APPLICATION OF LASER DOPPLER VIBROMETRY FOR STRUCTURAL DIAGNOSTICS ON COMPOSITE PANELS : NEW EXAMPLES

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Abstract. *The growing utilization of composite materials in structural and mechanical systems is increasing more and more the necessity of improving the damage detection techniques. This paper presents a case where a non-contact measurement system, a Scanning Laser Doppler Vibrometer, has been used to detect delaminations in a composite material plate designed for NDT Techniques collimation in aeronautical applications. The diagnostic technique is based on the measure of the mobility of the panel surface by laser Doppler Vibrometry. A software has been produced for data acquisition and vibrometer control in order to implement original acquisition strategy and data processing. Measurements are performed in an automatic way, without user interaction. Maps showing the detected defects are obtained which allows the assessment of the performances of this methodology. Results achieved by air-coupled ultrasounds are also compared.*

Keywords: *Damage Detection Techniques, Scanning Laser Doppler Vibrometer, Composite Materials, Non-contact Measurement System, Structural Diagnostics.*

1. Introduction

There are many methods that examine changes in measured vibration response aiming to detect, locate, and characterize damages in structural and mechanical systems (Farrar and Doebling, Kessler *et al*) and cost-effective and reliable technique which can be applied to a wide range of structures is the main goal for all researchers.

The interest in the ability to monitor a structure and detect damage at the earliest possible stage is pervasive throughout the civil, mechanical and aerospace engineering communities. Current damage-detection methods are either visual or localized experimental methods such as acoustic or ultrasonic, magnetic field, radiographs, eddy-current and thermal field methods. The main encouragement to go toward the vibration-based NDT techniques is that some traditional techniques present no good results in measurements realized in composite materials made with several interfaces.

The need for additional global damage detection methods that can be applied to complex structures and new-concept composite materials has led to the development of methods that examine changes in the vibration characteristics of the structure.

Damage or fault detection, as determined by changes in the dynamic properties or response of structures, is a subject that has received considerable attention in the literature. The basic idea is that modal parameters (notably frequencies, mode shapes, and modal damping) are functions of the physical properties of the structure (mass, damping, and stiffness). Therefore, changes in the physical properties will cause changes in the modal properties. (Farrar and Doebling, Zou and Link (1995), Castellini and Paone and Tomasini (1996), Castellini and Revel (1998), Castellini and Revel (2000), Willemann *et al* (2004))

A system of classification for damage-identification methods, as presented by Rytter (1993), defines four levels of damage identification, as follows:

- Level 1: Determination that damage is present in the structure
- Level 2: Determination of the geometric location of the damage
- Level 3: Quantification of the severity of the damage
- Level 4: Prediction of the remaining service life of the structure

In this work, the presented vibration-based method is classified as Level 1, 2, since the Level 3 will be faced in the next future and the Level 4 do not make part of the authors' purposes.

2. Measurement Setup

The case study, investigated in this work, is a delaminated composite panel made of 10 layers with Aluminium and fabric (GLARE). The panel is realised for aeronautic applications by Airbus Deutschland to calibrate certain NDT techniques. The delaminations are obtained with 9 discs of Teflon inserted between layers. The geometry of the panel and the position of the defects are shown in Fig. 1. The panel thickness is 10 mm and the delaminations are regularly distributed in space and depth.

Defects Positions:

