Evaluation of the Robustness of Surface Characterisation of Carbon Fibre Composites Using Wavelet Texture Analysis

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Abstract. The mechanical properties of advanced composites are essential for their structural performance, but the surface finish on exterior composite panels is of critical importance for customer satisfaction. Previous work by the authors established the feasibility of wavelet texture analysis (WTA) for the task of automatically classifying the surface finish of carbon fibre reinforced polymer (CFRP) samples based on computer image processing. This paper presents an evaluation of the robustness of the WTA method to common process errors that can occur in the imaging of material samples. WTA creates a rich representation of the texture in an image that includes features related to both scale and orientation. Principal components analysis was used to reduce the dimensionality of the texture feature vector to a single principal component that could be used as the basis for discrimination between grades of CRFP sample surface finish quality. The results obtained indicate that the WTA method is robust to: significant horizontal and/or vertical translations of the sample being imaged; significant rotation of the sample being imaged; and significant dilation of the sample being imaged. The results obtained suggest that as long as reasonable precautions are taken in sample imaging, then the WTA method will yield repeatable results.

Introduction

The mechanical properties of advanced composites are essential for their structural performance, but the surface finish on exterior composite panels is of critical importance for customer satisfaction [1]. To date, assessment of surface finish quality has tended to be based simply on human visual observation, which is therefore time-consuming and not directly adaptable to the automated manufacture of composite products [2,3]. It has been observed that many types of engineering surfaces contain textural features at multiple scales [4], and may be fractal (self-similar at different scales) in nature [5,6]. While there exist a number a numerical methods for characterising engineering surfaces, many require that the distribution of surface features is stationary (i.e., the frequency content does not vary with location), an assumption that is often not valid [4]. It has been shown that the wavelet transform has the ability to effectively characterise surface profile data that contain multi-scale features and are non-stationary [4], and are fractal in nature [5].

Previous work by the authors established the feasibility of wavelet texture analysis (WTA) for the task of automatically classifying the surface finish of carbon fibre reinforced polymer (CFRP) samples into two quality grades, based on computer image processing [7], and forthcoming work extends the application of the WTA method to the classification of three grades of CFRP surface finish quality [8]. This paper presents an evaluation of the robustness of the WTA method to common process errors that can occur in the imaging of material samples; those being horizontal and/or vertical translation, rotation and dilation.

Method

The CFRP panel used in testing here comprised three layers of 200g/m^2 carbon fibre plain weave cloth (supplied by ATL Composites – code ZP200) impregnated with epoxy resin (R180 epoxy resin and epoxy hardener H180 slow – supplied by Fibre Glass International, FGI). The CFRP panel was manufactured on a pre-released flat glass mould surface. Resin was introduced by hand using brushes and the panel was backed with a plywood base for flexural stiffness. Curing occurred under atmospheric conditions. Following curing, three smaller panels (one for each grade) were cut from the original panel. To create three different surface finishes (grades 1 to 3), coarse sandpaper was used to introduce a ‘random’ distribution of point defects. Each sample panel was positioned surface down on the sandpaper and the plywood backing was tapped a specified number of times with a mallet. The taps were of approximately even force/pressure and were distributed evenly over the back surface. Grade 1, 2 and 3 received 0, 10 and 30 taps respectively. The sample panels were scanned at 600 pixels per inch (approximately 236 pixels per cm) using a Hewlett-Packard HP3200C flatbed scanner to yield high resolution 8 bit (256 grey scale) images. All numerical analyses described hereafter were performed using the Matlab computing environment [9,10]. The wavelet analysis method is expedited by images that have linear dimensions of an integer power of two. To this end, all sample images used in the following analyses were sized to be 1024 by 1024 pixels for testing. Fig. 1 shows typical clear resin sample test images for the three grades of surface finish produced in this manner. The details of the further treatment of sample images are given in the evaluation subsections below.

