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Thermal NDE of delaminations in plastic materials by neural network processing

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Abstract

Neural networks are applied to the problem of detecting and classifying voids inside an opaque material at different depths. A classic one-side dynamic thermographic testing procedure is applied to artificial defects buried in 14 mm specimens of PVC. Experimental data are automatically processed, extracting the maximum and the corresponding time of thermal contrast profile versus time. A two steps procedure was developed and tested using an intentionally uneven heating of the sample. The obtained results are presented, demonstrating the robustness and accuracy of the developed technique.

1. Introduction

One of the most important requirements of a NDE method is the reliability. The aim of this paper is to present a robust automatic procedure to detect and characterize internal air voids by means of a quantitative thermographic inspection. Both detection and/or characterization of defects are widely investigated problems and thermal methods seem to gain interest when compared with others [1, 2] but probably they need to be developed deeper.

The huge amount of data managed in a dynamic Thermal/Infrared Non-Destructive Evaluation (T/IR NDE) requires powerful tools to obtain results in an acceptable time. The automatic handling of the test is a highly desirable goal [3], requiring a quantitative treatment of the thermal problem. Many approaches have been proposed to reach this result. This paper deals with the use of neural networks to identify and classify air voids inside a plastic slab. Neural networks provide a range of powerful new techniques for several researches and application fields including vision, robotics, control, speech recognition, handwriting, sonar, radar and time series analysis. They have several noticeable features including high processing speed and the ability to learn the solution to a problem from a set of examples.

The surface (x, y) temperature (T) evolution in time (t) allows one to solve the inverse thermal problem recovering defects depth (z) and location [4]. The thermal contrast ($C_{x,y,t}$), defined as normalized temperature increase due to the defect, contains all the required information, giving the advantage to be less affected by uneven distribution of irradiation of the target [5, 6]. Moreover it is still possible to obtain the searched results reducing data only to the maximum of the contrast (C_{max}) and the instant when it occurs (t_{max}) for each surface element.

The plastic material used for this test was chosen because it is easy to machine and widely available. A similar procedure could be profitably adopted for other materials as carbon fiber reinforced plastic (CFRP).

2. Neural networks

All kinds of neural network share the same basic structure which can be seen as a collection of parallel processors, often called processing units or neurons. They are connected together by unidirectional links, organized so that the network structure lends itself to the problem being considered. Currently most applications use a network class, the Multi-Layer Perceptron (MLP), based on the Back Propagation learning procedure, which allows one to simulate any multi-dimensional transfer function of practical interest [7]. It accepts a number of inputs and must provide one or more outputs whose values are continuous functions of the

The colour plates of this article are on page XII at the end of the book.

http://dx.doi.org/10.21611/qirt.1994.032

given input values. Processing units in a MLP are organized in layers, as illustrated in *figure 1*. Each unit is connected to all the units of the lower layer, so that the overall structure is a feed forward one. The first layer, called input layer, receives the input values. The last layer, or output layer, produces the network output. In practice one or two inner layers, called hidden layers, are defined. They act as feature detectors.

The precise form of the transformation is governed by a set of parameters called ***weights*** whose values can be determined on the basis of a set of examples of the required mapping. Weights are associated with the links between processing unit. Each neuron receives an input which is the weighted summation of the outputs of the lower layer processing units. The unit output is a non-linear function of its input. Very often a sigmoid transfer function is chosen (*figure 2*).