Delamination 1:   Between 1/2
Delamination 2:   Between 2/3
Delamination 3:   Between 3/4
Delamination 4:   Between 4/5
Delamination 5:   Between 5/6
Delamination 6:   Between 6/7
Delamination 7:   Between 7/8
Delamination 8:   Between 8/9
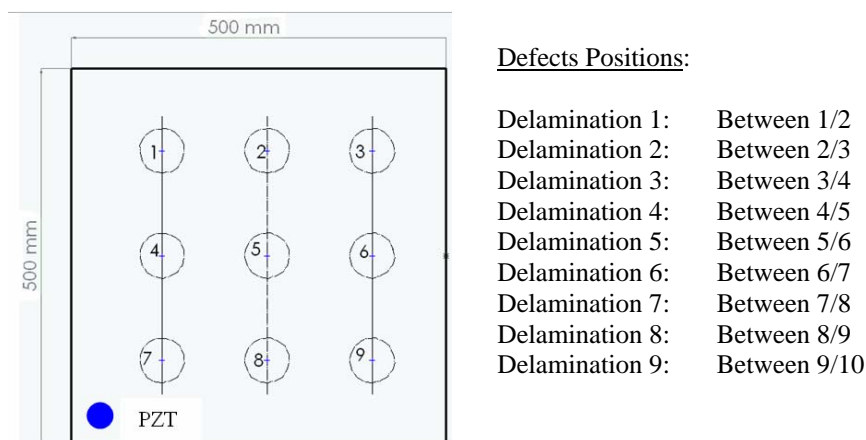Delamination 9:   Between 9/10

Figure 1 - The case study: a panel
(Defects are about 60 mm diameter)

The measurement system is composed by a Scanning Laser Doppler Vibrometer, which allow to analyse the vibrational behaviour of the panel up to 200 kHz with a high spatial resolution. The measurement grid had 32636 (199x164) points over the analysed surface, i.e. with a spatial resolution of about 2.3 mm.

The excitation was performed with a stacked piezoelectric actuator. For the practice damage assessment it is necessary to extend the bandwidth up to 200 kHz and only a piezoelectric actuator is able to obtain such performance; for the proposed damage detection procedure the measurement of the input force is not necessary (Castellini and Revel (1998), Castellini and Revel (2000)). In this case a white noise signal was used to drive the exciter. The panel was supported in free conditions, leaning over a soft layer of foam.

3. Statistical Methods used for Data Processing - Multivariate Analysis

Many times, throughout an experiment, a researcher is compelled to deal with a elevated number of variables but in the most of the cases, numerous variables are not so important to the problem under investigation. Therefore, some classification methods are employed to separate lower number of significant variables from the entire set of data.

Classification methods are statistical techniques used in several scientific areas such as chemistry, biology, biomedical, psychology, econometrics and many others. Principal Component Analysis (PCA), Partial Least Squares (PLS) and Principal Component Regression (PCR) are some examples of statistical methods and they are also considered Multivariate Methods (Tobias, Portier (2001)) .

Multivariate methods allow the simultaneous analysis of a dataset for exploring its overall structure, for measuring redundancy in the measurements, for summarizing the salient features, for forming groups of objects or individuals with common characteristics. Consequently, it also reduces the amount of data to analyse.

For that reason, different multivariate methods were incorporated in a software to examine a set of measured data obtained with a Scanning Laser Doppler Vibrometer. The main goal of this analysis is to gather characteristics which fit in the same group of points.

Principal Component analysis (PCA) is a multivariate projection method designed to extract and display the systematic variation in a data matrix. One of the major objectives in exploratory data analysis of multivariate data is dimension reduction: to screen data for obvious outliers, to select low-dimensional projections of the data for graphing and to search for "structure" in the data. The primary statistical tool to accomplish this is through the creation of Principal Components. A principal component is defined as a linear combination of projection of optimally-weighted observed variables.

The starting point for PCA is a matrix of data with N rows (observations) and K columns (variables), here denoted by X (Fig. 2). The observations can be analytical samples, chemical compounds or reactions, process time points of a continuous process, biological individuals, and so on. In this paper, every point of the scan grid is an observation and a frequency spectrum is associated to each one. These frequency spectrums are considered variables (K) since their values indicate the displacement, velocity and/or acceleration of the grid point in that specific frequency. As discussed previously by the authors (Willemann *et al* (2004)), the defected points present higher displacement values in certain frequencies when contrasted to the non-defected points at the same frequency.

