# AN EVALUATION OF ARTIFICIAL NEURAL NETWORKS APPLIED TO INFRARED THERMOGRAPHY INSPECTION OF COMPOSITE AEROSPACE STRUCTURES

H.Trétout, D.David, J.Y.Marin, M.Dessendre,
M.Couet and I. Avenas-Payan
Dassault Aviation, Saint-Cloud, France

## INTRODUCTION

The increasing use of composite materials on aircraft structures as well as their increasing average age have led to the search and the development of several global nondestructive testing techniques to scan large portions of the aircraft externally. One such technique is Infrared thermography. If rapid inspection can be expected, the size of the data and the complexity of the thermograms make the interpretation difficult. So in order to help the operator in the fulfilment of his job to achieve rapid, reliable and repeatable non destructive evaluation, we have caried out for the last four years a project named SEQUOIA, in which Artificial Intelligence has been integrated.The first approach presented at QNDE 93 was based on spatial analysis which revealed itself to be encouraging but insufficient and with not enough versatility [1]. A complementary approach is presented, it is based on the use of multi-layered Neural Networks. This classification technique is used to correlate temporal thermal signatures with sound and defected regions of an inspected part. As thermal modelling is now well developed and comprehensive, the investigative study relies on the training of the neural network on theoretical thermograms so that we can produce as many examples as one can think of. Different inputs for the neural network have been studied: raw data (temperature curves), derived data (derivative of temperature curves), contrast data (subtraction of reference from raw data). Multi-layer neural networks, as well as related algorithms such as Nearest Neighbour (KNN, Kmeans) and Learning Vector Quantization (L.V.Q) have been tested. The evaluation of the neural network process has mainly been based on its ability to reduce the errors, prior to uncertainties.

## PROBLEM - APPROACH

The interpretion of thermograms from infrared thermography inspection is a tedious and cumbersome process when one passes from laboratory samples to real aerospace structures and particularly in the field. The induced spatial and temporal temperature variations of the thermograms are due to several effects related essentially to :

- heat source distribution ,
- surface aspect (emissivity, texture),
- part geometry and fixings,
- part substructure (honeycomb, ribs, stiffeners),
- thickness variations ,
- flaws.

All these effects have a particular thermal behaviour that we have experimentally and theoretically identified from the knowledge of the thermophysical properties of the materials. In a first attempt a practical original concept has been investigated to integrate all the information an operator uses to make his diagnostic. The results obtained from various and multidisciplinary developments in image processing, geometrical (CAD-CAM) and theoretical modelling have allowed the setting up of a data base necessary for the development of a fast, evolutive and friendly user expert system. However the developed concept based on spatial analysis first and a linear process, in which all the different processing stages hang together without feed back, have shown some limits, mainly lack of versatility [1-2]. A new approach was defined, which has been to classify in a first step the temperature versus time curves corresponding to each pixel of a sequence of images, and in a second step to proceed to spatial analysis. So it appeared that a neural network would be quite appropriate to learn the differences between thermal curves corresponding to areas with defects and those corresponding to areas with a singular thermal behaviour but free of defects (see Figure 1). Neural networks are known for their high processing speed, high classification accuracy, low sensitivity to noise,and easy thresholding capability to yield a binary image for automated detection. Recently they have gained a lot of attention and have been investigated in conjonction with several NDT techniques, the training being done either with experimental ( real or simulated defects), or with theoretical data [3-4]. However results obtained with training on experimental data do not seem as encouraging as with those obtained with theoretical one's for two major reasons, firstly a large training set is required which is difficult to obtain with real cases, secondly simulated cases are not representative enough. Training with theoretical data can provide an almost infinite data base as long as the model is fidel, which is more the case for infrared thermography than for any other methods.

