An experimental technique for structural diagnostic based on laser vibrometry and neural networks

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In recent years damage detection techniques based on vibration data have been largely investigated with promising results for many applications. In particular, several attempts have been made to determine which kind of data should be extracted for damage monitoring.

In this work Scanning Laser Doppler Vibrometry (SLDV) has been used to detect, localise and characterise defects in mechanical structures. After dedicated post-processing, a neural network has been employed to classify LDV data with the aim of automating the detection procedure.

In order to demonstrate the feasibility and applicability of the proposed technique, a simple case study (an aluminium plate) has been approached using both Finite Element simulations and experimental investigations. The proposed methodology was then applied for the detection of damages on real cases, as composite material panels. In addition, the versatility of the approach was demonstrated by analysing a Byzantine icon, which can be considered as a singular kind of composite structure.

The presented methodology has proved to be efficient to automatically recognise defects and also to determine their depth in composite materials. Furthermore, it is worth noting that the diagnostic procedure supplied correct results for the three investigated cases using the same neural network, which was trained with the samples generated by the Finite Element model of the aluminium plate. This represents an important result in order to simplify and shorten the procedure for the training set preparation, which often constitutes the main problem for the application of neural networks on real cases or in industrial environments.

1. Introduction

The experimental investigation for structural diagnostic of mechanical components is a field where, in recent years, several efforts have been spent by researchers and technicians. In particular, attention has been focused on the possibility of on-line and in-field monitoring of the structural integrity, by using fast and reliable measurement techniques and automatic classification procedures.

At present, the measurement techniques mainly used for diagnostics are X-ray observation [1], eddy current and ultrasonic scans [2], infrared thermography [1] and coherent optical analysis [3], but these techniques have some limits. In fact they are time consuming and very difficult to be applied in in-field conditions. In addition, even if the detection of the defect can be accurate, its location and characterisation may be difficult in complex structures.

Other largely studied and applied diagnostic techniques are those based on vibration measurements, since they allow non-destructive evaluation of the structure under investigation. In this field, several strategies for structural excitation, vibration measurement and data processing have been presented, but results seem to be not yet completely satisfactory, in particular concerning the precise evaluation of the damage location. The usual approach consists in the determination of modal parameter changes due to the presence of the defect. However, this approach may give problems in dealing with thin and light structures, as panels of composite materials [4], where, if the defect is small, natural mode shapes may mask the local vibration pattern induced by the fault.

Laser Doppler Vibrometry (LDV) may offer large potentials to overcome such limitations, especially thanks to its high spatial resolution and reduced intrusivity [5]. Laser Doppler vibrometers are basically Mach-Zendher or Michelson interferometers in which the frequency light shift, induced by the Doppler effect when a laser beam is diffused by a moving surface, is measured. Such shift is proportional to the instantaneous velocity of the surface, which can be thus accurately evaluated [6]: the usual resolution of

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laser Doppler vibrometer is about 8 nm in displacement mode, or 0.5 μms^{-1} in velocity mode. In order to obtain a fast and accurate positioning of the measurement point, the laser beam can be deviated by a couple of mirrors, which are controlled by a dedicated PC and allow the subsequent measure in each point of a grid.

In previous works [7,8] the authors developed and applied an LDV based technique to measure delamination extension, depth and location in composite materials. A lumped parameter model was developed to describe the dynamic behaviour of a delaminated composite panel with the aim of determining which kind of measurement data must be extracted for damage monitoring and to design efficient post-processing algorithms for experimental LDV data. It was shown that the RMS values computed in different frequency bands are indicators of the delamination depth. In fact, the vibration exhibits a higher RMS value in the higher frequency bands, if the defect is deeper.

Following the model results, an experimental investigation by LDV was performed on panels with known detachments. Accuracy of the results was checked by comparison with thermal tomography, which at present is one of the most used measurement techniques for monitoring the state of composite materials. Experimental results showed the effectiveness of the model and the real applicability of the proposed technique. The presented methodology was proved to be efficient to determine also the delamination depth.

In [9], and more widely in the present work, the attention has been focused on the possibility to perform the procedure for damage detection automatically on-line. The underlying idea is that the proposed measurement technique supplies results that sometime are difficult to be interpreted, in particular for a non-expert operator. Furthermore, the reading of the results can be time consuming and thus not suitable for an in-field application. To this aim, a neural network can be employed to automatically classify the measured vibration data, previously processed with dedicated algorithms for feature extraction. The developed algorithms are based on RMS averaging in different frequency bands, according to the knowledge gained in the previous works by experimental tests and numerical modelling. In addition, the authors have investigated also the possibility to use the diagnostic procedure for other typologies of structures, further that for composite materials.

The main peculiarity and potential of the proposed approach are related to the exploitation of the neural network capability in generalising the classification results (i.e. in recognising different samples from those used to train the net), with the aim of finding a valid solution for the time consuming problem of the network training. Nowadays ANNs (Artificial Neural Networks [10]) are not always appreciated because of the need to have a large training set before starting with the classification work. If the variability of cases is large and the specific value of the analysed objects is high, it can be very difficult to produce a large enough statistical population to train the net.

In this work a procedure to produce a training set from simple and generic numerical models of defected panels is proposed, in such a way as to train the ANN without long series of experimental measurements on a real panel population. A FEM model of an aluminium plate with several different defects is used to generate samples to train an ANN able to work not only on real composite material panels, but also on a very particular panel as an ancient Byzantine icon. In this way the main aim of this study, i.e. the development of a tool able to automatically detect and characterise defects in different kind of structures, can be approached with success.

2. Experimental set-up

In this work the proposed measurement procedure is based on Laser Doppler Vibrometry, which is used to measure operational deflection shapes on defected structures. Such procedure is the evolution of a non-intrusive laser based measurement technique [11], which was successfully applied in a large variety of fields, ranging from human teeth to icons, from ancient frescoes to composite material panels. The procedure is based on the fact that information on the presence of a damage, or of a structural variation, can be retrieved by analysing structural vibration patterns induced by some input forces.

In this technique the application of non-contact and non-invasive instruments is a fundamental condition in order to avoid additional damages or loading induced on the test object by the diagnostic procedure and to facilitate the development of an automatic, remote detection system.

In the present work the reduced intrusivity is realised through the application of laser vibrometry. The high sensitivity of a laser Doppler vibrometer allows to decrease the detectable level of vibration (see Par. 1) and, then, to apply very low energy to excite the investigated structure. In addition, if a scanning device is used to move the laser beam on the structure under investiga-

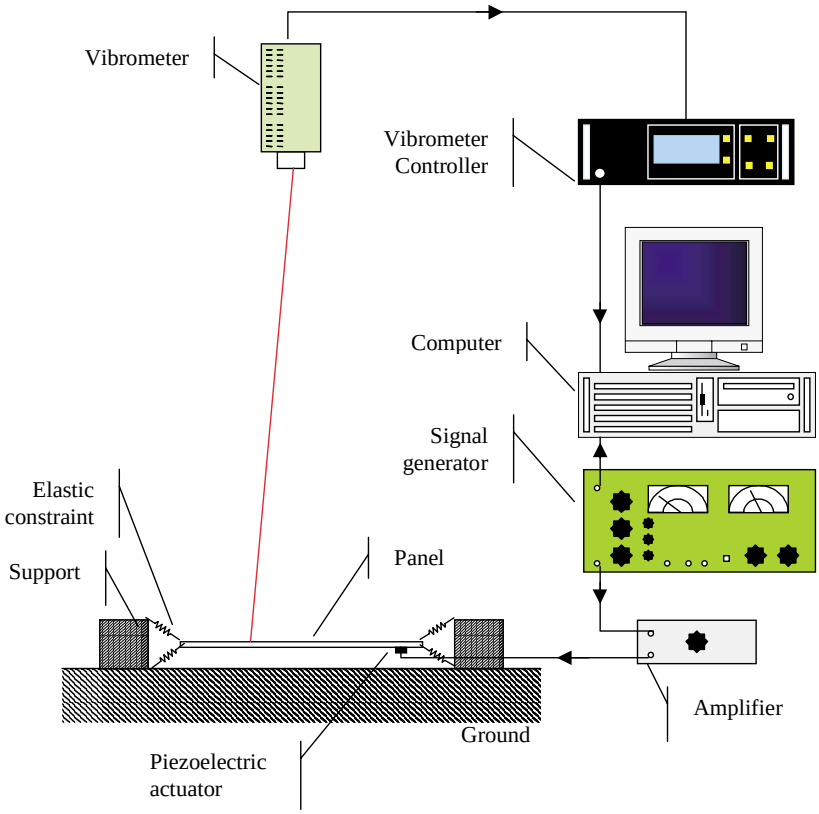

Fig. 1. Experimental set-up.

tion (SLDV, Scanning Laser Doppler Vibrometry), automatic measurements with high spatial resolution and wide frequency band can be performed. For each point the vibration velocity spectra can be measured and thus operational deflection shapes can be extracted.