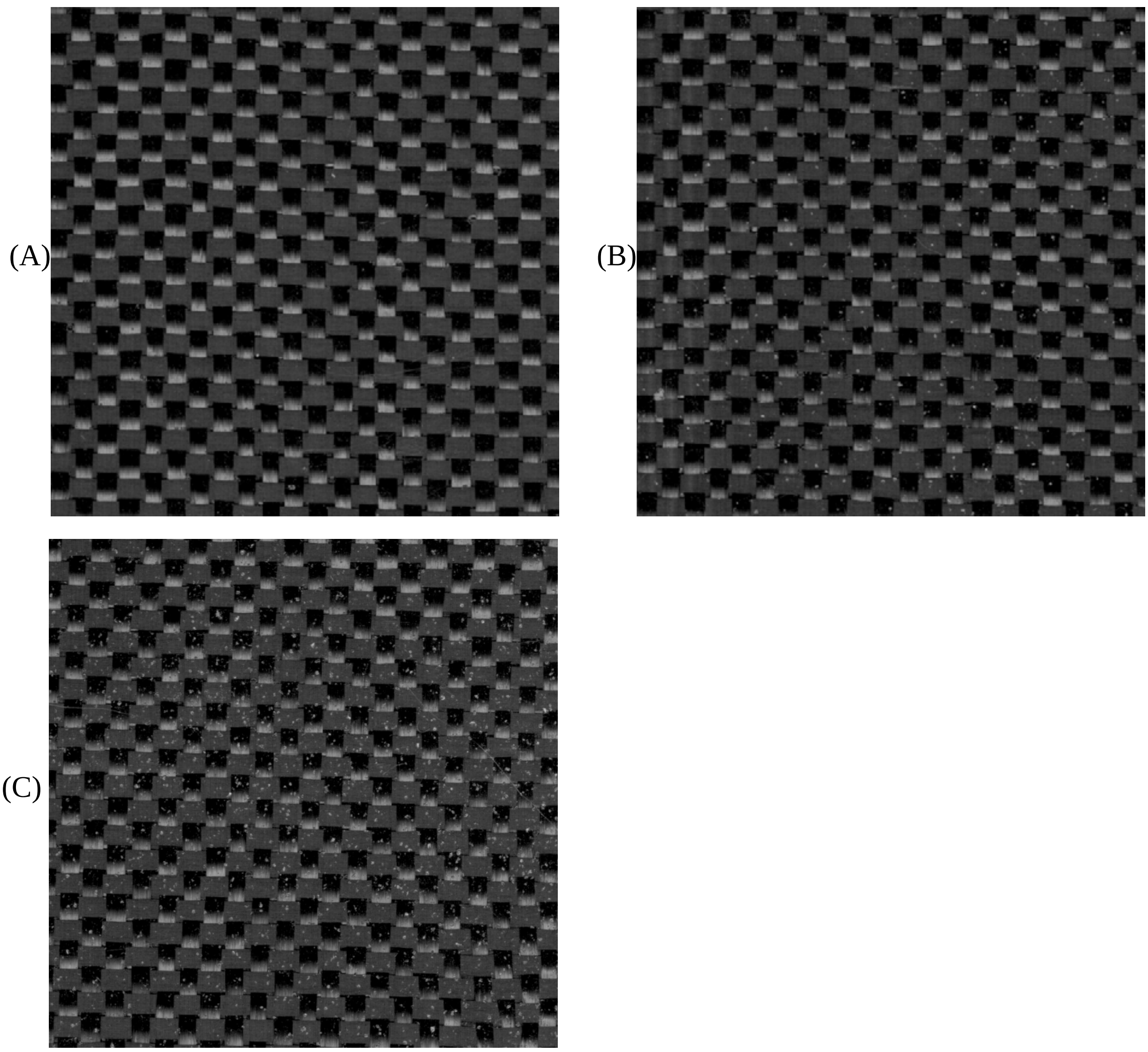

Fig. 1 Typical sample test images for (A) grade 1; (B) grade 2; and (C) grade 3 surface finish

Detailed mathematical treatments of the wavelet transform are available elsewhere [11], and we provide additional theoretical background in our previous work [7]. Essentially, the two dimensional discrete wavelet transform (2DDWT) produces a nearly orthogonal decomposition of an image into sets of coefficients that separately represent the information in the original image in three orientations (horizontal, vertical and diagonal) and different scales. The scale is a characteristic dimension related to the wavelet basis selected for the decomposition. The 2DDWT is an iterative decomposition, in which the scale doubles at each step, placing a limit on the number of levels of decomposition related to the wavelet basis and the size of the images. Wavelet analysis requires the selection of a wavelet basis for the decomposition. There are no definitive rules for selecting the 'best' wavelet for a particular analysis application [12]. A heuristic technique of analysing sample data with a range of candidate wavelets and applying selection criteria to identify the optimal analysis wavelet has been suggested [13].