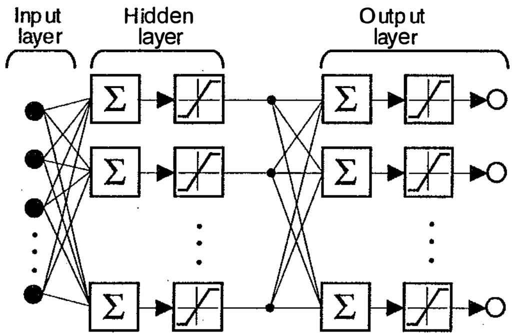

Fig. 1. - Neural network scheme of one hidden layer

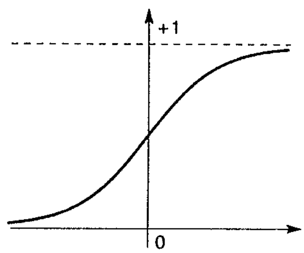

Fig. 2. - Sigmoid transfer function

The process of determining these parameter values is called learning or training. The learning process consists of an iteration of three steps: the presentation of an input (randomly chosen) from the training set, the evaluation of the difference between the actual output of the network and the desired one, and the consequent modification of some weights in order to reduce the error [8].

Learning may be computationally intensive since it often requires a large number of iterations in order to achieve the desired network behavior. However, once the weights have been fixed, new data can be processed by the network very rapidly. The capability of learning a general solution to a problem from a set of specific examples circumvents the need to develop a *first-principles* model of the underlying physical process, which can prove often difficult or impossible to find. Even when a model is known for the underlying process, it may be difficult to retrieve the desired parameters from the measured values due to the difficulty of the inversion procedure or its sensibility to noise [9].

Broadly speaking, neural networks should be considered as possible candidates to solve those problems which have the following characteristics:

- there are many data for network training, either measured or produced by reasonably accurate simulation;
- it is difficult to produce a simple model-based solution which is robust to modest levels of noise on the input data;
- new data must be processed at high speed, either because a large volume of data must be analyzed, or because of some real-time constraints.

Our application uses the MLP network to achieve a categorization: for this purpose the number of the output units has been chosen to be equal to the number of defect categories. When processing the sampled values of the time evolution of the thermal contrast, the output unit which yields the highest value is chosen as the representative of the defect class for the corresponding pixel.

A two steps architecture has been applied consisting of a flaw detector network, followed by a depth estimator network [10]. The first network is fed with couples of values (C_{max}, t_{max})

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extracted from thermal contrast profiles [11]. The flaw detection is applied to each pixel of the tested surface giving candidate flaw locations, after a suitable thresholding. The probability of any defect to be located at a certain point in the 3D (*x, y, z*) space is the output of the second step.

A training set of 547 examples has been used to set up the four layers detector network with two inputs and one output. Training data came from 12 tests performed on three PVC specimens, containing artificial defects. The numerical simulation of the test allowed us to complete the training set improving the network performances. In *figure 3* the training set is shown.

The estimator network consists of three layers. The input layer with 50 input units is fed with filtered contrast profiles. The hidden layer consists of 12 neurons. This number was determined after a careful optimization process. The output of the network is a 13 neurons layer where each defect is classified according to its depth. All the 280 contrast profiles used as training set are obtained experimentally.

Finally a new sample with four defects at different depths was used to validate the networks.

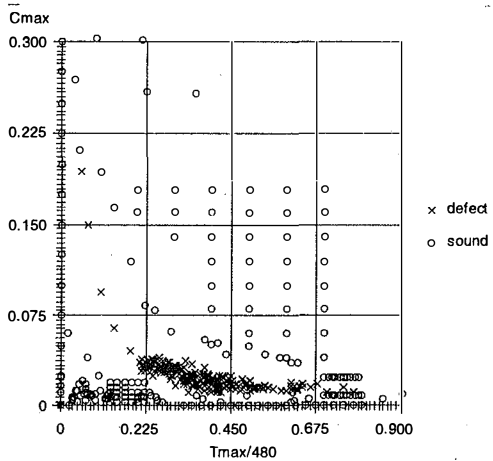

Fig. 3. - The training set used for the detector network.

3. Equipment and testing procedure

The adopted experimental set-up is shown in *figure 4a*. It includes two halogen-quartz lamps (1 kW each), an infrared camera and a proprietary synchronization device. Recording of dynamic temperature field was performed with an IR imager (Agema-900) that provides 12 bit images (thermograms) at a rate of 30/15 Hz. A digital processing system allows one to grab at the suitable frequency and pre-process sequences of IR images. The synchronization of the imager with the heating sources assures that the temperature recording starts at the very beginning of the cooling process.