A typical measurement set-up is shown in Fig. 1. Traditionally the specimen is excited by a white noise signal driving a loudspeaker or an electro-dynamic shaker. In this work the use of piezo-electric exciters is proposed in order to guarantee minimal loading on the structure and a huge excitation bandwidth (up to 100 kHz) avoiding problems of energy transmission, which can be typically encountered at higher frequencies. A small (10 mm of diameter) disk of piezoelectric ceramics was glued on the edge of the panel and supplied through a high voltage (1000 V maximum) amplifier. A white noise in a frequency range up to 100 kHz was used as driving signal and the investigated structures were suspended in free-free conditions.

In previous works [7] authors showed that the RMS values computed in different frequency bands can be employed as indicators of the delamination depth. In fact, the vibration exhibits a higher RMS value in the higher frequency bands, if the defect is deeper. Also the dimension of the defect influences the frequency range in which the defect can be detected: in particular, the higher frequency ranges are more sensitive to small defects in structures than lower frequency ranges. However, in the present work the dimension of the defects has been fixed at the same value for all the experimental cases and only the depth has been varied systematically. The information of defect dimension is available simply looking at extension on the map, and can be used to improve understanding on the single spectra.

Starting from these results, in the present paper the same measurement procedure was enriched with novel post-processing algorithms for the measured data, which are presented in the following section.

3. Data processing for feature extraction and classification

Data obtained by laser Doppler vibrometer were analysed using dedicated processing and classification

routines developed under the MATLAB® software. Such routines perform the complete elaboration of the measured signals and provide the management of result plots and data export. An artificial neural network (Par. 3.1) is utilised, which performs a classification in defected or non-defected measured points starting from selected features of the vibration velocity signals acquired by the laser Doppler vibrometer. The processing strategies for feature extraction are presented in Par. 3.2.

3.1. The neural network

The Artificial Neural Networks (ANNs) [10] are data processing algorithm's, in which computer programming try to emulate the processing scheme of the human brain and its capability to recognise features starting from the experience, thus generalising the knowledge in a continuos learning process.

From the computational point of view, ANNs are parallel distributed processors, based on low-level non-linear processing elements, the artificial "neurons", which are simple models of the real biological counterparts. Such neurons are interconnected together to build a complex network, whose behaviours surprisingly can resemble those of the brain: knowledge is acquired through a learning process and stored in the interneuron connection strengths, known as "synaptic weights". The procedure used to perform this learning process is usually called the "learning algorithm" and its function is to modify the synaptic weights of the networks in an orderly fashion so as to attain a desired design objective.

The ANNs, which hence are non-linear parallel adaptive circuits, have been applied to solve a large number of real problems. All these applications can be roughly divided into two groups: applications to data processing (non-linear identification and filtering, equalisation networks, etc.) and applications to pattern recognition (data clustering and classification).

In this research we used a particular neural network to classify the experimental data achieved by a scanning laser Doppler vibrometer, with the aim of distinguish between defected and non-defected points in the investigated structure.

In order to better understand how an ANN carries out a classification task, we can consider the case of the recognition of an original pattern from one corrupted by noise.

A classical way to approach this problem is to study the feature of the corrupting noise, find out its statistic and compute the probability of every kind of corrupted pattern.

Starting from a perfect information and model of the signal and the noise, i.e. of the statistics of the noise and the a-priori probability of each original pattern, it could be possible to classify the noisy pattern as the pattern with the maximum chance to be the original.

The neural network approach to solve the same problem is quite different.

It does not need any information or model because it can learn from examples (black box approach). Giving to the network a set of corrupted patterns (inputs) and the corresponding correctly classified patterns (target outputs), the learning algorithm modifies the synaptic weights and adapts the network until it is able to correctly classify. After this process the network is able to classify new unknown patterns, using the knowledge previously extracted by the learning set (generalisation capability).

Among the neural architectures, the so called Multilayer Perceptron (MLP) is the most used, due to its simplicity and yet its powerful capabilities. Therefore, we chose this architecture for our classification task.

The MLP is an artificial neural network composed of several artificial neurons, assembled into consecutive layers (see Fig. 2). The inputs of the network feed in parallel all the neurons of the first layer, while the outputs of this layer feed all the neurons of the second layer, and so on. Hence, the synaptic connections extend from a layer to the following one, and no connections among neurons of the same layer exist (feed-forward network). The outputs of the neurons in the last layer constitute the outputs of the network.

Each neuron is the simple processing element which computes the product between each input $x_i, i = 1, \ldots, n$ with the corresponding synaptic weight $w_{ki}, k = 1, \ldots, q$, performs the sum s_k of all terms and passes it to a non-linear function $sgm()$, called activation function, whose value is the output X_k of the neuron:

$$s_k = \sum_{i=1}^{n} w_{ki} x_i \tag{1}$$

$$X_k = sgm(s_k) \tag{2}$$

Usually the activation function has a sigmoidal shape, but in some cases it could be also linear or rectangular [10]. The output X_k of each k-th neuron is a component of the input vector for the subsequent layer. Finally, the output of the network is a vector Y with m

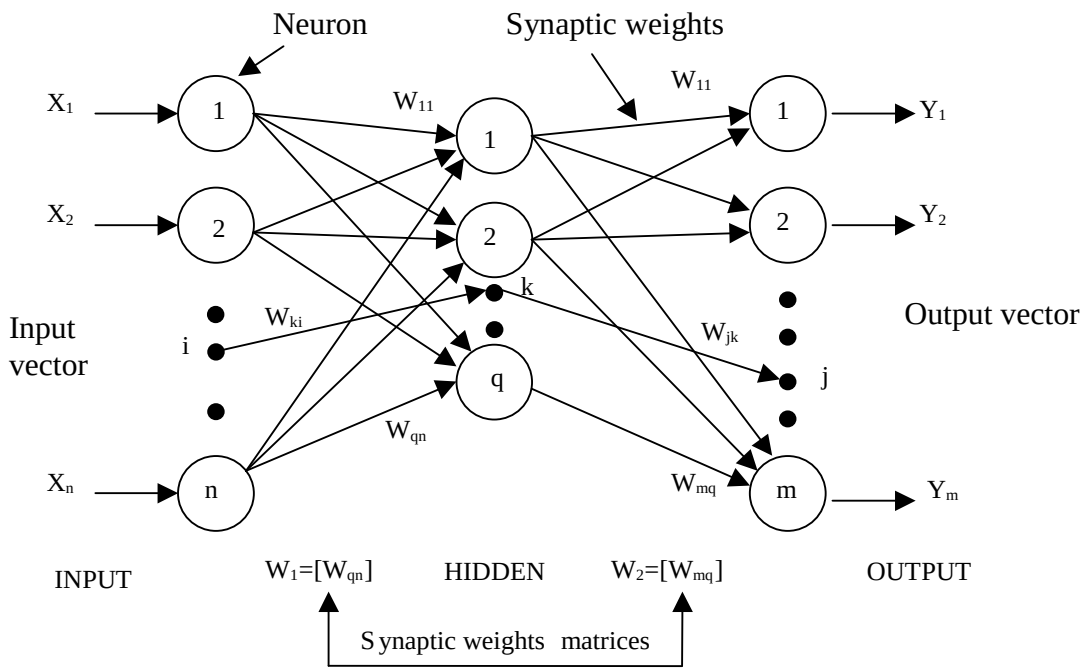

Fig. 2. Scheme of the Multi-Layer Perceptron artificial neural network.

components, where m is the number of neurons in the output layer.