## MODELLING : SIMULATION OF THE THERMAL BEHAVIOUR OF COMPOSITE MATERIALS

Composite materials used in the aerospace industry can be represented by a stack of several layers, differing in terms of materials,.or orientation. Defects such as delamination or foreign inclusion can be considered as additional layers. A thermal wall model [5-6] has been used which connects, in the Laplace space, flux and temperature from one side of a layer to the other side. Thus:

$$\begin{matrix} \Theta(li,p) \\ \Phi(li,p) \end{matrix} \qquad \begin{matrix} Ai & Bi \\ Ci & Ai \end{matrix} \qquad \begin{matrix} \Theta(li-1,p) \\ \Phi(li-1,p) \end{matrix}$$

The lay-up is expressed as the product of matrixes representing each ply. Then, we introduce the boundary conditions at l=0 and l=e which are connected with the continuity of flux, thus:

$$\begin{aligned} \Phi(0,p) &= h0 \,.\, \Theta(0,p) - Q \\ \Phi(l,p) &= h1 \,.\, \Theta(l,p) \end{aligned}$$

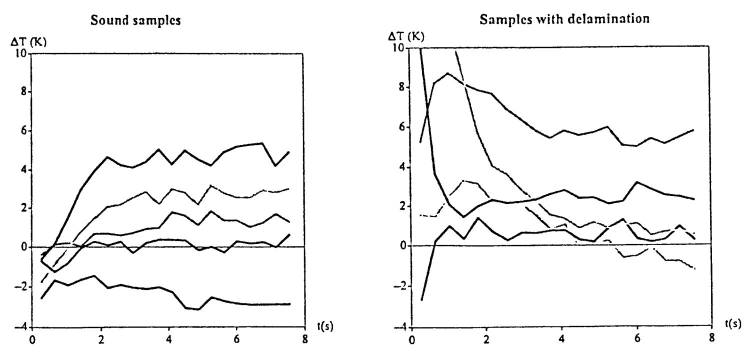



Figure 1 : Computed temperature contrast curves.

The numerical inversion of the Laplace transforms is obtained with the Gaver-Stehfest and Woo algorithm [7-8]. This model developped by LEMTA has been used to realize a software program named © Multicouche, giving the evolution of the front or rear temperature of the considered part, submitted to a very short heat pulse. The validity of the model has been checked elsewhere [1] by comparing the theoretical results with the experimental ones.

Theoretical curves have been computed with the © Multicouche program in the case of a typical CFRP plate and ramdomly generated for the training and the test of the neural network. The physical constants characterizing the material and the test conditions ( thermal diffusivity and conductivity, convection coefficients, position and thickness of the delamination, absorbed energy) have been randomly varied, taking into account the natural variability of these characteristics.

## NEURAL NETWORK - Selection and Description

The Neural Network precisely classifies thermal signatures that are thermal behaviour curves. We distinguish several steps in the image sequence processing :

- the acquisition delivers a set of images. Each image is the spatial representation of the inspected part at a given time. A pixel value in an image corresponds to the temperature of a particular point in the controlled object.
- preprocessing of the data is necessary so that data is represented as a set of curves. Each curve is the temperature evolution during the time for a particular point on the inspected part (see Figure 1).
- other preprocessings of the thermal signatures have been studied to help the efficiency of the network. The result is a curve that is input to the artificial neural network. One neuron is used for each point on the curve.
- each curve is classified by the neural network which output is a single real value. Put together, these results form one image. Each point of this image is the result of the artificial neural network for the studied point of the inspected part.
- post processing of the first resulting image is necessary to take into account the spatial dimension.

In order to evaluate the interest of a particular choice among preprocessing or parameter of the artificial neural network we have used a carbon epoxy part, 2 mm thick with five simulated defected regions (see Figure 2).