Figure 2 – Data Structure of Matrix X

The most powerful use of PCA is indeed to represent a multivariate data table as a low-dimensional plane, usually consisting of 2 to 5 dimensions, such that an overview of the data is obtained. The overview may reveal groups of observations, trends and outliers. Statistically, PCA find lines, plane and hyperplanes in the K-dimensional space that approximate the data as well as possible in the least square sense. It is easy to see that a line or a plane that is the least square approximation of a set of data points makes the variance of the co-ordinates on the line or plane as large as possible. Alternatively, PCA may be understood as maximizing the variance of the projection co-ordinates.

Prior to PCA, data are often pre-treated, in order to transform the data into a form suitable for analysis, i.e., to re-shape the data such that important assumptions are better performed. In fact, pre-processing can make difference between a useful model and no model at all. Scaling of data and mean-centering are the most common pre-treatments but, additional pre-processing tools like transformations, advanced scaling and data correction and compression can be carried out (Willemann *et al* (2004)).

A variable with a large range has a large variance, whereas a variable with a small range has a small variance. Since PCA is a maximum variance projection method, it follows that a variable with a large variance is more likely to be expressed in the modelling than a low-variance variable. In other words, scaling the data makes that all variables make the same contribution to the model.

Mean-centering is the second part of the standard procedure for pre-processing. With mean-centering the average value of each variable is calculated and then subtracted form the data. Based on Willemann et al (2004), this improves the interpretability of the model, but, in some cases, it is not necessarily advantageous to use this combination of pre-processing tools, and some other choice might be more appropriate.

By using PCA a data table X is modelled as:

$$X = 1 * \overline{x}' + T * P' + E$$

(1)

In the expression above, the first term, $1 * \overline{x}'$, represents the variable averages and originates form the pre-processing step. The second term, the matrix product $T * P'$, models the structure, and the third term, the residual matrix E, contains the noise.

The principal components scores of the first, second, third, …, components (t_1, t_2, t_3, …) are columns of the score matrix T (N x A). These scores are the co-ordinates of the observations in the model (hyper-)plane. Alternatively, these scores may be seen as new variables which summarize the old ones. In their derivation, the score are sorted in descending importance (t_1 explains more than t_2, t_2 explains more than t_3, and so on).

The meaning of the scores is given by the loadings. The loadings of the first, second, third, …, components (p_1, p_2, p_3…) build the loading matrix P. Note that a prime has been used with P to denote its transpose (P'= A x K).

Besides, the loadings define the orientation of the PC plane with respect to the original X-variables. Algebraically, the loading inform haw the variables are linearly combined to form the scores. The loadings separate and clarify the magnitude (large or small correlation) and the manner (positive or negative correlation) in which the measured variables contribute to the scores.

The value of A, the number of principal components, is usually determined by cross-validation. Cross-validation (CV) is a practical and reliable way to test the significance of a PC- or PLS-model. With CV the basic idea is to keep a portion of the data out of the model development, develop a number of parallel models form reduced data, predict the omitted data by the different models, and finally compare the predicted values with the actual ones.

4. Data Processing Software – PCA Analysis

A software was built to perform PCA analysis in a data set obtained by using a Scanning Laser Doppler Vibrometer. The major objective in this exploratory data analysis is to reduce the amount of information under investigation and to search for structure in the data set. Based on PCA theory, the software divides the data set in principal components and these PC represent the defected and non-defected points present in the structure. At the end of the data processing, a map showing the defects is presented.