In Fig. 3 a scheme of the data processing flow is reported, where the transformations operated on the vectors through the synaptic weights matrices have been put in evidence.

The learning algorithm is the procedure through which the network learns from the given examples, by suitably changing the synaptic weights. For the MLP, the classical learning algorithm is called Back Propagation.

The problem can be formally defined as the minimisation of an objective function in the space of some free parameters. The objective function here is the Mean Square Error (MSE) between the current and desired output and the free parameters are the synaptic weights of the network. To minimise such function a gradient descent technique is used: the idea is to move each weight in the opposite direction of the instantaneous estimate of the gradient of the objective function with respect to the weights.

For our experiments the learning set is constituted by input vectors extracted from vibration data achieved by numerical simulations and post-processed using the algorithms described in the next Par. 3.2. On the contrary, when the network is used for classification, the inputs are the Damage Index vectors extracted from experimental vibration spectra measured on each point of the panel and post-processed using the same algorithms of Par. 3.2. The output of the network is a single number between 0 and 1 which classifies such point as defected or non-defected. The classification is performed considering any output value between 0 and 0.5 as "non-defected" and any output value between 0.5 and 1 as "defected".

The networks used have 3 layers ($M = 3$) with the following number of neurons for each layer: 10, 3, 1. The dimension of the input vector ($n = 10$) depends on the signal processing strategy utilised to extract the features from the vibration data.

3.2. The algorithm for feature extraction

Artificial Neural Networks are very powerful algorithms, which allow to generalise the recognition of pattern with a "black box approach". Such capability is due to the simultaneous analysis of several different inputs through crossed weighting by synapsis of the neurons. Increasing the dimensions of the input vector and the number of hidden layers, theoretically it is possible to improve both the accuracy of the classification and the generalisation capabilities.

In practice, the application of large ANN can generate problems related to the need of larger training set in order to accurately determine a big amount of synaptic

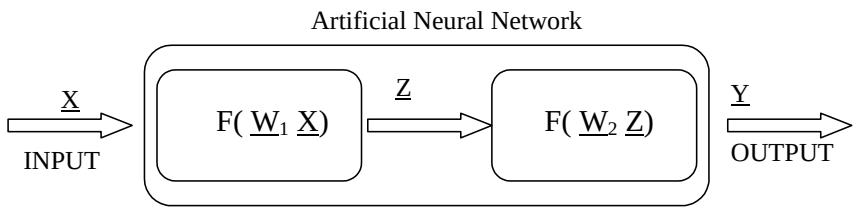

Fig. 3. Data processing flow in a M.L.P. network with 1 hidden layer.

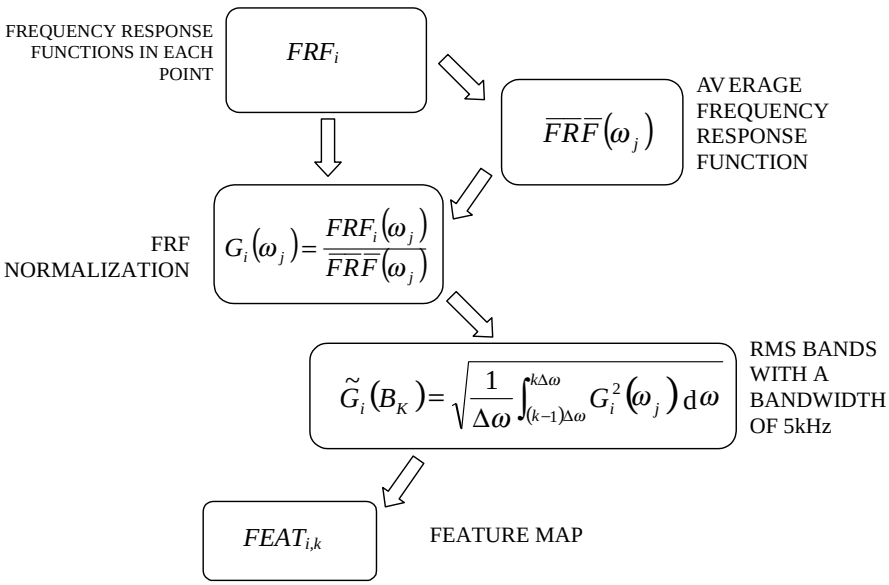

Fig. 4. Scheme of the procedure for features extraction.

weights, and to time consuming computations, induced by the number of degree-of-freedom in the classification.

A solution to this problem is the determination and extraction of some features of the signal, which concentrate the whole information in few characteristics interesting for the specific application, reducing the total amount of data. This approach is a sort of compromise between the "black box approach" and the "model approach", because the feature extraction is usually performed starting from considerations related to the knowledge of a problem model.

In the present case, once the vibration spectra have been measured in each point of the panel by the scanning vibrometer, a processing procedure must be used in order to generate a simplified and reduced input vector for the subsequent processing by the neural network. This procedure, called "feature extraction", aims to extract from the data the features which better highlight the differences between the two classes to be separated and, furthermore, to reduce the amount of data.

The procedure here utilised is schematically shown in Fig. 4.

In particular, the proposed procedure considers:

1) Measurement or assessment of vibration data (here named as "Frequency Response Functions" FRF_i) in each point i of the structure. Such data can be expressed as functions of different physical parameters of the structure: displacement, velocity, acceleration, dynamic flexibility (displacement/force), mobility (velocity/force) or inertance (acceleration/force). In the present case mobility functions are used, but the same approach can be easily applied for all the other mentioned quantities, as shown in the following points;
2) Calculation of the average FRF for each frequency ω_j, according to the expression:

$$\overline{FRF}(\omega_j) = \frac{1}{N}\sum_{i=1}^{N}\overline{FRF}_i(\omega_j) \qquad (3)$$

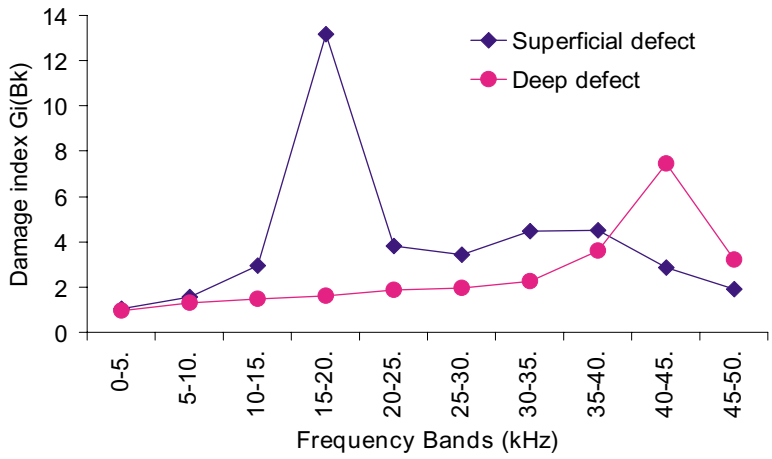

Fig. 5. Comparison between the Damage Index computed, starting from experimental data of the aluminium plate, for a superficial and a deep defect respectively in different frequency bands.

where N is the number of measurement points. This spatial average represents the general behaviour of the whole structure. Being the defects just a small and local alteration of a larger structure (for large defects it is not necessary to carry out detailed analyses!), we can assume that such average function is not affected by the presence of the defect itself. In other words, the average FRF is considered to be equal for the same structure defected or non-defected and represents a reference where the effects of the main global mode shapes can be found.

