Classification of delaminated composites using neuro-fuzzy image analysis

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Abstract

Computer assisted image analysis is often required in automatic visual inspection in manufacturing processes. However, in spite of years of research in pixel-based image processing techniques such systems are often unable to recognise characteristics that are obvious to human visual inspection. In this paper, we present a technique that combines conventional image analysis, neural networks and fuzzy decision-making. The motivation for this approach is to train the automated system on characteristics that would represent a naturally "perceived" image. The application is on detection of flaws in laminated composite materials. Initial results indicate that great improvement in classification accuracy can be achieved over the use of neural networks alone.

1 Introduction

Computer image processing and analysis is often required in automatic visual inspection in manufacturing processes. While trained human operators will most likely be able to grade a product accurately, their performance fails remarkably when they have to deal with high speed and repetitive tasks. On the other hand, in spite of several years of research in pixel-based image processing, techniques computerised image analysis systems are often unable to recognise characteristics that would be obvious to human visual inspection. In this paper we present an application combining conventional image analysis, neural and fuzzy techniques. The motivation for this approach is to train the automated system on characteristics that would naturally represent the "perceived" image. The application in this study is on classification of laminated composites by shearography imaging.

Detection and characterisation of damage and malformation in laminated composites by shearography is often difficult due to a lack of formation of clear fringe patterns. In this paper we have outlined a method for isolating fringes in poor quality shearographs and using neural fuzzy techniques to classify the laminated composites. The technique involves median filtering of the images and extraction of signatures of sampled pixel intensities along suitable axes. Neural networks are then used to classify each of the signatures separately. Due to the expectation of their failure to classify certain images correctly, a fuzzy inference system is used to provide the overall classification of the laminated composite by resolving indeterminate and conflicting classifications. An image gallery of only 20 shearographs was used, due to the expense of obtaining satisfactory shearographs. However, initial result indicates that the approach is viable.

2 Shearography: an overview

Shearography is a real-time nondestructive evaluation technique that has been widely used for damage detection. The nondestructive procedure involves video imaging of a surface displacements illuminated by laser. A specially designed CCD camera produces two laterally sheared images of the surface. Shearography is based on the phenomenon that coherent waves of light having different path lengths produce a fringe pattern when interference occurs. This fringe pattern represents changes in the out-of-plane displacement derivative of the surface under test. The out-of-plane displacement derivative, is a representative of strain. Discontinuities in a material will give rise to strain concentrations when the object is loaded, through presure or thermal excitation [1]. The strain concentrations form a fringe pattern and this can be used to detect and analyze flaws. The mathematical foundations and techniques used in shearography are described in [2, 1].

During shearographic examination, the test specimen is excited while illuminated by laser light. An image shearing CCD camera captures the displacements on the surface. The images are then processed by computer. Obtaining realistic results is dependent upon an appropriate method for exciting the specimens and the image analysis technique. Electronic shearography (ES) has mainly been used in damage detection and has also been successfully applied in detecting delaminations in composites. However, characterization of damage continues to be a problem, especially for flaws other than delaminaions. On the other hand, ES has also been used for other applications such as measurement of surface coordinates and slopes of curved structures and in vibration analyses. There is need for more studies in the development of quantitative and qualitative approaches in detecting and evaluating different types of damage and flaws using shearography. This paper presents an initial study in combining ES with neural fuzzy classification techniques.

3 Shearograph Image Processing

Neural and fuzzy classification techniques do not offer a “magic bullet” to solve difficult classification problems. Therefore, it is generally acknowledged that conventional signal pre-processing using conventional techniques is advisable. In this section we describe the steps of image pre-processing that have been proposed. In our approach we attempt to derive a perceptual rather than pixel-based processing of the image. In other words, we wish to extract features that would be apparent to human visualisation.