Wavelet texture analysis (WTA) creates a texture feature vector based on the wavelet detail coefficients (*cD*) from all decomposition levels, and from horizontal, vertical and diagonal orientations. This permits a rich representation of the texture in the image to be used as a basis for classification that includes features related to both scale and orientation. In this case, the elements of the texture feature vector are constructed from an energy measure of each set of wavelet detail coefficients. A range of energy measures are possible [14]; here we use the square of the Frobenius norm of the wavelet detail coefficients, normalised by the size of the coefficient set, as the energy measure. The construction of the texture feature vector for each sample image is given by Eq. 1:

$$E_{jk} = \frac{1}{M \times N} \left\| cD_j^k \right\|_F^2 \quad (-J \le j \le 1; k = h, v, d) \tag{1}$$

where j is the wavelet analysis scale/level, J is the maximum analysis scale, k is the wavelet detail coefficient set orientation (horizontal, vertical or diagonal), and $M \times N$ is the size of the coefficient set. Hence, the texture feature vector for each sample image contains $3J$ elements. The square of the Frobenius norm of matrix A is defined as:

$$\left\| \mathrm{A} \right\|_F^2 = \sum_{i,j} \left| a_{ij} \right|^2 \tag{2}$$

The texture feature vectors for all of the test samples can be used in multivariate analysis to classify the samples. Principal components analysis (PCA) transforms a set of correlated variables into a smaller set of uncorrelated variables called 'principal components'. PCA uses linear matrix algebra to generate the principal component scores from the original variables such that each principal component is a linear combination of the original variables, and taken together, all of the principal components form an orthogonal basis for the space of the original data, containing no redundant information [15]. This process generally results in a small number of principal components embodying most of the information in the original variables, with a rapid fall-off in importance beyond the first few principal components. In the application described here, four non-overlapping sample images drawn from each of the three surface finish grade panels were used as calibration inputs for WTA. A range of wavelet basis and decomposition levels were trialled to find a combination that yielded good ability to discriminate between the grades based on using only the first principal component (PC1) score. Good results were obtained using the Daubechies wavelet with seven vanishing moments (db7) and three levels of wavelet decomposition. Using these parameters, PC1 explained more than 96 percent of the variance in the original texture feature vector set. These WTA parameters were used to compute all the PC1 values in the following analyses.

Results and Discussion

Robustness to translation. For each of three finish grade panel images, an 'original' sample was created by placing a 1024x1024 selection frame in the centre of the panel image and extracting the view (original). The frame was then translated 200 pixels left and a second image (west) was extracted. The frame was then translated 200 pixels up and a third image was extracted (north-west). The frame was then translated 200 pixels right and a fourth image was extracted (north). This procedure was repeated eight times, and the resultant image set contained the original image, plus eight others containing translations to the cardinal and ordinal compass points of 200 pixels relative to the original image. To test the robustness of the WTA method to translation of the sample under test, PC1 scores for all nine images for each of the three grades were computed using the PCA parameters previously determined, and the results are plotted in Fig. 2.

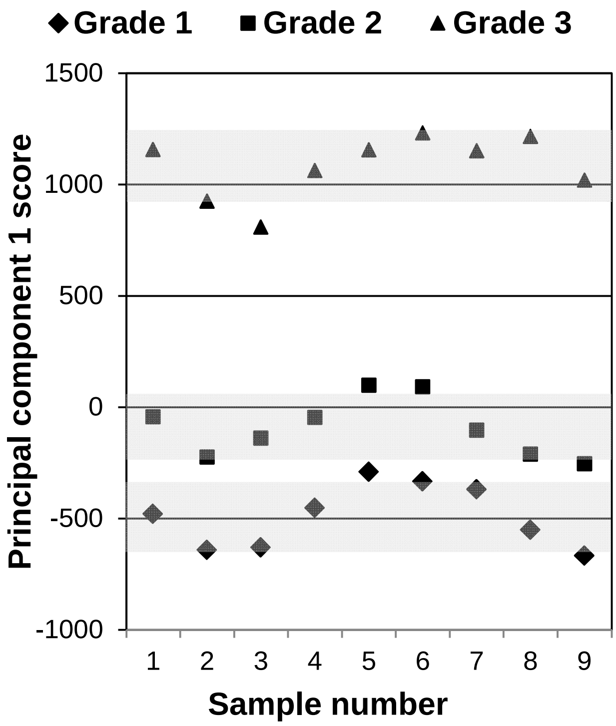

Fig. 2 PC1 scores for image translation samples

Variation in the PC1 scores between the translated images is observed within each grade; however there is no overlap between the grades, indicating that the WTA method is robust to significant horizontal and/or vertical translation of the sample being imaged. While there is some commonality of the surface area of the original panels present in each of the nine translation samples for each grade, they are all individually valid/feasible samples drawn from the three original panels. The grey bands in Fig. 2 represent the 99 percent confidence intervals for the mean of the nine samples for each surface finish grade. There is no overlap between the confidence intervals, providing an additional indication of the general reliability of the WTA method.