3) FRF normalisation (see Fig. 4). The FRF_i are normalised with respect to the average FRF computed at step 2. The differences between the spectrum FRF_i and the average FRF represent a defect in the point i and can be highlighted through this operation: in fact, if we assume that the mobility is higher in the defected point, the normalised FRF will present an higher level in that point. The identification of the FRF variation is possible only if the energy level is sufficient to put in vibration the investigated points. However, more piezo disks – positioned in different points – can be used, in such a way as to excite the whole structure. In addition, the effects of particular mode shapes or of local excitation near the driving point, which can generate fictitious defects, are eliminated by normalising. This step is very important also because it allows to classify, with the same neural network, tests and structures where different parameters have been measured (e.g. the network can be trained with a set of normalised mobility functions, but in a later test it could be used to classify features extracted from a set of acceleration functions). In fact, the normalised function is specifically employed to describe the local variation of a quantity with respect to its spatial average value.
4) Calculation, for each considered point, of the RMS value in frequency bands with a width of 5 kHz. In this way it is possible to reduce the total amount of data and to smooth the effects of noise and mode shape residual effects. The bands can be selected, case by case, in order to analyse the distribution in the frequency domain of the defect behaviour with a sufficient detail. The result, $G_i(B_k)$, can be named as "Damage Index" and represents the input vector for the neural network. The condition for having the point classified as "defected" is to have a Damage Index value bigger than 1 in one of the frequency bands. In fact, when the Damage Index vector is about 1 in all the frequency bands, it means that the measured FRF presents a mobility level very similar to the one of the average FRF and therefore the point should be classified as "non-defected". The magnitude of the Damage Index is not indicative of the defect depth, which is identified by the frequency band where the Damage Index has a value bigger than 1.
5) Feature map extraction, showing the value $G_i(B_k)$ computed for each point and for each frequency band. These maps can be used to have a localisation of the defect by superposition of the map to the image of the structure. Examples of results will be shown in the following Paragraphs.

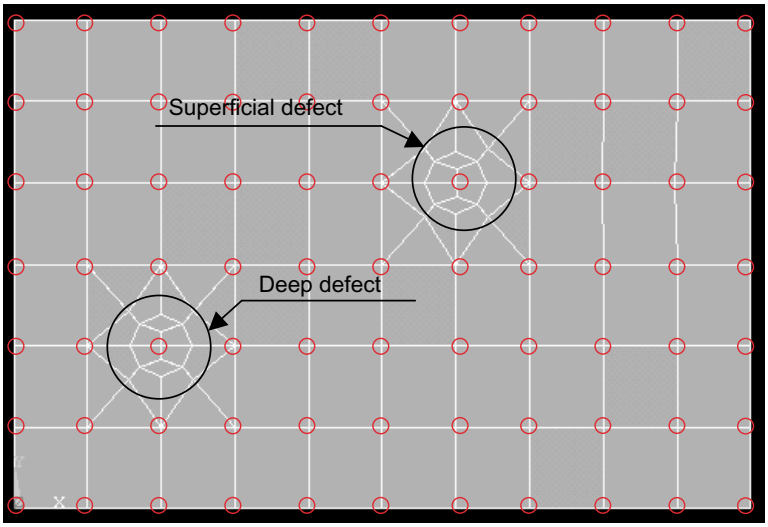

Fig. 6. Numerical model of a plate with two defects.

In Fig. 5 an example of features calculated on the aluminium plate is shown. In particular, a comparison between features extracted for a superficial and a deep defect respectively in different frequency bands is presented, showing how the proposed features extraction procedure is able to highlight defects and to discriminate their depth with a reduced amount of data. The application of an experience-based data classification approach, as that of Artificial Neural Network, can allow to distinguish between pseudo and real defects, improving the accuracy of the whole diagnostic procedure.

4. Numerical simulation

In order to improve understanding on effects of different kind of damages (in terms of local FRFs) and to easily produce a large population of defect cases, a Finite Element (FE) model was developed. The application of a numerical code allows, in fact, to produce a model of real panels and to simulate defects with different depth, shape and position simply changing some parameter in the code. It is therefore quite easy and fast to obtain a large statistical population of very "controlled" defects, which can be used to generate the learning set to train the neural network.

The FE model was developed by the commercial code ANSYS. The large frequency band and the high frequency resolution (about 50 kHz of band with 800 spectral lines, corresponding to a resolution of 62.5 Hz) necessary for an exhaustive local analysis in the damage region (Fig. 6), and the complexity of the model required to have this resolution, induce long computational times and output files with a dimension of about 400 Mb of data for each simulation.

The research started from a very simple case study. A model of an aluminium plate was developed using 2D elements [12], which have 8 nodes and present the capability of representing the proprieties of different layers in function of the depth. The material was represented with isotropic and homogeneous aluminium with a damping of about 0.05%.

The simulated defects are basically thought as internal lack of structural material. They are introduced considering some parts of these layers as constituted by very soft and light material, representing thus the contribution of the defect void. In practice, the defect was modelled as shown in Fig. 7, where 5 different defect depths are represented. This assumption does not take into account the contribution of the layer of material which "closes" the defect in the lower part. In fact, the contribution of this part to the local vibrational behaviour, measured by the vibrometer on the opposite side, is usually very low. The same assumption was assumed in [7] to simulate delaminations in composite panels and it gave satisfactory results. In this way it is possible to simplify the model avoiding a more complex 3D analysis.

The FE model was not developed in order to reproduce exactly the behaviour of a specific object, but in order to represent the qualitative features of the vibration spectrum on a point over a defect, in particular trying to predict what the laser vibrometer could measure in that point.

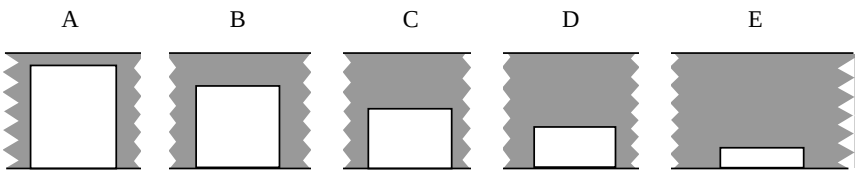

Fig. 7. Scheme of the damages at different depth in the numerical simulation.

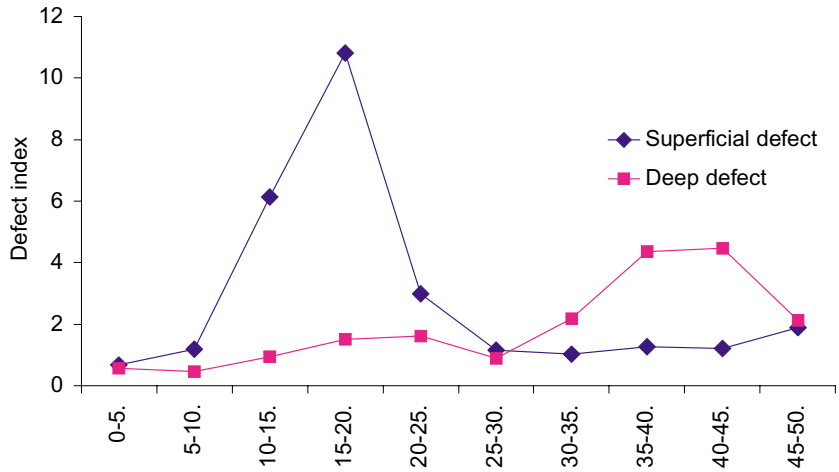

Fig. 8. Comparison between the Damage Index computed, starting from numerical data of the aluminium plate, for a superficial and a deep defect respectively.

Once the model was validated by comparison with experimental data, it was utilised for the generation of the neural network training set. The training set was constituted by 1100 Damage Index vectors relative to non-defected points and by 170 to defected points with different characteristics (as shown in Fig. 7).

As it is usual with numerical techniques, the data are analysed in a not uniform grid, but with a higher spatial density of nodes in those portions of the structure where discontinuity (as cavity, cracks, defects or edges) are present. This is important to have a correct numerical approximation of the large gradients of stress and strain, which can be found in these parts. The number of control points is thus very high around the defects, but this attributes a not uniform statistical weight to each node, when the average FRF is computed. In addition, with experimental techniques, which should be here simulated, vibration data are usually taken in a regular grid. The points over the defect represent a low percentage of the total number of measurement points, and this allows to assume the average FRF not affected by the presence and characteristics of defects.

Therefore, in order to have a correct distribution of information in numerical results and to allow a good simulation of experimental data, the outputs of the FE model was taken over the regular grid represented by small circles in Fig. 6, where only uniformly distributed nodes are considered.

As example, the Damage Index, computed starting from the numerical results on a superficial and a deep defect respectively, is shown in Fig. 8. Even if the FE model is not able to exactly determine frequency response functions and mode shapes of the structure up to 50 kHz, the trend is very similar to the one presented in Fig. 5 for the experimental results: the deep defect exhibits a higher Index in the higher frequency bands. In addition, it is worth noting that the numerical mesh was optimised for the frequency range higher than 10 kHz, where most of the defects are detectable.