Three specimens made of Polyvinyl Chloride (PVC) with size 150x150 *mm* and 14 *mm* thick have been tested, including four internal cylindrical voids each (20 *mm* in diameter) as shown in *figure 4b*, served as artificial defects. The defects depth varied from 4 to 9.5 *mm*, with thickness ranging from 0.5 to 6 *mm*.

Samples have been heated for 5 *s* and sequences of 500 IR images taken at 1 Hz frequency, representing the surface temperature evolution, have been recorded on a high-speed hard disk. All specimens were tested four times, after a 90 degree rotation around the z axis, in order to have the maximum heating coincident with every defect. The specimens surface was painted with *Graphite-33* coating providing the emissivity of 0.98.

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Experimental data were transferred to a Sun Sparc station to be processed before using them as network input. Processing steps include: thermal contrast evaluation, low-pass filtering and format rearrangements. Such sequences contain all the information we need to characterize the defects, each pixel being a function of two spatial *(x, y)* and a time *(t)* co-ordinates. Considering the same pixel *(x', y')* (that is fixing a point in the space domain) and scanning a sequence, the result is a temperature time evolution.

A numerical simulation of the direct thermal problem was carried out in order to predict the amount of energy to supply during the test and to reduce the number of measurements to execute. The thermal diffusivity of the used plastic material was experimentally determined by the modified Parker's method [9].

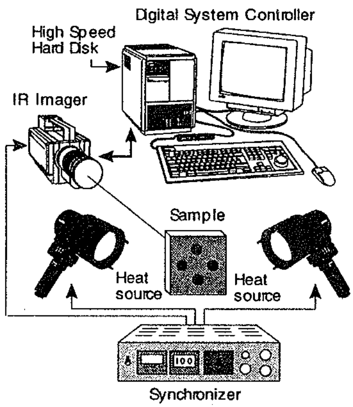

Fig. 4a. - Experimental set-up

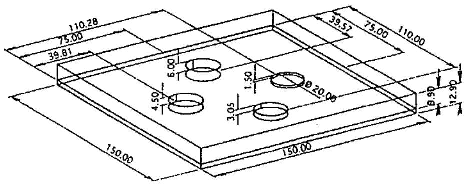

Fig. 4b. - Scheme of defects contained in a specimen

4. Experimental results.

The two steps of the architecture we propose have a common preliminary stage to obtain contrast time profiles. To do this a known sound point or area is chosen as reference and then for each other point the thermal contrast is calculated as follows:

$$C(x,y,t)=\frac{T_{x,y}(t)}{T_{x,y}^{max}}-\frac{T_{x_{ref},y_{ref}}(t)}{T_{x_{ref},y_{ref}}^{max}} \qquad (1)$$

Experimental curves in time corresponding to four defects at the depth z = 4, 5.5, 7 and 8.5 *mm* are shown in *color figure A* together with a non-defect profile.

In the first stage concerning the flaw detection, from each sequence we obtained two synthetic images, called *maxigram* and *timegram*, representing the maximum value of thermal contrast and the time at which it occurs. These data and results of numerical simulations (547 couples of values altogether) have been used as training set for a four layers network with two inputs and one output. As the training was completed, the network was fed with data extracted from a *maxigram* and *timegram* that were not used in the training stage: the results illustrated in *figure 5*, are very promising. In fact, by virtue of the very good generalization performance of the network trained with the *back-propagation* algorithm, it has been possible to detect a defect whose depth was out of the range used during the training. *Color figure B* shows a raw image, belonging to the analyzed sequence, taken at the best time for the defect visualization.