We start by showing an example of a shearography image (Figure 1a). To the human eye the main feature in the image are distinct fringe patterns. However, closer examination shows that they are in fact not so easily identifiable, which can be a problem to conventional automatic image processing. For example, as a first step, it would be useful to threshold the image to separate the fringe patterns from the background using the image histogram. Unfortunately, the intensity histogram, shown in figure 1b, reveals a unimodal distribution. This makes thresholding considerably more problematic as most algorithms expect bimodal (or more generally multi-modal) histograms so that threshold points are well defined. A second difficulty is that the images are very noisy, as seen more clearly in the enlarged section in figure 1c. This also reveals how the histogram is unimodal despite the visual appearance of the image seemingly being composed of well separated dark and light patterns. The bands are in fact made up of a mixture of isolated points distributed over a wide range of intensities. Therefore there is no peak at the dark end of the histogram (large intensity values infigure 1b) as the contributions of the dark fringes are spread so thinly as not to form a discernible peak.

To overcome the above problems, the first stage of processing applied is to blur the image using a Gaussian filter (the value of $\sigma = 2$ was used) to merge the isolated points and form more distinct (on a local scale at least), less noisy fringes. The result is shown in figure 1d. Since it is known and assumed that the main feature in the image are the fringe patterns, it is necessary to isolate these. To find the centre of the fringe patterns the horizontal and vertical lines of symmetry in the image are first located. The intersection of these lines of symmetry will correspond to the centre of the fringe patterns. In our approach we assume that these correspond to the horizontal and vertical lines such that pixel intensities reflected about the lines match the corresponding pixels. The intensity similarity is measured using Pearson's moment correlation coefficient, which indicates the degree of linear relationship between two variables:

$$r = \frac{\sum_i (a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_i (a_i - \bar{a})^2}\sqrt{\sum_i (b_i - \bar{b})^2}}.$$

To locate the vertical line of symmetry, for example, this is applied at each possible position of x, producing the correspondences

$$a_i = I_{x+i,y}, \quad b_i = I_{x-i,y}; \quad \forall i, y$$

The value of x for which r is maximum is selected as the line of symmetry. The horizontal line is found similarly.

An additional practical detail is that the values of $x \pm i$ and $y \pm i$ must remain within the bounds of the image size. Thus, as the lines move towards the image edges then many pixels cannot be used as they have no correspondences. The problem that arises is that close to the edges only a small region of the image is included in the symmetry test. This can result in false centre of symmetry since the rest of the image may be featureless, in which case any line provides a high correlation. To avoid this problem the candidate lines are only considered within the middle portion of the image, that is, if the image width is w then potential vertical lines of symmetry are restricted to $x = [\frac{w}{4}, \frac{3w}{4}]$. As shown the method works well, and has generally been found to be reliable. However, given the variability of the images, errors can still occur. An example is given in figure 1g in which the pattern is rather larger than previously. The detected centre of symmetry is not at the centre of the complete pattern, but the centre of one of the eyes of a dual pattern.

Locating the fringe centre is advantageous for two reasons. Firstly, it eliminates the two degrees of freedom necessary for pixel-based processing. Secondly, it permits a translation-invariant description of the patterns in the image. In other words, the image can now be processed in terms of the patterns, which we have assumed should be present, or absent, in the images. But, as has been described above, examining the image along the lines of symmetry has its drawbacks, because it may not be possible to perceive the existence of fringes by traversing a symmetry line, even where it is known that the fringes exist. It is for this reason that extra decision-making is necessary from examination of more than one line of symmetry.

To reduce the quantity of data the image intensities are sampled along the horizontal and vertical lines of symmetry to generate 1-D signatures, as shown in figure 2a. Two approaches to resampling these slices were considered. The first is to generate, for a fixed number of lines, the optimal polygonal approximation with respect to the incurred integral squared error. This was implemented using a dynamic programming scheme [3]. The second is much simpler and faster, and just performs a regular subdivision and sampling of the curve. These levels of compression were found to be the limit to which the visual characteristics of the original image were preserved. Figure 2b and figure 2c show the results applied to the horizontal slice. The optimal approximation was set to extract 30 lines while the regular subdivision used 100 samples.