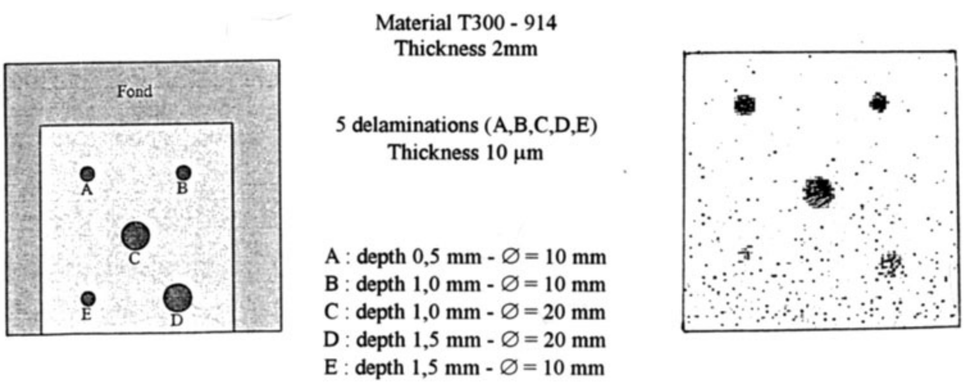



Figure 2 : Results of tests on detection sensitivity.
(left) - Part design (right) - Results of detection by Neural Network

Input neurons are grouped by three ; the first hidden layer computes four characteristics and countains 4 x 18 neurons ; the 16 neurons of the second hidden layer receive neurons from the previous layer by groups of three ; the output is given with one neuron. With such an architecture we increase the number of neurons (110 instead of 49) but the number of connections remains approximately the same (513 instead of 524).

WEIGHT SHARING - Several connections are constrained to have the same weight [4,9]. The parameter space is diminished. This technique is often used with signals having repetitive characteristics along the time. More investigation should be necessary to give a final conclusion.

These two enhancing techniques have given similar promising performances after training with the test set and the simulated sequence of images, mean square error is arround 0.085, the rate of correct answers is 98% and the three shallow defects are clearly detectable.

Outputs

The first level of processing is the detection of a defect. One neuron is suffficient which real value gives the probability of the presence of a defect : -1 indicates the presence of a defect for sure, 1 indicates the absence of a defect for sure, 0 indicates a complete uncertainty. We tested more sophisticated output that help for the identification of the defect. Several neurons are put in the output layer, each one is responsible for one characteristic of the defect among the ones that define the thermal behaviour of a material, for example depth or contact resistance. This technique is a way of distributing the final result on several parameters. A decision system will remove more easily uncertainties and ambiguïties. This system is based on simple rules.

## NEURAL NETWORK TRAINING

Training consists in updating parameters of the neural network for a specific problem. Three choices have to be done : the training set, the test set and the algorithm that computes the connection weights.

TRAINING SET - It is a set of examples that illustrate as largely as possible the space of possible curves for our specific problem. This set contains 500 curves, one half correspond to a sound part, the other half correspond to a defected part. Each curve is computed with the LEMTA model [5-6] using physical parameters that characterize the material and the test conditions. For a particular curve, each parameter is randomly chosen between limits. These limits depend on the specific situation that we want the neural network to be trained.

TEST SET - It is a set of curves that are computed in the same way as the training curves. The test set contains 500 curves, one half corresponds to a sound part, the other half correspond to a defected part. It is used to evaluate the performances of the neural network. Once the neural network is trained, each curve of the test set is input to the network. We compare the output of the network with the known correct answer. Statistics are computed, especially a mean squared error and a percentage of correct answers. The neural network is sufficiently trained when the mean squared error is low enough, and the percentage of correct answers high enough. If these values remain constant, it is better to stop the training phase, otherwise there is over training, that is the network will not be able to correctly classify a curve other than the ones in the training set.

TRAINING ALGORITHMS - The algorithm that has been used is the back propagation of the stochastic gradient. That is, weights of the neural network are updated after each presentation of an example of the training set. The general formula for updating the weight Wij of the connection between neuron i and neuron j is the following :

Inputs of the Artificial Neural Network (ANN)

To make sure the training is correct, the input to the ANN must be sufficiently representative of the different classes of the problem. Thus it is often interesting to process the data before it is input to the ANN.