The in-house software is able to show results from every step of the PCA process, but only two software outcomes are shown in the next figures. Figure 3 shows the graphic that represents the variance values for the k-variables. This graphic demonstrates that only the first components (about 20 – highlighted by the dotted line ellipse) have relevant information, which proves that is not necessary to consider all calculated Principal Components. Indeed, 2 to 5 principal components are typically sufficient to approximate a data table well (Willemann *et al* (2004)).
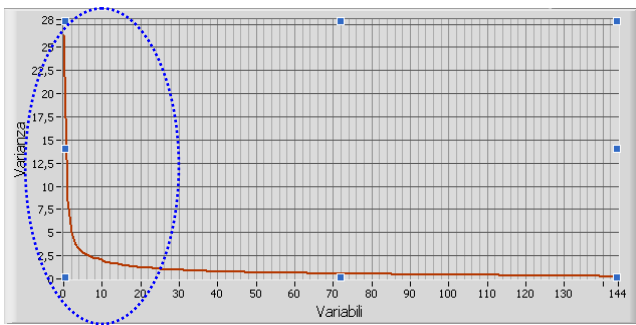

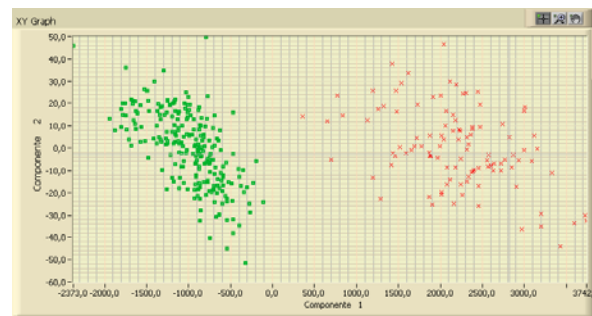Figure 3 – Variance values for the k-variables

Figure 4 – Plot of two Principal Components

In the graphic of the Fig. 4, the two first principal components have been plotted and the two clouds of points, which can be clearly visualized, represent the non-defected points (left cloud) and the defected points (right could).

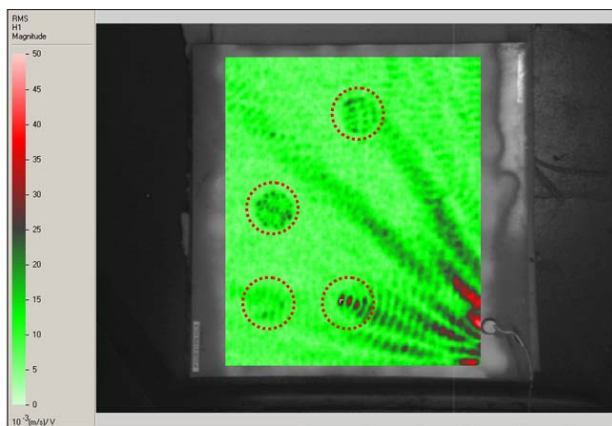## 5. Results and Comparisons

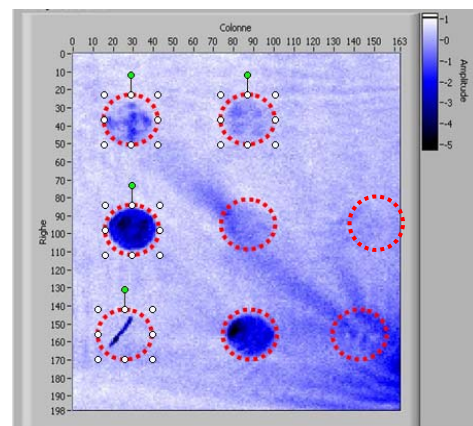Figure 5 – Commercial Software for Vibration Analysis

Figure 6 – In-house software

This section starts showing a measurement processed via the commercial vibrometer software (Fig. 5). For damage detection, this software needs the operator's interaction to search, manually, for the exact frequencies where the defects

come up. This operation, which requires a lot of time and patience, implies also in a very low frequency resolution. In the case that a high frequency resolution is desired, a much more time is also employed to the measurement process.

The contrast of the defects is another problem that must be considered when using the commercial software. In the Fig. 5, the defects are not so contrasted and, in some cases, it is very difficult to distinguish them from the noise or from the energetic path caused by the PZT actuator. In addition, the shape of the defects is also not quite well defined. Using this commercial software, only four defects from a total of nine show up at 55,50 kHz and there is no frequency value where more than four defects are visualized at the same time. Finally, after the complete analysis of this data set by using the commercial software, only five of the nine defects were assessed.