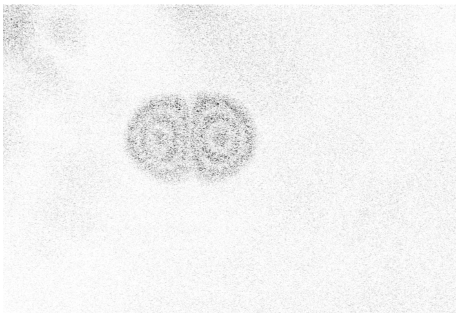
4 Neural Network Classification

The data obtained from the image processing described above, was used to train conventional backpropagation networks to classify the signatures obtained from the images. Due to the cost of carrying out experimental shearography it has not been possible to obtain a large enough collection of images. A gallery of 20 flawed laminations was used, which provides 80 different signatures of the two types. The non-flawed laminations were represented by images made up entirely of random background noise, thus, another 80 of such "non-flawed" signatures were collected. The pixel intensities were normalised in [0.0, 1.0]. These data was separated into two equal sets for training and testing.

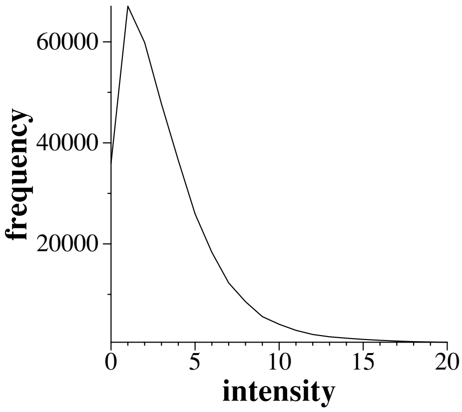
The network parameters were determined as is common through experimentation. This includes the number of hidden nodes and the learning rates. The other considerations were that the network is trained to learn outputs of 0.1 and 0.9, instead of 0 and 1, respectively. In practice, to improve network learning efficiency, networks are also trained to accept value in excess of 0.8 as close enough to 1, and conversely, values less than 0.2 as close enough to 0. Output values outside these ranges are usually considered indeterminate. The output of a neural network, in many cases, will lie in the indeterminate region, unless thresholding is applied. In this work, an output is assigned a fuzzy measure of belonging to any of the three possibilities. However, since in a classification task we require a definite output, a decision-making system is used to resolve contradictory and indeterminate classifications.

5 Fuzzy Inference Aggregation

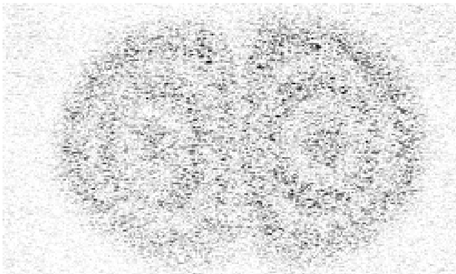
The fuzzy inference system is designed to be used in the testing or operation stage to determine the overall output from classification networks, which are trained with



