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RECOGNITION OF SUBSURFACE DEFECTS IN MACHINED CERAMICS BY APPLICATION OF NEURAL NETWORKS TO LASER SCATTER PATTERNS

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ABSTRACT

Laser scatter has shown promise as a method to characterize damage microstructural variations as well as a method to characterize surfaces in optical translucent ceramics. Because large volumes of data need to be handled (and sorted) quickly, automated pattern recognition methods using neural networks have been implemented to recognize differences in patterns. A He-Ne laser ($\lambda=0.632\mu$) has been used to obtain scatter patterns from hot pressed Si_3N_4 with various microstructural variations. By use of a backpropagation neural network running on an IBM PC clone 486/33 machine, a correlation was established between subsurface microstructure and position in Si_3N_4 ball bearings. The data were confirmed by destructive analysis.

INTRODUCTION

Laser scattering images mainly consist of speckles whose sizes depend significantly upon the texture, porosity, and density of the material under study. Our goal was to demonstrate an approach to implement a detection scheme for materials that vary in these characteristics. The material used in this paper is from hot pressed

Si_3N_4 with microstructural variations which allow the demonstration of this technique. The scatter patterns are varied and noisy. To extract information our technique must handle these conditions. We chose to use a neural network system because it can handle noise and variations in the solution in a natural manner. An additional reason for choosing a neural network is the speed with which the solution, if found, can be implemented.

BACKGROUND

Backpropagation: Backpropagation [4,6] is a multilayered neural network architecture. Often the architecture consists of three layers: an input layer, a hidden layer and an output layer. Each layer has a specified number of neurons or nodes. Each node represents a function, the output of which is an input to each node of the next layer. In addition a weight value is associated with each connection between nodes of different layers. The neural network is *trained*, the objective of which is to change the weights so as to match a set of inputs with a desired set of outputs. The training consists of input-output vectors called a *training pair*. In our system the training pair consists of a set of real numbers as input, and a 0 or 1 as output depending on the desired result.

The system is trained according to equations 1 - 7. In the following equations, the subscript i represents a node in a layer adjacent to the output layer j , where a node in the output layer. Input and output training pair is denoted by p

$$(1) \quad \text{net}_j = \sum_i w_{ji} * o_{pi}$$

o_{pi} is the i th component of the layer.

$$(2) \quad k = \text{net}_{pj} + q_j$$

$$(3) \quad o_{pj} = f_i(\text{net}_{pj}) = 1 / (1 + e^{-k})$$

θ_j is a bias and it can be learned in the same way as any other weights

$$(4) \quad \delta_{pj} = (t_{pj} - o_{pj}) o_{pj} (1 - o_{pj})$$

t_{pj} is the target input for the j th component of the output pattern of the pair p , and o_{pj} is the j th part of the actual output pattern obtained upon the presentation of the input pattern of p .

$$(5) \quad \delta_{pi} = o_{pi} (1 - o_{pi}) \sum_k \delta_{pk} w_{ki}$$

δ_{pi} is the error signal for the hidden layers.

$$(6) \quad \Delta_p w_{ji} = \eta \delta_{pj} o_{pi}$$

$$(7) \quad w_{ji}(t+1) = w_{ji}(t) + \Delta p w_{ji}$$

$w_{pj}(t+1)$ is the new adjusted weight after training session. η is the training rate for a particular training session. For a more detailed derivation of the above equations see [4].

Prior to the commencement of training, the weights of the system are set to small random values and the following algorithm is applied:

1. Choose a training pair and present the input vector to the system.
2. Obtain the output of the network
3. Calculate the difference of the result and the desired value (target).
4. Adjust the weights of the system
5. Repeat steps 1 through 4 until the error for all training pairs is acceptably low.

Ceramic Ball Under Laser Scattering: The laser scattering images used are those of a particular ceramic ball bearing from hot pressed silicon nitride. This particular ball has a subsurface density variation as illustrated in Fig. 1.

Figure 1 Location of ceramic ball subsurface defects

The subsurface defect starts somewhere between 30° and 40°. The images taken at the angles from 40° to 90° are very similar and different from those taken at the angles from 0° to 30°. Figure 2a is an image taken at an angle between 0° and 30°, and Figure 2b, is an image taken at an angle between 40° and 90°. Note the change in the granularity of the images. [See 7 for a more detailed discussion of how the images were obtained.]