Some tests were also performed in order to show that the results, in terms of features extracted, are not sensitive to the location of the driving point. This is important to generalise the achieved results, in the sense that they can be considered as exploitable in a larger population of experimental cases.

5. Experimental results

The results achieved by numerical simulations of the vibrational behaviour of non-defected and defected

panels, with different characteristics, were used to extract data and features to train the neural network. The network was then used for classification in operating tests on real panels and structures.

Even if the model is referred to a homogeneous aluminium plate, the obtained network was applied, besides on a real aluminium plate (Par. 5.1), also on panels composed of different materials and structural characteristics, as a panel of composite material (Par. 5.2) and an ancient icon (Par. 5.3).

5.1. Tests on an aluminium plate

In this first case the investigated structure is an aluminium rectangular plate ($300 \times 200 \times 6$ mm) with two defects at known depth (3 and 5 mm respectively). This structure corresponds to the one developed in the numerical model employed for the network training, reproducing correctly both the material and the geometry of the real object.

In Fig. 9 the Damage Index maps extracted from experimental data at different frequencies are shown. These maps (as those reported in Figs 12, 13, 17 and 19) represent the distribution of the Damage Index (or of the RMS velocity values, in Figs 12 and 17) on the structure at the different frequency bands used for the computation of the RMS values. In practice, to each point in the maps corresponds a laser vibrometer measurement point: the quantities reported in the maps are achieved by processing the vibration data measured on each of these points.

In each frequency band the defects are correctly highlighted with good SNR: the superficial defect is evident almost at all the frequency band (as shown in Fig. 5), while only in the higher range the deep defect appears. This allows to distinguish the depth of the defect and also to detect some pseudo defects, which appear without a repeatable behaviour at higher frequencies, probably due to noise in the measurements or to particular effects on the edges. It is also evident that in a similar application it is not necessary to investigate a very large frequency band, as in other cases (e.g. composite materials).

The features, in terms of Damage Index for each point, were then processed by the neural network for classification: some example of results are shown in Figs 10 and 11. In particular two maps are shown, which was obtained by analysing the whole panel (Fig. 10) or just a small part of it in the defected region with a higher spatial resolution (Fig. 11). Enhancing the resolution it is possible to improve the ANN capability. In fact, any detected defect can be checked repeating the analysis in a small region, eliminating any possible noise effect or pseudo defect simply by increasing the information on the defect itself. It is worth noting that all the pseudo-defects appeared in the Damage Index maps (in particular in the 45–50 kHz band) are not classified as defected points by the neural network, which seems therefore to be suitable also for dealing with noisy data.

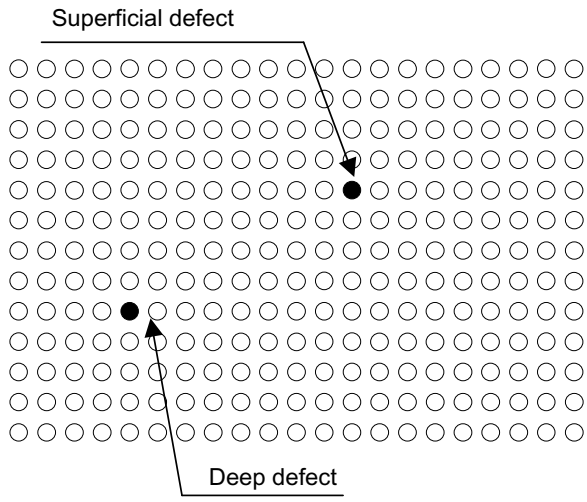

Fig. 10. ANN output related to experimental data of the aluminium plate.

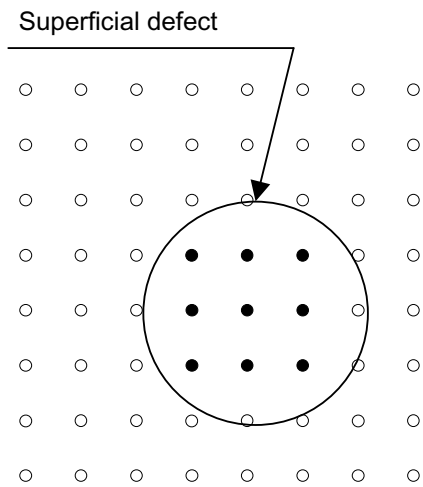

Fig. 11. ANN output related to an high resolution grid measured on the aluminium plate.

5.2. Tests on a composite panel

The composite structure investigated in the second case study is a Fiberglas panel composed by 7 layers of

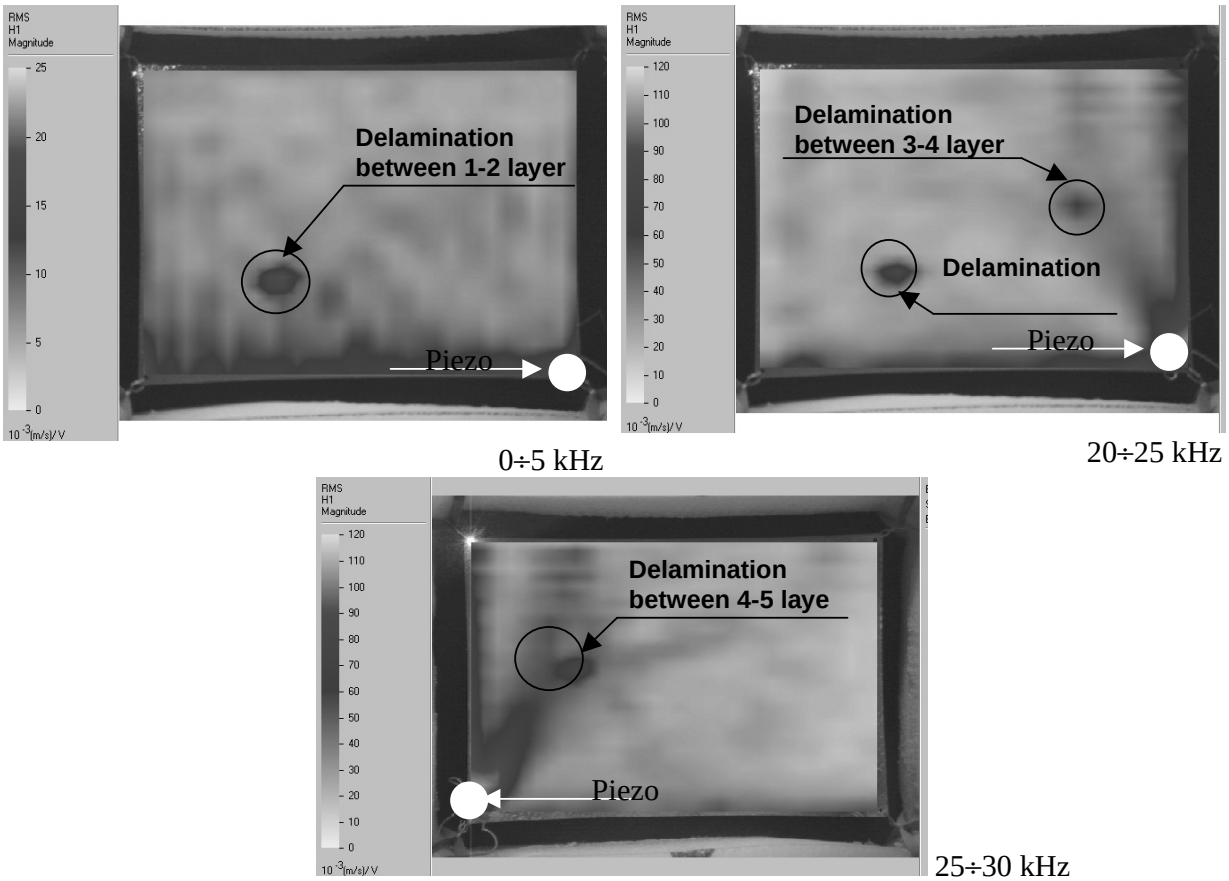

Fig. 12. RMS maps of FRFs at different frequency bands measured on the composite panel.

canvas immersed in a matrix of epoxy resin. Defects are obtained by introducing, between layers 1–2 and 3–4, wax disks in known positions during the lamination procedure. The wax is removed, through the panel porosity, by heating the solid epoxy matrix, in such a way as to create empty cavities between the layers.