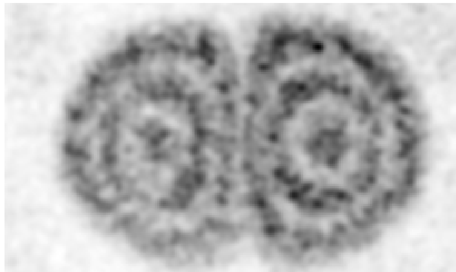
(a) delamination fringe pattern



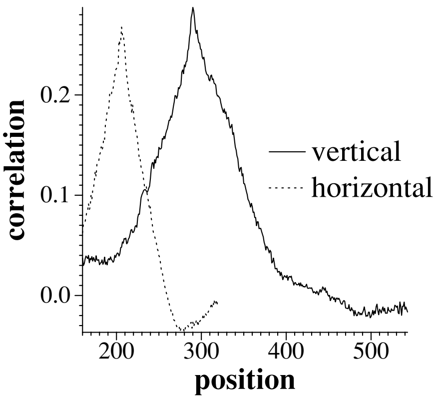
(b) intensity histogram



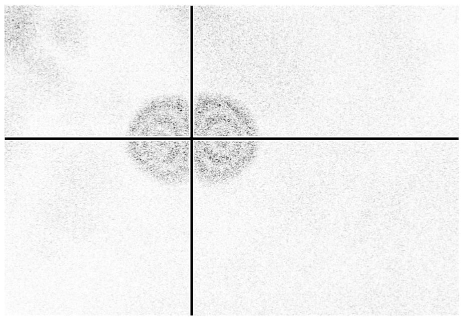
(c) enlarged section



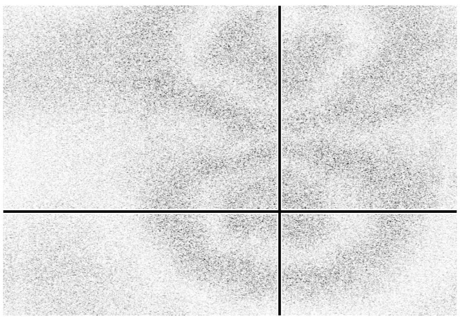
(d) enlarged section after blurring



(e) correlations about lines

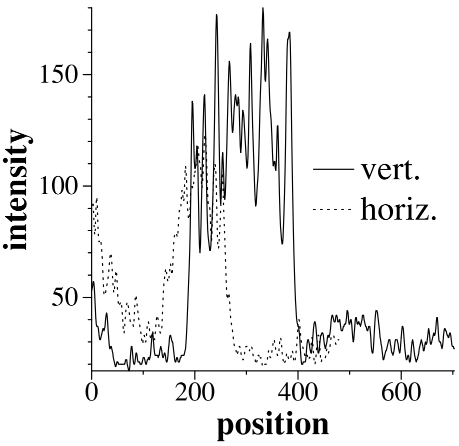


(f) detected lines of symmetry

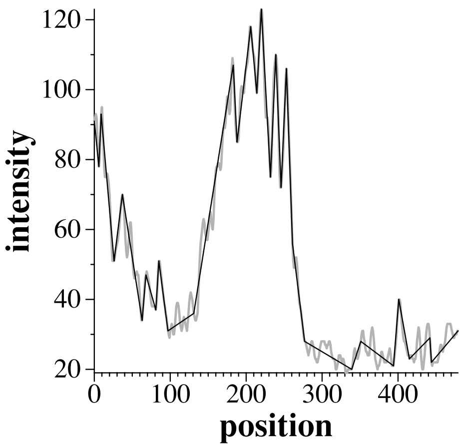


(g) detected lines of symmetry

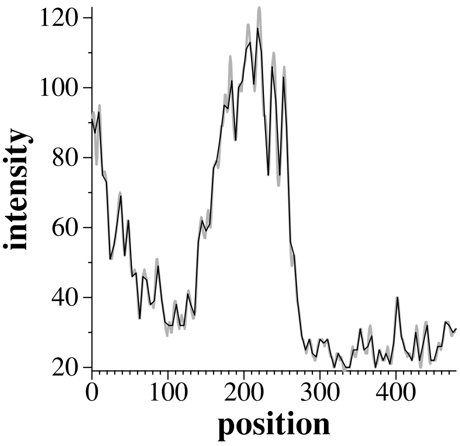
Figure 1: Locating the fringe pattern in the shearograph images



(a) intensity slices though lines of symmetry



(b) optimal polygonal approximation



(c) regular (static) sampling

Figure 2: Representing the fringe pattern by horizontal and vertical 1D intensity slices through the detected centre