Robustness to rotation. For each of three finish grade panel images, an 'original' sample was created by placing a 1024x1024 selection frame in the centre of the panel image and extracting the view. The image was then rotated through plus and minus eight degrees, in two degree increments, and frame images were extracted at each increment, resulting in nine rotated sample images. As above, the PC1 scores for all nine images for each of the three grades were computed and the results are plotted in Fig. 3.

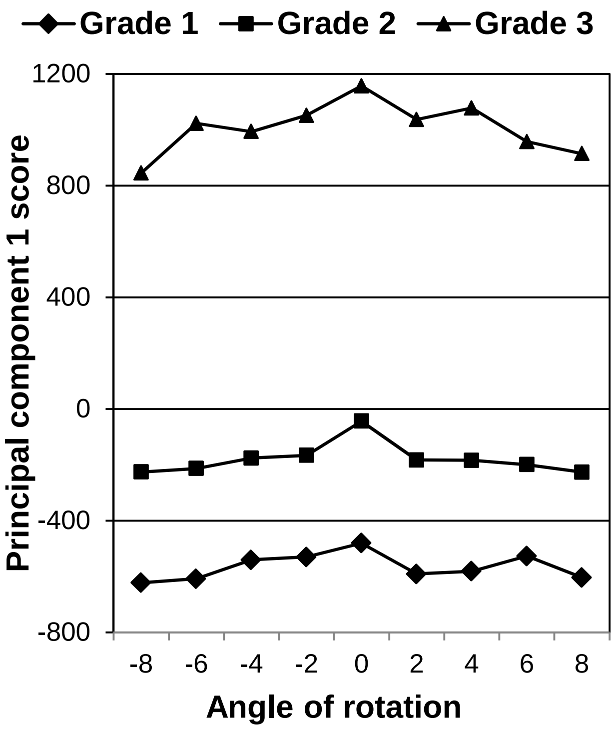

Fig. 3 PC1 scores for image rotation samples

Variation in the PC1 scores between the rotated images is observed within each grade; however there is no overlap between the grades, indicating that the WTA method is robust to significant rotation of the sample being imaged. This test process was repeated, except that the sample image rotation increment was increased to 40 degrees, producing nine new test images with rotations in the range -160 degrees to +160 degrees. PC1 scores for all nine images for each of the three grades were computed and the results are plotted in Fig. 4.

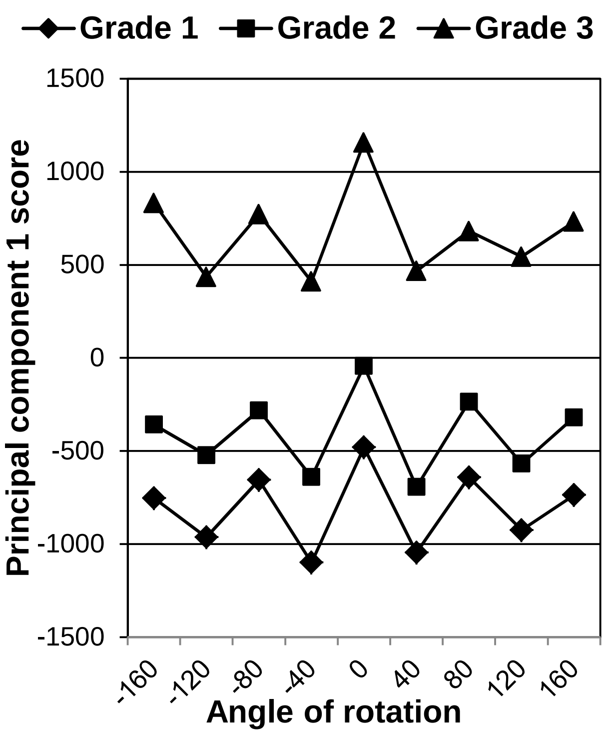

Fig. 4 PC1 scores for image gross rotation samples

Here, while the PC1 scores for the three grades are clearly separate at any given angle of rotation, across the full range of sample rotation some points of overlap between grade 1 and grade 2 are observed, indicating that the WTA method is not robust to gross rotation of the sample being imaged. This is not an unexpected result, given that the 2DDWT produces coefficients related to the orientation of features in the data under consideration, which in this case are CFRP samples with a distinctive cross-hatch weave pattern.

Robustness to dilation. For each of three finish grade panel images, an 'original' sample was created by placing a 1024x1024 selection frame in the centre of the panel image and extracting the view. The image was then dilated (magnified) through plus and minus eight percent, in two percent increments, and frame images were extracted at each increment, resulting in nine dilated sample images. As above, the PC1 scores for all nine images for each of the three grades were computed and the results are plotted in Fig. 5.