RMS maps and Damage Index maps measured on the composite panel are shown in Figs 12 and 13 respectively. The delamination between layers 4–5 is obtained by measuring with the laser vibrometry on the opposite side of the same panel and looking in correspondence of the defect between layers 3–4. Results highlight that the Damage Index is able to extract the defect characteristics (shape and depth) with an efficient data compression procedure in the different frequency bands.

Some residual noise is still present on the maps. Such noise is mainly due to the path of energy transmission from the piezo-electric exciters, glued in correspondence of the white disk indicated in Fig. 12. The feature extraction algorithm is able to attenuate such noise, but only partially. The delamination between layers 6–7 (which should be found in the measurement on the opposite side in correspondence of the defect between layers 1–2) cannot be found in the considered frequency bands. In [7] it was shown that a higher frequency range, up to 100 kHz, must be used in this case.

The extracted Damage Index vectors were classified using the neural network trained on the data from the numerical simulations of the aluminium plate. Results are shown in Fig. 14.

The application of the ANN allows to improve the situation and gives the possibility of an automatic classification procedure: the influence of noise is significantly reduced and relegated on the edge close to the driving point. In this case, repeating the analysis with some parameter modified, as the excitation point location or the measurement grid, it is possible to eliminate any doubt on the classification results, simply comparing the network outputs in the different cases. In fact,

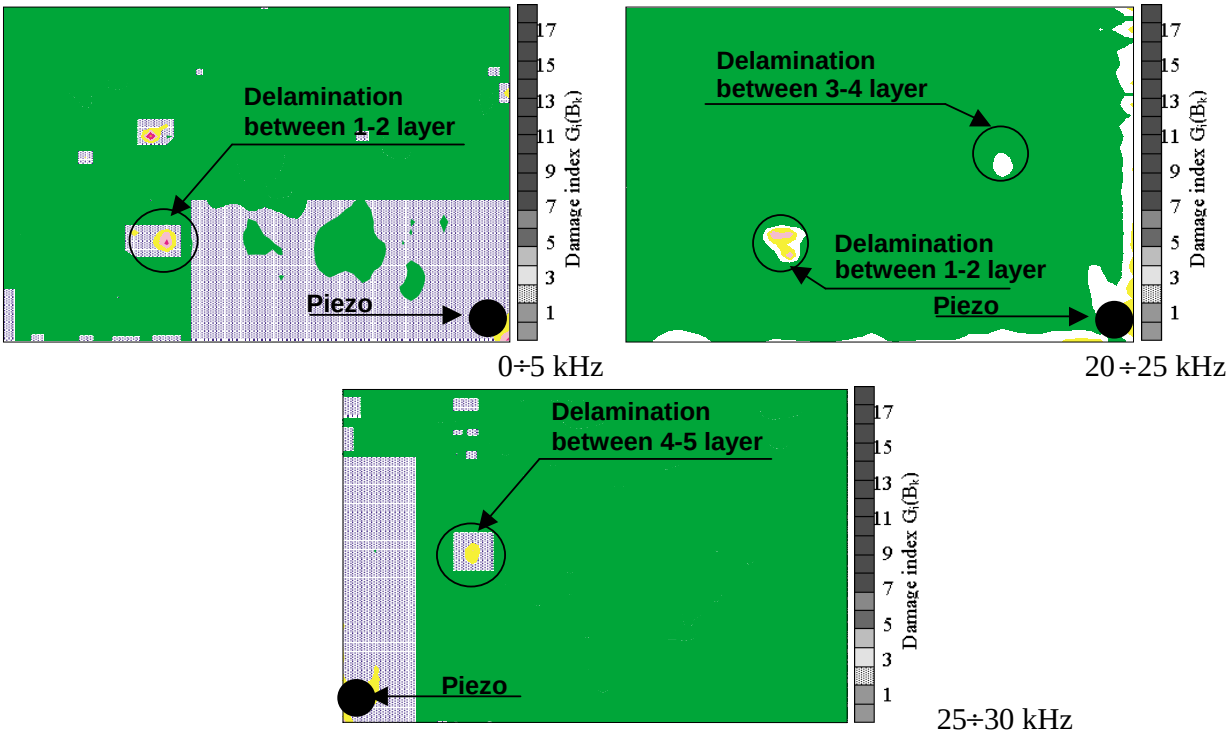

Fig. 13. Damage Index map on the composite panel in different frequency bands (experimental data).

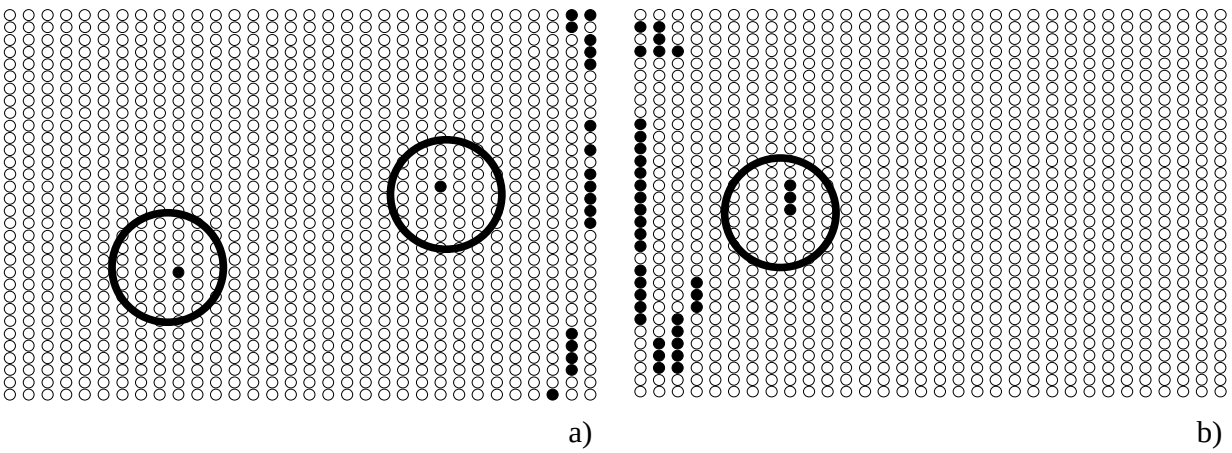

Fig. 14. ANN outputs for the composite panel (black: defected points). a) between layers 1–2 and 3–4; b) between layers 4–5.

only the points classified as "defected" in all the tests will be surely located in correspondence of a damage.

5.3. *Tests on an ancient icon*

The last case study was a Byzantine icon of the century XVII (Fig. 15). Icons and paintings often present problems related to structural damages and, therefore, a non-invasive diagnostic technique, as the one here proposed, can be of interest for the monitoring of the conservation state of many artworks.

For the icon, the problem of the reduced correspondence between training set and classified object is even more evident.

Byzantine icons were usually constituted of four layers (Fig. 16): the wooden panel, the canvas, the paint layers (including the gilding) and finally the varnish

Fig. 15. The Byzantine icon (century XVII).

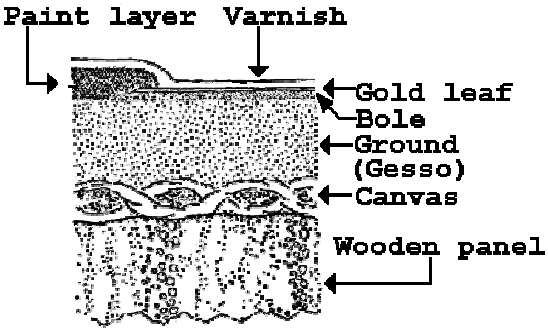

Fig. 16. Scheme of the structure of the icon.

coating. The wooden panel of the painting was made of one or more boards, often of different dimensions, which were connected to each other by nails. This was critical for the good preservation of the icon since properly cut and well-dried boards would, to a great extent, prevent the warping of the icon.

Between the wooden panel and the preparation ground, a piece of thick linen fabric was laid, in order to support the paint layer during future movements of the wooden support (contraction/extension). Animal glue or skin glue was usually used for fixing the fabric onto the panel. The drawing was executed directly onto the ground. This could be a freehand design or more often a copy of a drawing from another icon.

