Neural Network Based Automatic Defect Detection in Infrared Thermography

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Abstract

Early, accurate, and automatic detection of defects is an essential aspect of quality improvement. This paper employs a classification-based automatic defect detection method using Gabor filter features. The thermal patterns of various defects are used to provide the primary information for defect detection. Considering the desirable characteristics of spatial locality and orientation selectivities of the Gabor filter, we design filters for extracting defect features from the thermogram. The feature vector based on Gabor filters is used as the classifier's input, a Feed forward neural network (FFNN) on a reduced feature subspace. A finite element method and experiment were adopted to simulate a Carbon fiber reinforced polymer (CFRP) material with void holes as defects. The thermogram will be convolved with Gabor filters by multiplying the image by Gabor filters in the frequency domain. Features are a cell array containing the result of the convolution of the image with each of the forty Gabor filters. The input vector of the network will have large values, which means a large amount of computation. So we reduce the matrix size to one-third of its original size by deleting some rows and columns. This work aims to implement a classifier based on neural networks (Multi-layer Perceptron) to differentiate defect and non-defect patterns.

Keywords: *Defect detection, Gabor wavelet, Gabor Filter, feed forward neural network classifier.*

1. Introduction

Inefficiencies in industrial processes are costly regarding time, money, and consumer satisfaction. In order to sustain or increase the current level of performance in the highly competitive global market, the industry should improve the quality of the production process. It has been learned that the price of a material is reduced by 45%–65% due to the presence of defects. Early and accurate detection of defects and classification is an essential aspect of quality improvement. The accuracy of manual inspection is not good enough due to fatigue and tediousness. The solution to the problem of manual inspection is the automated, i.e., neural network-based part inspection system. Automated part inspection systems mainly involve two challenging problems: defect detection and classification.

Feature selection plays a vital role in developing automated defect classification capability. For an appropriate feature set, the distinguishing qualities of the features should be high, and the number of features should be small. Moreover, an appropriate set of features considers the difficulties in the feature extraction process [1]. A defect inspection system aims to detect and classify surface defects that impair product quality with regard to the requirements set by the user. The requirements mainly deal with the product's suitability for its intended use. In the worst case, the defects may make the product functionally deficient or unusable.

Infrared thermography (IRT) has emerged widely as a method for Non-destructive testing (NDT) as it offers non-contact, comprehensive area detection of material defects. It is based on the physical phenomenon that any object of a temperature above absolute zero emits electromagnetic radiation. The infrared camera further covers the emitted radiation into temperature and produces thermograms [2-7]. This work uses Frequency modulated thermal wave imaging (FMTWI) [8-12] to get the thermograms actively. FMTWI imposed a suitable band of frequencies over the test sample within single experimentation. This work aims to implement a classifier based on Multi-layer Perceptron for automatic defect detection in a

CFRP sample. This work presents an approach combining FMTWI with FFNN for a fast, accurate way to detect and classify sub-surface defects. The multi-layer feed-forward neural network is just several layers of single-layer perceptron neurons bonded to one another [13]. This explains the term ‘multi-layer’. The term ‘feed-forward’ means that any neuron's output will be recurrent to the previous layers of the network.

2. Modeling and simulation

In this work, a 3D Finite element analysis (FEA) has been carried out on a steel sample using COMSOL Multiphysics. This software simulates designs, devices, and processes in all engineering, manufacturing, and scientific research fields [14-17]. COMSOL Multiphysics is a simulation platform that provides fully coupled multiphysics and single-physics modeling capabilities. The Model Builder includes all of the steps in the modeling workflow, from defining geometries, material properties, and the physics that describe specific phenomena to solving and post-processing models for producing accurate results. A CFRP sample is modeled with six blind holes as defects (shown in Fig.1), and has been modeled with a finer mesh using 3D tetrahedral elements.