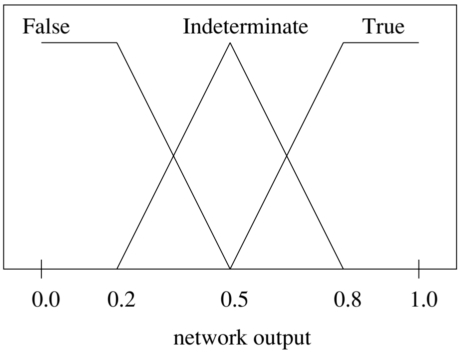


Figure 3: Fuzzy partitions

orthogonal 1-D signatures of images. An output from each network is assigned a fuzzy measure to indicate the degree to which it is "False" (no defect), "True" (defective) or "Indeterminate"(unknown), in terms of identifying a delamination in the tested material. At present two networks are used. The final decision is evaluated using fuzzy rules constructed to represent the authors' interpretation of the problem, that is, how likely it is that the shearographs belong to one of the two possibilities. The fuzzy partitioning used is shown in figure 3 and the inference rules in Table 1

Fuzzy measures and fuzzy integrals were introduced by Sugeno [4] as a means of determining concepts which are heavily influenced by human perception. A fuzzy integral is a function which can be used to aggregate information from multiple sources. Thus, a fuzzy integral can be understood as the degree of agreement between opposite tendencies or degree of agreement between objective evidence and the expectation. In this paper, the degrees of agreement for each classification are summed over all classification rules, with the final class being determined by the maximum sum:

$$\begin{aligned} \phi(C_j) &= \sum_{\forall \mathcal{R}_i = C_j} \min_i \mu_i \\ j^* &= \arg\max_j \phi(C_j) \end{aligned}$$

where C_j is the j^{th} class of output, $\mathcal{R}_i$ is the output of the rule triggered by the inputs, and μ_i are the fuzzy measures of the outputs of the neural networks, and j^* is the determined final classification.

horiz. / vert.	False	Indeterm.	True
False	F	F	*
Indeterm.	F	*	T
True	*	T	T

Table 1: Fuzzy Rules for Output Class Aggregation (F=False; T=True; *=Conflict)

Type	Sens.	Spec.	ppr	npr
NN30	0.53	0.58	0.69	0.67
NN100	0.55	0.52	0.61	0.63
FNN30	1.0	1.0	1.0	1.0
FNN100	1.0	1.0	1.0	1.0

Table 2: Performance for network classification

6 Results and Discussion

The performance of the neural-fuzzy classification is measured using a number of metrics. The classification of each network is evaluated in terms of its sensitivity, specificity, positive prediction ratio and negative prediction ratio. Sensitivity is a measure of the accuracy to determine a positive outcome, given that the outcome was indeed positive. Conversely, specificity is a measure of the accuracy to determine a negative outcome, given that the outcome was negative. The positive prediction ratio (ppr) is the percentage of actual positive outcomes, while the negative prediction ratio (npr) is the percentage of actual negative outcomes in a test.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$ppr = \frac{TP}{TP + FP}$$

$$npr = \frac{TN}{TN + FN}$$

Table 2 shows the result obtained from the classification tests, using two signal processing approaches and in combination with the fuzzy aggregation. NN30 is the network using 30 sample points obtained through polygonal approximation of the image signature. NN100 is the network with 100 regularly sampled inputs. FNN30 and FNN100 refer to the combination of these networks with a fuzzy decision-making system.

The networks were trained for a predetermined number of cycles sufficient to reduce the network error to an acceptable level. The result shows that while the classification accuracy was low in all cases using the neural networks alone, it was possible to classify shearograph images with certainty when the neural networks were combined with a fuzzy decision-making system. This result, however, is tempered by the small training and test set available at the moment. We anticipate reporting similar improvements with a larger gallery of images.

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