RAW CURVES - Raw curves for a defect or a sound part are too close, therefore training reaches 50 % of correct responses with difficulty and the test with the image sequence gives a uniform grey response, that is a complete uncertainty.

DERIVATIVE OF RAW CURVES - Already used in a similar application [4]. In our case the results are deceiving, furthermore noise is enhanced. One reason might be the low acquisition frequency of the thermal camera that is used. The computed derivative is not really an instant derivative because the ellapsed time between two measured temperatures is too long.

CONTRAST CURVES - A constrast curve is the difference between the studied signature and a reference one. Ideally the reference signature is of a sound material, similar to the one studied.

For testing the training, the reference signature is the one with mean parameters. For an image sequence, the reference signature is the mean of all the points except the nontypical ones. A non typical point has a signature that varies too much apart from the mean. This preprocessing gives the best result, which is consistent with the theorical study. Noise has been added to the training data, to enhance performances of the ANN; it has to be equivalent to the one of the experimental data.

Architecture

MULTI-LAYERED NEURAL NETWORK - We have used a multi-layered neural network, which is a classical architecture for classification problems. The selected artificial neural network has the following characteristics :

- 20 neurons as input (because the thermal signature at one point is given by a curve with 20 measurements),
- 16 neurons on the first hidden layer,
- 8 neurons on the second hidden layer,
- 1 neuron as output which gives a real value between -1.0 and + 1.0.

Several tests on different architectures lead to the following conclusions :

- the more hidden layers, the more precise the result is,
- the more numerous neurons, the more precise the result is,
- in a two hidden layers ANN, the first layer detects primary characteristics, the second layer detects secondary characteristics.

By a precise result we mean that the answers indicate either one class or the other (output value -1 or +1) and there is very little uncertainty (output value is 0 when the answer is uncertain). We do not look for a very precise answer of the ANN because the network is only responsible for the time dimension ; the global problem also includes a spatial dimension that is to be treated by post processing, using image processing techniques.

POSSIBLE ENHANCEMENTS - Techniques exist in simplifying the neural network, so that its size is minimum while keeping good performances. Two are related to the definition of the architecture :

LOCAL CONNECTION - In a standard neural network, every neuron of layer n is connected to all the neurons of layer n + 1. In our case neighbour neurons in the input layer are neighbour measurements in the time domain. Close neighbours are coherent; neighours that are far from each other are not.

$$Wij(t+1) = Wij(t) + \varepsilon ij \frac{dcout}{dWij}$$

where $\varepsilon ij$ is the learning rate of connection (i, j).

Weights are initialized with a random value in the interval [-1/fanin (x), +1/fanin (x)],.where fanin (x) is the number of input to the neuron from which connection x comes from. The learning rate $\varepsilon ij$ is constant and set to :

$$\frac{1}{fanin(i,j)}$$

It is possible to decrease manually the learning rate with such an algorithm (first order). We regularly test the neural network and examin the mean squared error and the percentage of correct answers. When these values do not progress we manually decrease the learning rate.

Another type of algorithm (second order) has been used, that is able to automatically decrease the learning rate. The same formula for updating the weights is used as in the first order algorithm but the learning rate is not constant :

$$\varepsilon_{ij} = \frac{\lambda}{\mu + hij}$$

where $\lambda$ and $\mu$ are constant ( typically $\lambda = 0.001$ and $\mu = 0.05$), and

$$hij(t+1) = (1-\gamma)hij(t) + \gamma \frac{d^2cout}{dWij^2}$$

where $\gamma$ is a constant (typically = 0.05) that controls the degree of modification of hij.

In order to reduce the complexity of the algorithm (initially $0(n^3)$) several approximations exist. Among those the one of Levemberg - Marquardt [10] reduces complexity to 0(n). Second order algorithms are slower than first order algorithms in learning. Convergence to a solution is more systematic, and no learning rate adjustement is needed.