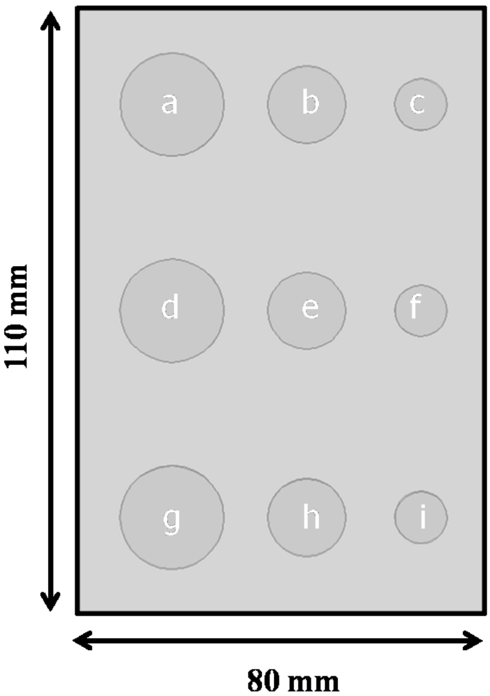

Fig.1 Layout of the modeled CFRP sample with blind holes.

The defects dimensions are shown in Table 1.

Table.1 Defects dimensions

Defect	Diameter (mm)	Depth (mm) from the front surface
a	10	2
b	7.5	2
c	5	2
d	10	1
e	7.5	1
f	5	1
g	10	0.5
h	7.5	0.5
i	5	05

The FEA is carried out by imposing an LFM heat flux (with frequency varying from 0.01 Hz to 0.1 Hz for 100 s) over the surface of the test material, and the infrared camera captures the resultant surface thermal response at a frequency of 25 Hz. The simulations are carried out under adiabatic boundary conditions, with the sample at an ambient temperature of 300 K. The simulated data is further processed using FFNN.

3. Training and testing

3.1 Multi-layer feed-forward neural network

It is just several layers of single-layer perceptron neurons bonded to one another. This explains the term ‘multi-layer’. The term ‘feed-forward’ means that any neuron's output will be recurrent to the previous layers of the network.A multi-layer feed-forward neural network can be created with:

net = newff(P,T,[S1 S2 …])

Where P is an R-by-Q matrix of Q input vectors of R elements each and T is an S-by-Q matrix of Q target vectors of Q elements each.

S1 is the number of neurons in the first layer of the network. In this work as we want to distinguish between defects and non-defects we only need one neuron in the last layer which is called usually the output layer.

So, if we want to have 10 neurons in the first layer and 1 output neuron in the output layer, and we want to create this network, we should write:

net = newff(P,T,[10 1])

Consider that we have 30 images containing defect and 40 images containing non-defect. Each of the images is of size 27x18. with a height of 27 pixels and a width of 18 pixels. So each is actually a matrix and the size of all the matrixes is equal.

Training

The Multy-layer perceptron with the training algorithm of feed propagation is a universal mapper, which can, in theory, approximate any continuous decision region arbitrarily well. However, the convergence of feed-forward algorithms is still an open problem. It is well known that the time cost of feed-forward training often exhibits remarkable variability. It has been demonstrated that, in most cases, the rapid restart method can prominently suppress the heavy-tailed nature of training instances and improve the computation efficiency.

Multi-layer perceptron (MLP) with feed-forward learning algorithms is chosen for the proposed system because of its simplicity and capability in supervised pattern matching [13]. Our problem has been considered suitable with the supervised rule since the input-output pairs are available. For training the network, we used the classical feed-forward algorithm. An example is picked from the training set, and the output is computed.

The training phases are like changing the weights and bias of the neural network and testing it on our training set. Then it adds small corrections to the initialized weights and again tests it. To train the neural network we should write:

net = train(net,P,T);

This line simply trains the network, 'net' based on the P and T inputs and their desired outputs, and then it puts back the trained network inside 'net'.

