert that the damage has been localised. About the quantification it can be noted that the second corrosion step has increased all the indexes.

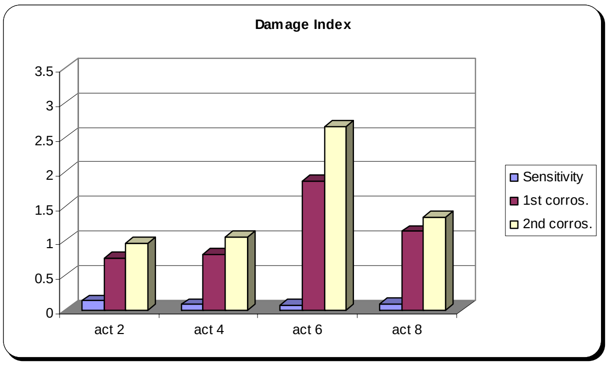

Figure 6: Corrosion damage

About the Neural Network technique, it is possible to notice (fig. 7) that the healthy configuration do not exceed the threshold, while the corrosion curves exceed the value itself. It can be noted that the network was able to quantify the increasing of the corrosion.

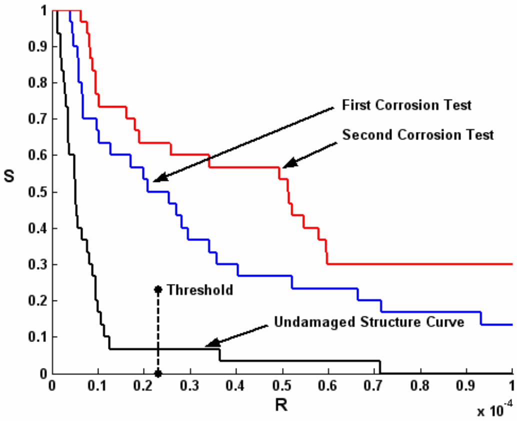

Figure 7: Neural network output

With regard to the second test-article, the experimental test has consisted in three impact tests. A sphere made by steel, whose mass is 146,4 grams and the diameter is equal to 4 centimetres, has been used for the impact. The edges of the composite panel have been stiffened, and the panel has been placed horizontally.
For the first impact test that sphere has been dropped from a height of 2 metres, so the impact energy has been equal to 2,87 Joule, close to the piezoceramic patch #4, outside of the patches array; for the second impact test the sphere has been dropped from a height of 2,80 metres, so the impact energy has been equal to 4,02 Joule, close to the patch #2, and, for the third impact test, the height was equal to 3,30 metres, and the impact energy has been equal to 4,74 Joule, internal to the array. The chart (fig. 9) represents the global Damage Index obtained by means of the Vibrometer. It can be observed, from the chart, that all the impacts have been identified by the Laser Scanner.

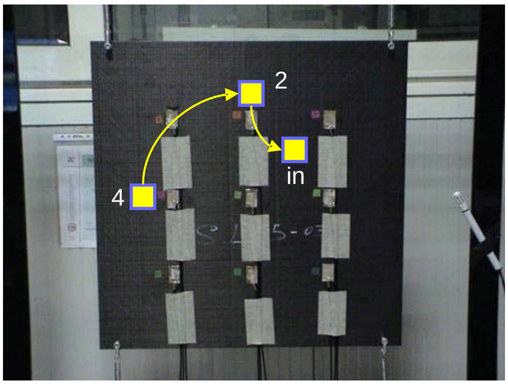

Figure 8: Impact tests locations

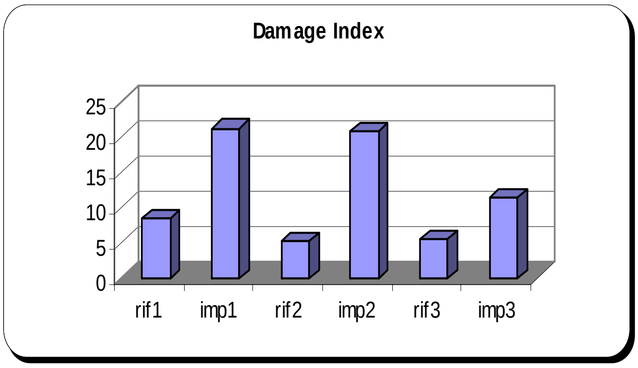

Figure 9: Global impacts Damage Indexes

The neural network has confirmed it (fig. 10), in fact its output puts the impact curves far from the undamaged structure curve.

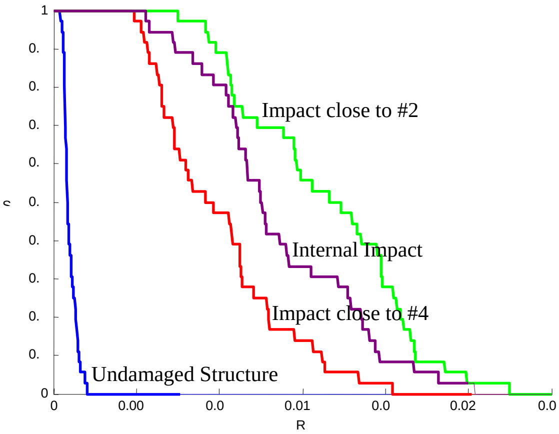

Figure 10: Neural Network impacts output

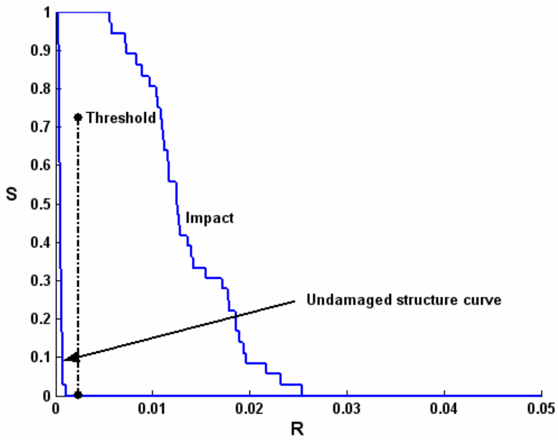

Figure 11: Neural Network impact #2 output

The FRFs, which have been acquired after the impact test, are definitely changed. The graph showed in the figure 11 represents the neural Network output about the second impact, after that the threshold was determined.
That damage imposed on the composite panel could be a delamination.

Conclusion

The aim of that work has been the development of Non Destructive Tests (NDT) which meet to most of the mandatory requirements for effective health monitoring systems, simultaneously reducing as much as possible the complexity of the data analysis algorithm and of the experimental acquisition instrumentation; these peculiarities may, in fact, not be neglected for an operative implementation of such a system.
Both of the techniques identify and quantify damage on aeronautical structures; moreover, the Damage Index one is able to localize. In order to use those techniques we do not need to damage the structure; we do not need to use Finite Element Methods; we do not need to determine structure's modal free. Furthermore, the methods are independent of structure and damage. Those techniques promise to bring a step forward for the implementation of an automatic "health monitoring" system which will be able to identify a structural damage in real time, improving the safety and reducing maintenance costs.

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