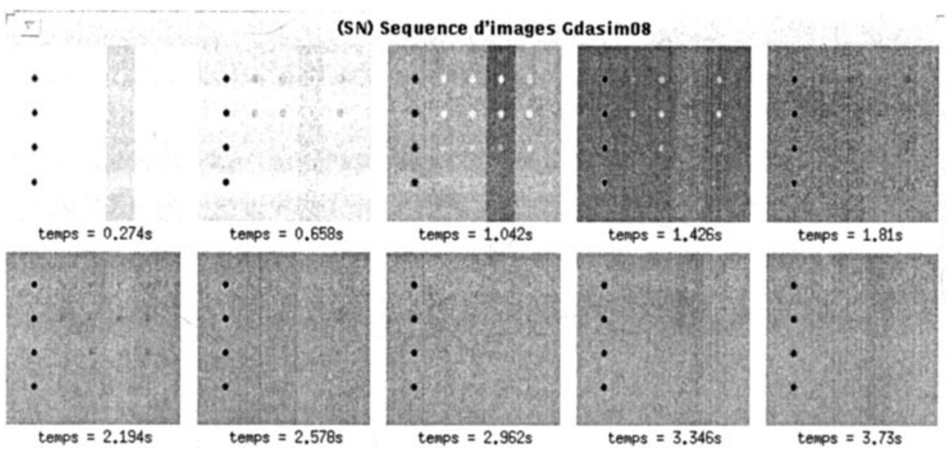
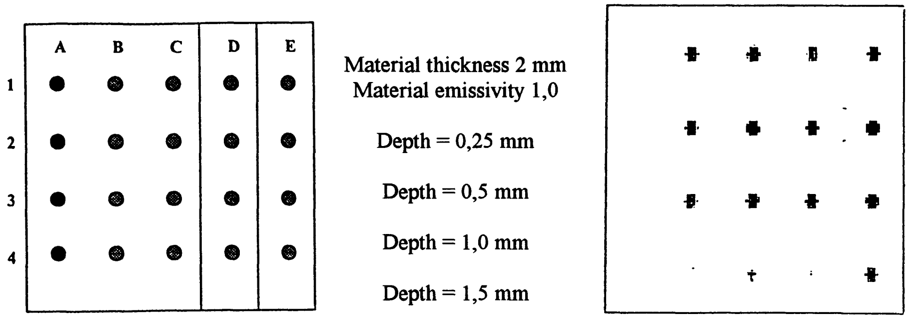



Figure 3: Simulated sequence used for testing the detection selectivity.




Column A : holes Column B : delaminations ∅ 10 mm Column C : delaminations ∅ 20 mm
Col. D : delami. ∅ 20 mm, emissivity 0,9 Col. E : delami. ∅ 20 mm, thickness 2.2 mm

Figure 4: Results of test on the detection selectivity.
(left) - Part design (right) - Results of detection by Neural Network

## RESULTS

After determining the best way of preprocessing the data, tests have been realized on simulated and real thermograms, which correspond to whole parts providing images of about 256 x 256 pixels.

The first simulated sequence was aimed at the determination of the detection sensitivity on delaminations, considering five flaws in a sound CFRP plate, at different depth, each one equivalent to a 10 µm thick air gap (Figure 2.left). Then, a Gaussian-type noise was added to the theoretical thermograms, increasing its level up to 1 °C. This test showed that an addition of 0.3 °C is still acceptable (Figure 2.right). With a higher noise level, the uncertainity increases too much, as well as the number of erroneous answers.

The second simulated sequence ( see Figure 3) was aimed at the verification of the insensitivity of the neural network to other cause of variation of the thermal curves (variation of thickness, variation of emissivity, presence of holes, background, etc.). This test was of major importance since it gives a measure of the ability of the neural network to detect only delaminations. The results (see Figure 4) are very encouraging since only delaminations located in a CFRP plate at the depth of 0.25 mm, 0.5 mm, 1.0 mm and 1.5 mm are detected, while its thickness varies between 2 and 2. 2 mm, and its emissivity from .9 to 1, either the holes, nor the background are detected.