Testing

For distinguishing between defect and non-defect, we only need one output neuron. This is true as long as we do not want to use orthogonal codes for the desired output of our network. As an example, assume that we have one output neuron, and the value of this neuron for defect patterns is 0, and for the non-defect pattern is 1 for Log sigmoid neurons (or -1 and 1 for tangent sigmoid). If we want to use orthogonal codes, we should have two output neurons with tangent sigmoid as their activation functions. For defect patterns, the value of one output neuron is -1, and the second is 1. For non-defect patterns, the values are reversed. Here we have an advantage in that if the value of two output neurons is both the same, we can conclude that the network is not sure about the type of the input pattern. Even it can be added to the training set for clarification.

In the defect detection system, we have chosen the high value (near 1) as the representative of defects and the low value (near -1) as the non-defects. So we have used one output neuron, and in each call to the network, we only ask for the simulation of one feature vector, one feature vector at a time. So that means our answer always will be a scalar value.

3.2 Generating train sets

We created two folders. One is called 'defect', and the other is 'non-defect'. There are several images in PNG format in each of them. These images are the training sets that we have generated. As we can see, all of the images are 27x18. We searched the internet, found some defect images, and put them in the folder. We added some more defect images to the folder. Finding non-defect images was usually strange because a defect is defined, but a non-defect can be anything. To do this, we started with 5 or 6 random non-defect images. First, we trained the neural network for the first time and tested it over an image without any defects.

Testing employed cutting every possible 27x18 patch from the image and converting them into a vector format. Then we gave each vector to input the trained neural network. During testing holes, we got a high response for some of them, say over 0.9. In those cases, we got them and put them in the non-defect folder. Then we trained the network again and did the same procedure again.

One thing is very important due. Our training set should always have a balance between the number of defects and the number of non-defects. Every non-defect image we add to the training set will lower the effect of detecting defect images.

3.3 Gabor feature extraction

Gabor features are simply the coefficients of the response of Gabor filters. Gabor filters are related to Gabor wavelets. Each Gabor wavelet is formed from two components; a complex sinusoidal carrier placed under a Gaussian envelope [18-21].

When the input data is too large or is suspected to be redundant (it does not have much useful information), it will be transformed into a reduced representation set named features. The process to obtain this vector of features is feature extraction. Consider that we have a different defect image from different defects. In defect detection, we are interested in highlighting those parts of the defects common for all defects. All the defects have holes. We need features that can highlight them. Of course, in defect recognition, we need features that can successfully distinguish different defects. Gabor features can do both. Gabor features have been used for both purposes. These help in removing useless and redundant information, and what is left can be used for defect detection or recognition. Now the aim of the later stage, the classifier, which in our case is a neural network, can be to recognize or detect them.

Gabor filtering is done by convolving images with Gabor kernels. Each window that contains a Gabor wavelet is a Gabor kernel, and as described before, the size of the kernel are always odd pixels. After creating all the required kernels, which are about 40, each kernel should be convolved with the window. The convolution of f and g is written by f*g. In 2D, we can consider that we put both images on top of each other and we multiply each of their pixels. Then we sum them all into one scalar value, which belongs to the location of the pixel at the center of the window. After that, one should move the kernel and compute the results for another location until we have the result for all the values of the pixels.

3.4 Pre-selection

To cross-corelate a defect-like sub-image of size 27x18 with theinput image to produce the defect-like image, a template defect.Cross-correlation is a measure of similarity that we can read more about here9. It is simply aconvolution but theoretically speaking, we do not rotate the kernel. Our only intention is to roughlyguess the location of the defects to avoid inspecting every location.

3.5 Search Algorithm

In the pre-selection stage, we recorded the location of all the pixels that should be checked in aimage-like matrix caled cell.state. Actually the word 'state'is coming from the fact that each pixelcontains a 1 or a 0 as its value. The ON pixels which have 1 as their values, are the location of thecenter of the 27x18 windows that should be checked.