Afterwards, the same data set was analysed by the developed software and its result is shown in the Fig. 6. The most important advantage of the new software is that the visualization of the results is made in just one graphic. In this situation, eight from nine defects were found out at the same time. The deepest delamination was not evidenced because, based on previous experiments, the PZT actuator was not able to give sufficient energy to excite that point of the plate. That is why, new excitation techniques are being tested. Furthermore, the central defect in the Fig. 6 is not so evident because the graphic was reduced to fit in this paper, but in the original screen it can be absolutely noted. Another concern is the first defect, the most superficial, in the lower left corner which comes up as a line. In the author's opinion, the Teflon disk used to reproduce the delamination was pressed in a such strong mode which affected the vibrational behaviour of this fabricated defect.

This result (Fig. 6) was obtained with a algorithm based on multivariate analysis and no filter was applied to the data set. The original measurement had a bandwidth of 200 kHz and 250 Hz of frequency resolution (800 spectral lines). The in-house software analyzed a selected bandwidth from 2 kHz to 120 kHz using 2 kHz as frequency resolution. Observe that the assessed defects are well shaped, the time for the analysis was actually reduced, and it also demonstrates that time measurement can be also reduced since data processing has been performed using a frequency resolution eight times lower than the frequency resolution used during the measurement.

Obviously, these defected panels are just for experimental investigation and the defects were found because their positions were previously known. However, these fabricated defected panels are very useful to investigate the behaviour of different defects and to search for new measurement strategies. For instance, they could help to find a hypothetical two steps damage detection strategy: firstly, the structure is excited with a large bandwidth signal; the results are then analysed, and the probable defects found at the first step may be further analysed using sinusoidal excitation at a certain frequency or frequencies. Certainly, the sinusoidal excitation will improve the visualization of the defect. However, it is just an simple example of measurement strategy.

Just for comparison reasons, the same panel was measured with air-coupled ultrasound technique. Figure 7 shows the results from a Ultrasound Direct Transmission mode presenting an excellent result because all the defects were detected. However, in this case, the ultrasound just detected the changes in the material of the panel since, as said before, the defects were generated with Teflon disks placed between the layers.
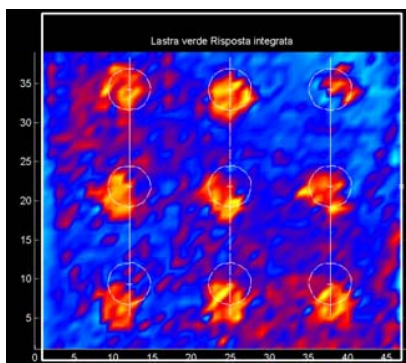

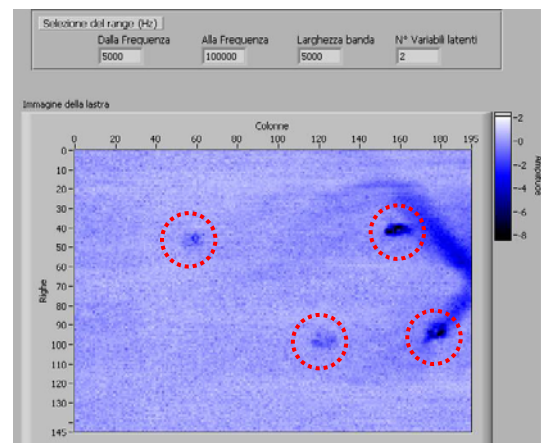Figure 7 - Composite Panel analysed by Ultrasonic

Figure 8 – Carbon-Fibre Composite panel

Several composite material panels have been measured and tested. Figure 8 shows a result attained from a measurement in a IS1 panel where the defects were made by impact. These were real defects and just one of the five defects was not evidenced because it was located in the internal structure of the panel, on a bar used for reinforcement. Also in this situation, the energetic path can be seen. In this case it was not a problem, but in many measurements it is very hard to make a distinction of defected points from high displacement non-defected points.