Finally, the third sequence used in this work was a real one. This part presents nine delaminations (Figure 5 left). On these nine flaws, only four are clearly detected, while three other ones can be slightly perceived (Figure 5 right). These results are not entirely satisfactory and demonstrate the need for complementary work. At the present time, we explain these discrepencies by:

- the difficulty to convert accurately the infrared flux into temperature. If we compare the theoretical temperature with the experimental ones, a 5°C drift is observed at the beginning of the thermogram, droping to 2°C at the end of the thermogram.
- few points are presenting an anomalous noise level.

## CONCLUSION

A Neural Network technique has been successfully applied to processed thermal data, it should lead to a sensible improvement in the exploitation of thermograms. Through the evaluation of several parameters an optimized set of Neural Networks has been obtained, which led to a very good classification of areas related to defects and other themal causes with both experimental and theoretical data. The results are encouraging, the training time is relatively short, about 10 mn, the best classification error-ratio is low, about 0.5%, and experimental data have been tested.


Column A : depth 1,2 mm    Column B : depth 0,75 mm    Column C : depth 0,45 mm

Figure 5: Sequence on a real part presenting nine delaminations.
(left) - Part design (right) - Results of detection by Neural Network

Temperature contrast curves used as input data were better than derivative curves, however they require a very good and precise theoretical base to generate accurate temperature reference curves. The results which have been enhanced by post image processing to take into account the spatial information would be usable in the SEQUOIA concept to ease its expertise. Performances would be increased but versatility might lead to a large set of specialized Neural Networks. Different Neural Network architectures have been investigated and will be in future work to get a better understanding of the operation and to improve the generalization. Further improvements in sensitivity and versatility rely on new IRCCD cameras utilization and image processing optimization.

## REFERENCES

1. D. David, J. Y. Marin and H. Trétout, "Automatic defect recognition in composite aerospace structures from experimental and theoretical analysis as part of an intelligent infrared thermography inspection system", Thermosense XIV SPIE's OE/Aerospace Sensing, Vol.1682, pp182-193, 22-24 April 1992.
2. D. David and all, "SEQUOIA : artificial intelligence applied to the infrared thermography inspection of composite aerospace structures", Poceedings of the Review of Progress in QNDE, Vol .13, Brunswick, Maine, USA, July 1993.
3. D. R. Prabhu, M.N. Abedin, W. P. Winfree, and E.I. Madaras, "Disbond detection through ultrasonic signal classification using an artificial neural network", IJCNN, Seattle, July 1991
4. D. R. Prabhu, P. A. Howel, H. I. Syed and W. P. Winfree, "Application of artificial neural networks to thermal detection of disbonds", Poceedings of the Review of Progress in QNDE, Vol. 11, Brunswick, Maine, USA, July 1991.
5. A. Degiovanni, "Systèmes multicouches: problèmes liés à l'homogénéisation des caractéristiques thermiques", Revue générale de Thermique, N° 339, pp 117-128, Mars 1990.
6. A.S. Houlbert, A.S. Lamine, et A. Degiovanni, "Modélisation d'un défaut limité en vue du contrôle non destructif des multimatériaux anisotropes", Int. J. Heat Mass Transfer, Vol. 13, N° 4/5, pp 1125-1138, 1991.
7. H. Stehfest, "Algorithm 368. Numerical inversion of Laplace transforms", A.C.M. Vol. 13, N° 1, pp 47- 49, January 1970.
8. H. Stefhest, "Remark on algorithm 368. Numerical inversion of Laplace transforms", A.C.M. Vol. 13, N° 10, p. 624, October 1970.
9. Y. Le Cun, "Generalization and network design strategies", Dept. of computer science, Uni. of Toronto, Ontario ,Canada, 1989.
10. S. Backer and Y. Le Cun, "Improving the convergence of back-propagation learning with second order methods", Proceedings of the 1988 Connectionist Models Summer School, pp 29-37, San Mateo, Morgan Kaufmann, 1989.