Now we should make sure that when the algorithm finishes, the values of all the pixels are -1. Duringthis phase the value of some pixels may change. According to defined rules, some pixels may changetheir velues form -1 to 1. Other pixels may change their values to -1.Now, according to the result for this pixel, we should make a decision about other pixels in the neighbourhood.Now, according to the result for this pixel, we should make a decision about other pixels in the neighbourhood.

4. Results and discussions

The present works highlight the capability of the proposed approach in detecting the defects present in a CFRP sample. In this approach, the test material can undergo a known controlled frequency modulated thermal stimulation sweeping its entire frequency range from 0.01Hz to 0.1 Hz in 100 s, and the infrared camera captures the corresponding thermal response over the surface. Additive white Gaussian noise with a signal-to-noise ratio being 40 dB is added to the obtained thermal response for the imposed incident heat flux. Noise is artificially added to test the capability of the proposed approach to detect the subsurface density variations.

The neural network responds to most of the candidate locations. There is only a matter of deciding which locations to choose as defects.Fig.2 illustrates the candidate locations.Fig.3 shows the marked detected defects.

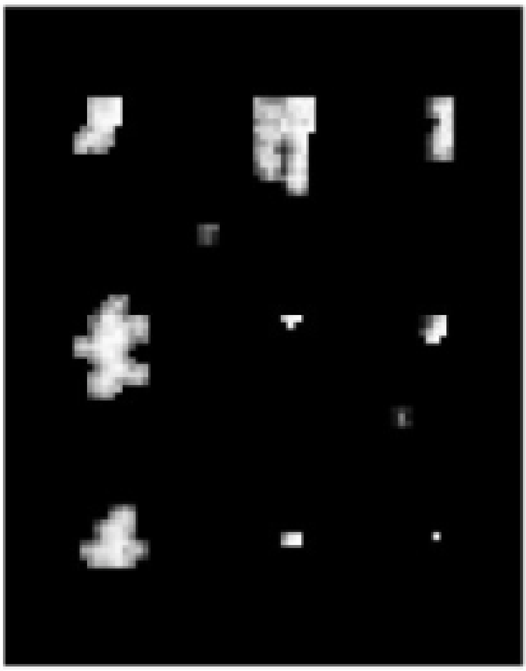

Fig.2 Chosen candidate locations for defects.

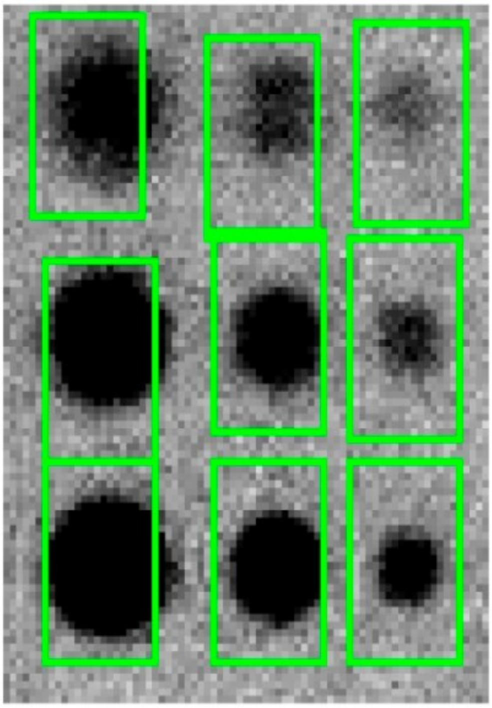

Fig.3 Marked defects

5. Conclusions

It is well known that the aerospace composite materials need to be light in weight, but still highly functional and dependable. The defect could cause catastrophic component failure, incur unnecessary costs. Non-destructive testing prior to installation of aerospace components, and periodically throughout their functional lifetime, can effectively prevent these failures. This study does try to evaluate NDT with neural networks on the simulated CFRP specimen. The results imply that the proposed method can effectively discriminate between the defect and non-defect patterns.

6. References

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