A real advantage of this new software is the single image presented at the end of the data processing because simple algorithms of image processing can be used to highlight the defects present in the analysed structures. By using image processing algorithms, it is possible to improve the results (by applying threshold or noise reduction tools to the images)

and to use the new cleaned images to train PLS algorithms. PLS algorithms are another multivariate analysis technique which needs to be trained before finding out the best principal components to better characterize the defects. PLS is better than PCA because always the first components found by the algorithm are those that extracts the real significant information from the data set under investigation.

Figure 9 shows a honeycomb composite material panel under investigation. This panel contains three circular defects artificially placed in three different depths. The frequency range used for the measurement was 200KHz with 400 Hz frequency resolution. The previously described algorithms were applied and the results are shown in the next figures. The same frequency range and resolution used in the measurements were used to obtain the map in the Fig. 10: in this case, the second principal component was able to evidence the defects present in the structure. In the second processing, the range frequency was reduced to 7 kHz: at this time, the defects were highlighted by plotting the first principal component. Dropping the frequency range has a big advantage because it reduces the amount of data to process.

It is important to emphasize that, in this experimentation, every grid point was measured just once aiming to reduce the measurement time. It is well know that no averaging measurements have a low signal noise ratio and that is why, a filter was applied. The final result is shown in the Fig. 11. We can notice that the three-dimensional representation in the second case (Fig. 11) is much better than the previous processing (Fig. 10)

Figure 12 contains the measurement result of a thin composite panel which has two delaminations. Acoustic excitation was used in this experiment. As the speaker was not able to reach frequencies above 15 kHz, only the most superficial defect showed up in this measurement. However, it can be noted that acoustical excitation is more uniform and less intrusive than piezoelectric excitation since, in this result, no filter was applied. Excitation and spatial resolution are very important in damage detection based on Laser Doppler Vibrometry measurements.
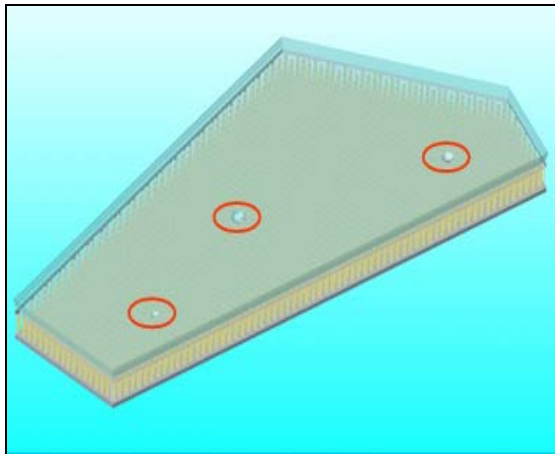

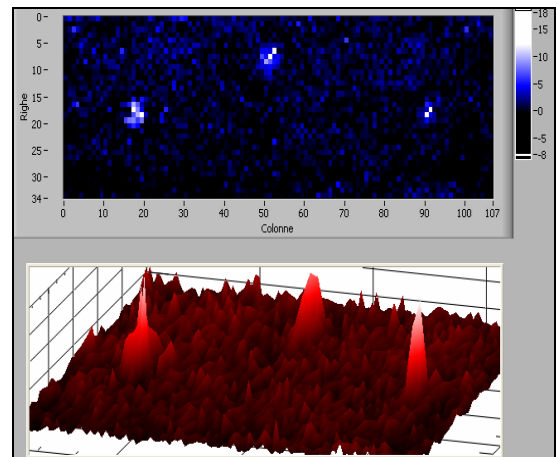Figure 9 – Defected Honeycomb Composite Panel