The painter in order to give more brightness to the colours and to protect his picture from dust, grime and light radiation applied a varnish coating over the paint

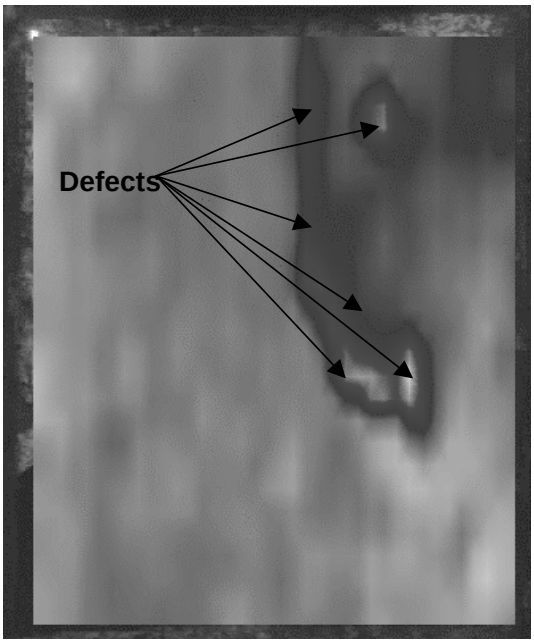

Fig. 17. The RMS map of FRFs measured on the icon in the 0–50 kHz band.

layer which was made by dissolving or fusing a natural resin in a fluid which allowed it to be brushed over the painting. Some natural resins used in picture have been the mastic, dammar and sandrac.

As regards defects characterization, we are always looking for detachments and delaminations, this time working with more complicated structures, formed by more layers and having smaller dimensions. The interest of a repeatable and objective measurement technique for icons is motivated by diagnostic and monitoring needs, but also for certification and insurance purposes, in case of claims for damages occurred during exhibitions and transport.

The RMS map of the FRFs measured on the icon in the 0–50 kHz band is shown in Fig. 17. Some regions on the structure are clearly highlighted and they correspond to the defected part indicated by the restorer. A first useful indication can be thus achieved directly by the RMS maps.

However, the most interesting results come from the application of the feature extraction algorithms and from the classification by neural network. The Damage index extracted for a defected and a non-defected point respectively is compared in Fig. 18, showing the capability of the index in suitably differentiating damaged points.

This is confirmed also by the Damage index maps computed in the 5–10 kHz and 20–25 kHz bands

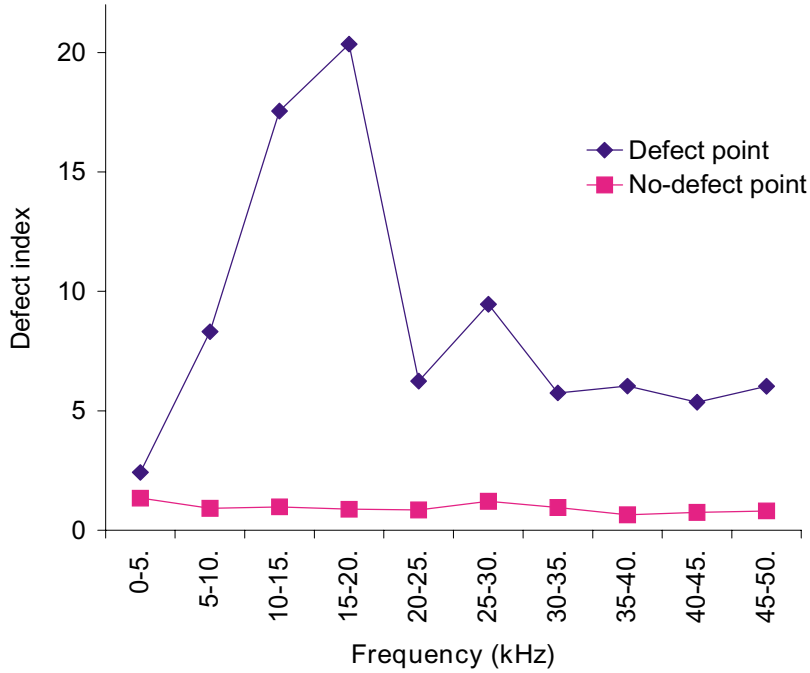

Fig. 18. Comparison between Damage Index for a defected and a non-defected point in the icon.

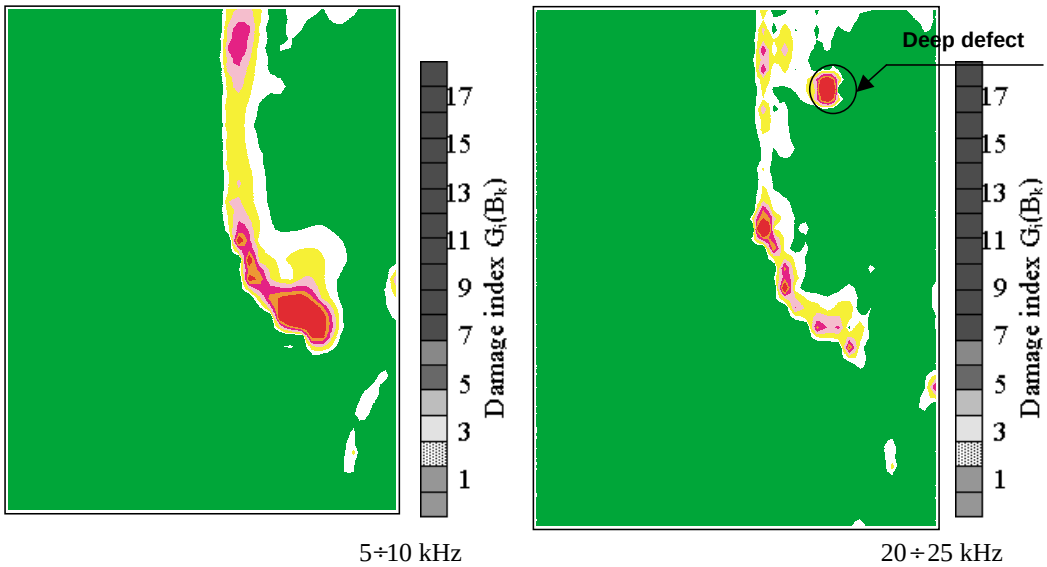

Fig. 19. Damage Index maps for the Byzantine icon at different frequency bands.

(Fig. 19), which seem to add some information concerning the depth of the defects. In fact, a new damaged zone is appearing only in the 20–25 kHz map, representing probably a deeper defect.

In the last step the neural network, previously trained on the numerical data of the aluminium plate, was employed for the automatic classification task. The results, shown in Fig. 20, demonstrate that the network is able to recognise the defected points also on the Byzantine icon, which is a structure significantly different from the simple one used during the training.

This is possible only thanks to the developed feature extraction algorithms, which guarantee the generation of an adimensional parameter sensitive to the

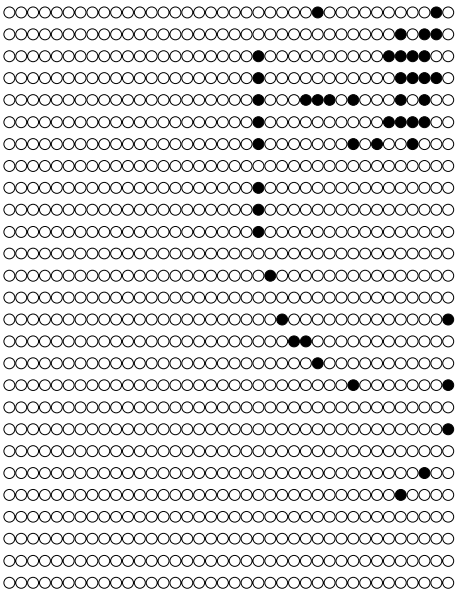

Fig. 20. ANN outputs for the Byzantine icon (black: defected points).

presence of a defect, and to the generalising capabilities of the neural network. In order to describe how the feature extracted is similar and representative for the three investigated cases (which have so different structural characteristics!), the Damage Index vectors for defected and non-defected points are compared in Fig. 21. The behaviour of damaged and undamaged parts seems to be the same on the different structures and this is the "key point" in the developed diagnostic tool. In fact, this allows to make the monitoring procedure in a large variety of cases automatic, which is the main goal of the present work. In addition, it is not necessary to use any normalisation for the Damage Index vector, when it is employed as input for the neural network. In fact, the condition for having the neural network output bigger than 0.5 (i.e. the point is classified as "defected") is to have a Damage Index value bigger than 1. When the Damage Index vector is about 1 in all the frequency bands, it means that the measured FRF presents a mobility level very similar to the one of the average FRF and therefore the point should be classified as "non-defected".