An operator analyzing these raw images must distinguish between the overheating due to the non uniform irradiation of the surface and the searched effect of defects. This problem is

http://dx.doi.org/10.21611/qirt.1994.032
fully solved by a good choice of the informative parameter and of the network as shown in *figure 5.*

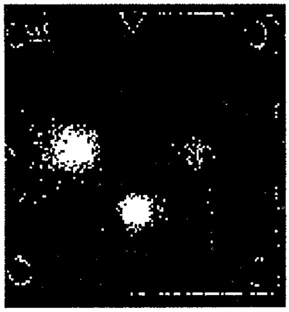

Fig. 5. - Output of detector network

In the second stage, devoted to the defect characterization, a three layers network with 50 inputs and as many outputs as are the depth classes one wants to estimate has been used. In our case the network had 13 outputs: 12 defect depth classes and a non defect class. Generally it is possible to calibrate outputs giving as results the real depth, expressed in metric units.

Sequences of 50 values obtained filtering the contrast profiles have been used as training data. The outputs, whose values are between 0 and 1, provide a sort of probability distribution. The criterion adopted for decision making has been "*winning takes all*" that is the output unit with the highest value is chosen as the representative of depth class.

This second step is sufficient both for detecting and characterizing defects but it becomes very heavy in terms of computing time when applied to the whole sample surface. For example the time needed to process 9000 surface points (100x90 pixel) is 6 minutes, using a PC, plus the pre-processing time that takes some minutes itself.

That is why the first step has been maintained individual: in fact, the detector network allows one to choose, in a quick way, just the points of interest that will be processed by the estimator network. Furthermore for some cases only the defect detection is of interest.

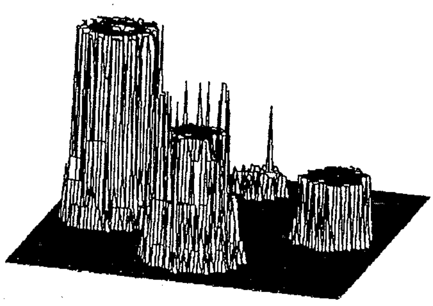

Fig. 6a - Output of the estimator network

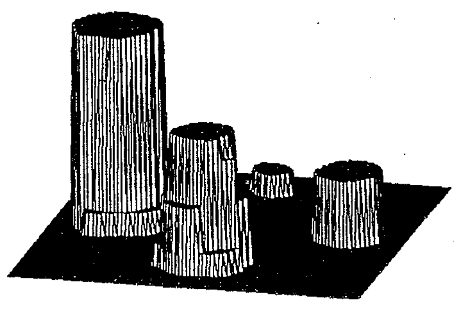

Fig. 6b - Defect estimation after low-pass filtering

The *figure 6*a shows the output of the estimator network applied to a specimen containing four defects (3.90, 5.40, 6.85, 8.40 *mm* in depth). A 5x5 median filtering is then applied to improve results, as illustrated in *figure 6b*. The network depth resolution is 0.5 *mm*; the first classes were recognized without any error, while a maximum error of one class occurred for the deepest classes. It is important to note that no false alarms have been detected. Another important feature of this processing procedure is the robustness to the artifact due to the non

http://dx.doi.org/10.21611/qirt.1994.032
uniform heating of the target. In fact we stressed this aspect using two focusing lamps to stimulate the sample. Consequently two overheated spots, overlapping two defects were clearly visible during the tests (*color figure B*). This notwithstanding, the quantitative results of *figure 6a,b* are not affected by these artifacts.

5. Conclusion

A new processing procedure based on neural networks application has been tested using plastic material. The very good results obtained allow one to identify delaminations inside an opaque body and to measure the depth. An important aspect arisen during the validation tests is the capability of the proposed processing to minimize the effect of the non-uniform heating of the surface. Additionally no false alarm has been encountered.

The computing time required for the whole processing is of the order of ten minutes, that is roughly equal to the testing period. A significant reduction of this time is easily achievable.

Finally a new version is under development in order to estimate both depth and thickness of defects.

Acknowledgments

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