METHOD

The approach used in our analysis was to take a one dimensional Fourier transform (1DFFT) on the rows (or columns) of the images to obtain a parameter of the two-dimensional image. Four parameters were obtained from the Fourier transform. The raw data were real valued, and therefore the magnitude of the

transform. The raw data were real valued, and therefore the magnitude of the output of the 1DFFT by 256 was symmetric about the y-axis. The range of x-axis was -128 to 128. The y values from 1 through 16 of x-axis were added; and the total was divided by the sum (SUM) of y values from 1 through 64. The second parameter was the total of y values from 17 through 34 divided by SUM, the third parameter was the total of y values from 35 through 50 divided by SUM and the fourth parameter was the total of y values from 51 through 64 divided by SUM. Inputs of the network were normalized between 0 and 1 inclusive, and thus each total of 16 y values were divided by SUM. The total of y values from 65 through 128 was so small compared to SUM that the y values were not considered as inputs to the network.

The neural network was trained to respond with a 0 for inputs from the images taken at angles 0° and 30°, and the network was trained to the output 1 for images from angles 40° through 90°.

(a) (b)
Figure 2. Scatter patterns produced from a) polar and b) equatorial regions of a ceramic ball bearing

After the neural network was trained, it was presented with the Fourier transform of data from individual images. The system then determined from the input data a value for the output. A value near 0 would indicate an image the system expected near the equator and a value near 1 would indicate an image the system calculated to be near the polar region.

It was decided to try individual rows from the images, then to compare those results with the average of several individual rows. The reason for this

RESULTS

The results of the approach were excellent in determining not only if the image was from the defective region, but the neural network method accurately determined where on the ceramic ball bearing the change in subsurface attributes took place.

We will examine the tables and graphs from a one 1DFFT and an average of eleven 1DFFT's. This gives an indication of the results we were able to obtain.

Table 1: Results from one 1DFFT

Angles	0	10	20	30	40	50	60	70	80	90
Output	0.0016	0.0004	0.1706	0.0028	0.6919	0.2825	0.9874	0.998	0.3715	0.9876

Graph 1. Results of the Backpropagation Network of one DFFT

We compare the results of using a system based on one DFFT in Graph 1 with the results we have obtained from averaging a number of DFFT's in Graph 2. We can see that the results from averaging a number of DFFT's together give us a significantly clearer picture of the delineation point of where the subsurface defects are. In further testing we found that eleven DFFT's gave us as clear a result as we

were able to obtain from a significantly larger number of DFFT's. In fact we tested up to two hundred and fifty six and found no change in the result.

Table 2: Results from Eleven 1DFFT's Averaged

Angles	0	10	20	30	40	50	60	70	80	90
Output	0.0521	0.0021	0.0152	0.026	0.8225	0.9099	0.9627	0.9797	0.9081	0.9114

Graph 2. Results of the Backpropagation Network of eleven averaged DFFT's

CONCLUSION

In order to improve signal to noise ratio, instead of taking one 1DFFT, more 1DFFT's were obtained and averaged by the total number of 1DFFT's performed. Its result is clearly seen in the graphs which show an improvement in the classification of the images. Averaging eleven 1DFFT's evenly spread out across the whole image was enough to give us a satisfactory answer. This result of the study on application of neural networks to laser scattering images for detection of subsurface features shows a potential for useful applications of neural networks to laser scattering images for other various feature recognition.

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LASER SPECKLE MICRO-STRAIN MEASUREMENTS ON SMALL DIAMETER FIBERS

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ABSTRACT

Micro-strain measurements of small diameter fibers were performed using Yamaguchi's speckle-shift technique. This novel technique requires no specimen surface preparation and allows micro-strain measurements for an extremely small gauge length (on the order of 0.1 mm). It provides a strain resolution of approximately 15 micro-strain ($\mu\epsilon$). Studies performed at room temperature have demonstrated that the system can be used to measure strain in ceramic fibers and metal wires as small as 21 μm in diameter. These micro-strain measurements were used to determine Young's modulus of sapphire, silicon carbide and polycrystalline alumina fibers. The results obtained were in excellent agreement with literature values.

INTRODUCTION

Accurate axial and radial strain measurements are necessary to predict mechanical and thermo-mechanical performance of fibers. The correct determination of strain is essential for the understanding of the performance of fibers as a reinforcement at elevated temperatures. Yet, strain measurements on small diameter fibers are extremely difficult to perform and even more so at elevated temperatures. Thus, measurement technology is not available to test these fibers. All available techniques utilize extensometers or markers for visual measurement of strain in test specimens. These conventional techniques require a specific gauge length and can not measure the strain on a small spot. Furthermore, they lack the proper gauge length and/or resolution to measure strain accurately, and therefore introduce a considerable amount of error. These errors are exaggerated at elevated temperatures due to temperature gradients. The reported strain is the total integrated strain over the whole length of the specimen rather than at a corresponding temperature. Thus techniques are necessary to determine the strain in fibers at a point or in a very small area.

The laser speckle-shift strain measurement technique met the stringent requirements for strain measurement of small diameter fibers. This technique was based on original work by Yamaguchi and modified to measure strain on small areas.^{1,3} This system was first developed at NASA LeRC by Lant and Quaish,⁴ and modified by

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