6. Conclusions

In this work an experimental structural diagnostic technique based on laser vibrometry measurement techniques and neural networks for data processing is presented. The idea underlying the proposed approach is very simple and confirmed by previous works [5,7, 8]: the mobility of the structure tends to increase in correspondence of damaged or delaminated parts. The forced vibration of the structure is thus measured using a laser scanning vibrometer and the results, after the application of feature extraction algorithms based on RMS averaging, is classified by a neural network, in such a way as to implement an automatic procedure to use on-line or in- field.

It is worth noting that the technique can be utilised for different kinds of structure: in the present work it was successfully applied on an aluminium plate, on a composite Fiberglas panel and on a Byzantine icon of the XVII century. This was possible only thanks to the developed feature extraction algorithms, which guarantee the generation of an adimensional parameter sensitive to the presence of a defect (as shown in Fig. 21), and to the generalising capabilities of the neural network.

Because of these peculiar characteristics, also the problem of generating a suitable learning set to train the ANN can be easily solved. In fact, the learning set can be generated from very simple cases, which can be assumed to behave as the real ones, in general more complicated. It is sufficient to state that in this research the neural network, employed for the classification task in the three investigated cases, was trained with the data extracted from a Finite Element model of an aluminium plate with damages of different typologies!

The laser vibrometry seems to be the only measurement technique suitable to be coupled with the developed processing algorithms, since no other available non-invasive techniques are actually able to quickly supply vibration data in a large frequency band with high spatial resolution. The measurement chain and post-processing procedure have proved also to be quite insensitive to noise.

Future development of this work will be the application of the proposed technique to other typologies of structures and the utilisation of neural networks – with more than one output neurons – for the automatic classification of the depth and of the "severity level" for the detected damages. This step seems very near to be done, since the mentioned information are already contained in the Damage Index vector.

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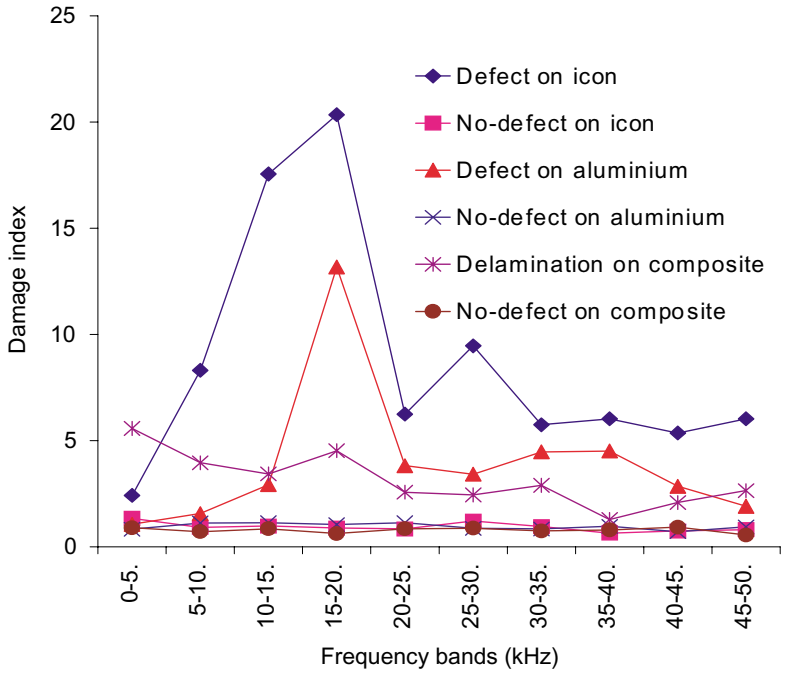

Fig. 21. Comparison between Damage Index for different structures.

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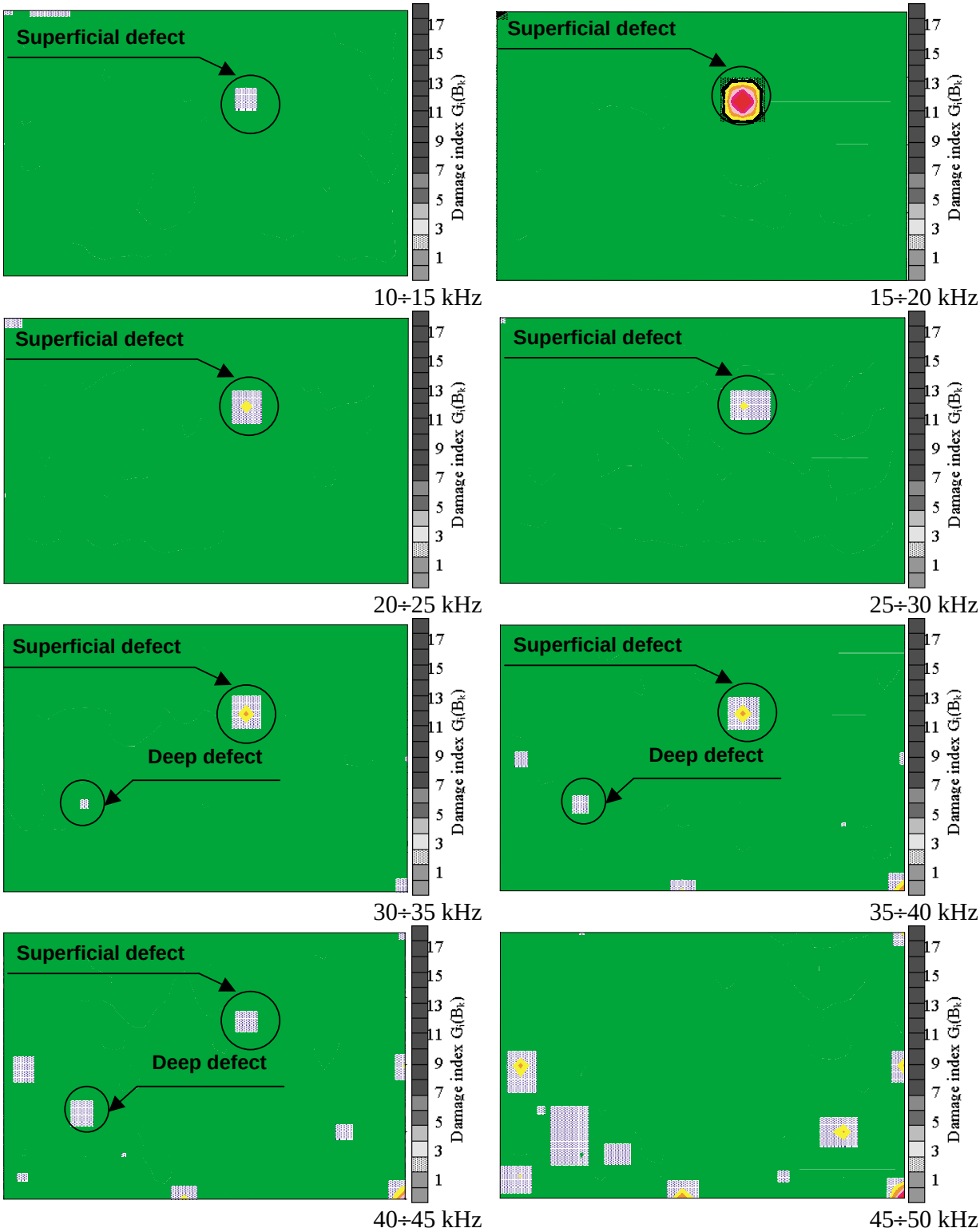

Fig. 9. Damage Index maps on the aluminium plate in different frequency bands.