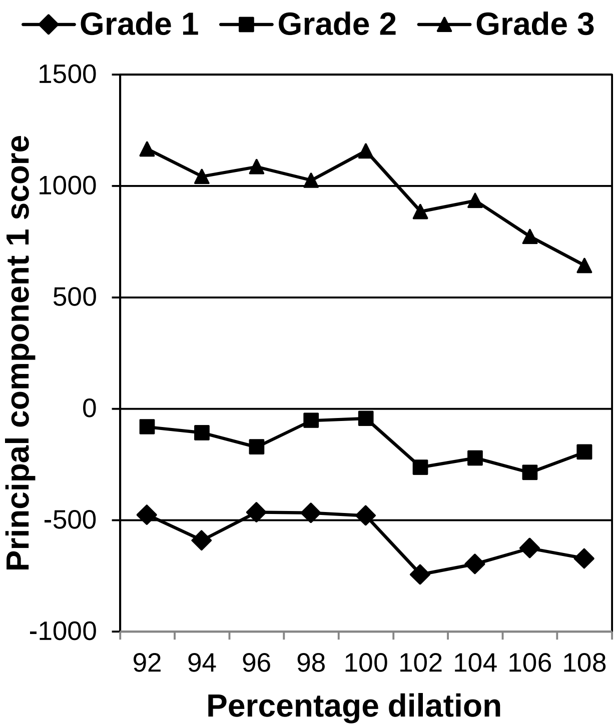

Fig. 5 PC1 scores for image dilation samples

Variation in the PC1 scores between the dilated images is observed within each grade; however there is no overlap between the grades, indicating that the WTA method is robust to significant dilation of the sample being imaged. This test process was repeated, except that the sample image dilation increment was increased to 10 percent, producing nine new test images with dilations in the range 60 percent to 140 percent. PC1 scores for all nine images for each of the three grades were computed and the results are plotted in Fig. 6.

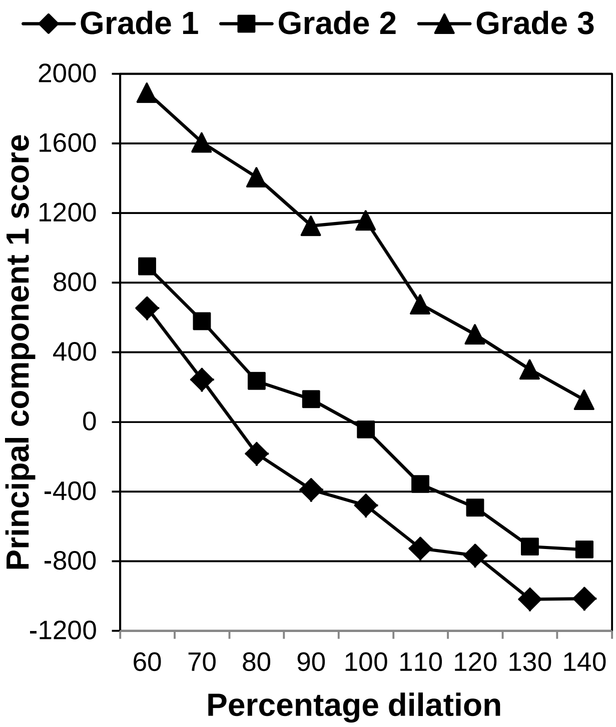

Fig. 6 PC1 scores for image gross dilation samples

Here, while the PC1 scores for the three grades are clearly separate at any given percentage dilation, across the full range of sample dilation overlap between all three grades is observed, indicating that the WTA method is not robust to gross dilation of the sample being imaged. This is not an unexpected result, given that the 2DDWT produces coefficients related to the scale (which is related to size for a given wavelet analysis basis) of features in the data under consideration.

Conclusion

A previously described new method for the task of automatically classifying the surface finish of carbon fibre reinforced polymer based on wavelet texture analysis was further evaluated to assess its robustness to common process errors that can occur in the imaging of material samples. The results obtained indicate that the WTA method is robust to: significant horizontal and/or vertical translations of the sample being imaged; significant rotation of the sample being imaged; and significant dilation of the sample being imaged. It is noted that gross rotation or gross dilation of the sample being imaged can result in variations in the data obtained that would be large enough to impact of the repeatability of the WTA method. This observation is consistent with the nature of the 2DDWT, which is linked to the orientation and size of features in the data under analysis. The results obtained suggest that as long as reasonable precautions are taken in sample imaging, such as using a test rig to standardise sample imaging conditions, then the WTA method described here will yield repeatable results that are useful in practice.

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