Figure 10 – Second Principal Component
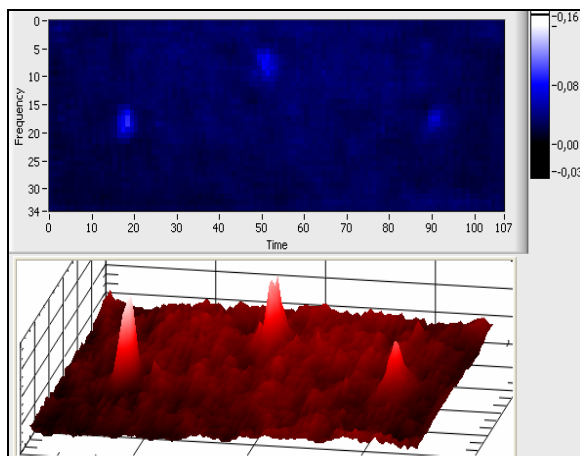200 kHz Frequency Bandwidth

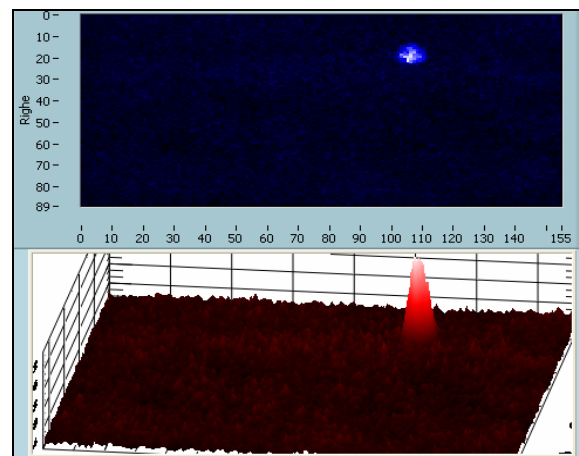Figure 11 – Filtered First Principal Component
7 KHz Frequency Bandwidth

Figure 12 – Defect in a Glass Resin Composite Panel

7. Conclusions

The use of the Scanning Laser Doppler Vibrometry in damage detection is gaining an increasing interest, as it offers large potentials, in particular for:

- non-contact measurement capability;
- reduced intrusivity;
- high spatial resolution;
- high sensitivity;
- suitable for investigation at higher frequencies (a large number of applications, requiring measurements at very high frequencies, cannot be accomplished using accelerometers);
- extraction of dynamic information;
- performing test not only in laboratory, but also in operative conditions (in-field) (e.g. maintenance of aircrafts);
- eliminating induced damages or other secondary effects on the structure (e.g. water penetration and corrosion in traditional ultrasonic tests);
- performing non-destructive testing with easy experimental set-up and reduced time for the object preparation.

However, an "intelligent" signal post-processing procedure must be designed and applied to the measured data, in order to highlight and extract the relevant information and reduce the time for data interpretation.

In this paper were presented some directions that can be taken to the incessant improvement of the damage detection techniques. Statistical Processing helps to pre-process the information contained in the measured data set by reducing its amount of data. Consequently, multivariate analysis methods give different tools to try to eliminate the systematic effects caused by noise (energetic path), facilitating the data processing. Moreover, information about depth and dangerousness of the defect can be related by using statistical correlations as well.

As cited before, measurement time is also a problem. To measure large quantities of points, depending on the quantity of averages and the number of spectral lines that are settled up for each point, the acquisition time could be massive. Because of this, efforts are being made to find out optimal settings for the measurements.

Some research is also being made in the area of composite materials excitation. It is important that the energy used to excite the plate should be constant and high for the entire frequency band.

The final goal of this work will be to completely automate the damage detection measurement procedure, further improving reliability, easiness and to reduce the amount of the relevant data to be managed. In particular, experimental data obtained with a Scanning Laser Doppler Vibrometer are showed and the achieved results demonstrated that the SLDV can be successfully used to detect defects in composite materials. Adding other post-processing algorithms, filters and new measurement strategies this device will be able to assess the defects in different types of composite materials. This seems a necessary step to bring these methodologies towards the daily practice of industry, maintenance and on-line quality control.

8. Acknowledgements

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5. Responsibility notice

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