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Surface evaluation of carbon fibre composites using wavelet texture analysis

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Abstract

Strong and lightweight fibre reinforced polymeric composites now dominate the aerospace, marine and low-volume automotive sectors. The surface finish on exterior composite panels is of critical importance for customer satisfaction. This paper describes the application of wavelet texture analysis (WTA) to the task of automatically classifying the surface finish of carbon fibre reinforced plastic (CFRP) samples into two quality grades. Automatic classification was successful for all but four samples out of 14400 classification trial configurations, representing 403200 sample classification attempts (28 attempts per configuration). This work establishes the principle of WTA as a basis for automatic surface finish classification of composite materials.

Keywords: A. carbon fibre, D. surface analysis, E. automation, wavelet texture analysis

1. Introduction

Strong and lightweight fibre reinforced polymeric composites (for example, Glass-fibre Reinforced Plastic, GRP, and Carbon Fibre Reinforced Plastics, CFRP) now dominate the aerospace, marine and low-volume automotive sectors. More recently, environmentally-friendly fibre reinforced composites based on natural fibres and bio-based resins are also finding favour. 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]. Customers demand a flawless (Class A) surface finish, but this can be difficult to achieve on composite surfaces. Dry spots can occur in wet lay-up processes, and the strong reinforcement fibres can 'read through' to the exterior surface, spoiling the cosmetic appearance [2]. While it important that there is further research into materials and manufacturing process to improve surface finish [3], it is essential that composite manufacturers have reliable and repeatable methods for evaluating surface texture. To date, assessment of surface finish quality has tended to be based simply on human visual observation. While this method has been found to deliver results that are acceptable to customers, it is generally performed using several observers in order to produce statistically meaningful results [4], and is therefore time-consuming and not directly adaptable to the automated manufacture of composite products [5].

Systems for the objective assessment of surface quality do exist – divided into two categories: contact measurement (generally employing a stylus used to trace a profile of the surface under examination) and non-contact measurement (generally employing optical sensors to capture an image of the surface under examination that is then processed by computer). Both types of system are capable of accurate measurement of specific surface parameters, but currently struggle to replicate the human visual assessment of surface finish [5], and commercially available systems (for example, the BYK-Gardner Wave Scan DOI instrument is used to assess surface finish [6]) are typically very expensive. A non-contact computer vision system has been demonstrated in a reinforced polymer composite manufacturing application to provide good results in evaluating standard surface roughness parameters [7].

It has been observed that many types of engineering surfaces contain textural features at multiple scales [8], and may be fractal (self-similar at different scales) in nature [9, 10]. 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 [8]. 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 [8], and are fractal in nature [9]. For the comprehensive characterisation of surface features and texture, these inherent abilities of the wavelet transform place “it way ahead of other traditional methods” [11], and are why it is “generally considered to be state of the art in texture analysis” [12].

Wavelet analysis has been applied to the characterisation of material surface parameters. Data from 2D wavelet multiresolution analysis were used as the basis for a successful empirical parametric mapping between material surface images obtained via computer vision acquisition and standard surface roughness parameters obtained using conventional stylus measurement [13]. In a study to enhance the surface roughness of polymeric filtration membranes via plasma treatment, a wavelet-based characterisation of surface roughness data was used to establish the optimal plasma treatment duration, and was found to provide a more complete characterisation of surface roughness than standard measures [11]. For the objective assessment of surface features of textiles, wavelet-based analysis of computer vision data was shown to be able to distinguish surface imperfections from the underlying fabric weave [14], and more generally to be able effectively characterise fabric surface texture [15].

Wavelet analysis has also been applied to the analysis of surface characteristics of reinforced polymer composites. The utility of wavelet analysis of eddy current sensor data for the identification of surface defects in CFRP composite materials has been demonstrated [16]. Wavelet techniques have been used to analyse surface data to characterise and understand the hydrophobic characteristics of epoxy nanocomposite surfaces [17]. Wavelet analysis has also been used more widely in the identification and characterisation of internal defects in reinforced polymer composites [18, 19].

It has been observed that for resin transfer moulded composite plates with surfaces that have approximately similar quality, human visual observation generally outperforms objective (mathematical) methods in the differentiation of sample surface quality – possibly because the standard surface roughness parameters commonly used may not provide an unambiguous indicator of surface quality that agrees with human visual assessment [5]. Direct measurements of standard surface roughness parameters yields only height information about the morphology of a surface and not a total characterisation of a surface [11]. The desirability of objective techniques for the characterisation of surface quality of reinforced polymer composites that can provide the same results as a human subjective evaluation is noted [5].

Physiological experiments have shown that the visual cortex appears to perform a 2D multi-scale decomposition of the visual field into a range of frequency bands/channels [20]. There is considerable similarity between the wavelet transform and biological visual systems. This similarity has resulted in its use in biologically inspired computer vision systems [21]. The 2D wavelet transform is a mathematically robust analysis tool for the characterisation of material surface finish data in ways analogous to human visual processes, and offers practical and rigorous methods for the objective classification of surface quality. This paper demonstrates the application of wavelet texture analysis methods to the task of automatically classifying the surface finish properties of CFRP samples into two quality grades. We seek to establish the feasibility of this approach as the basis for automated non-contact classification of composite surface finish using image analysis methods analogous to the functioning of the human vision system.

2. Material and methods

To assess the feasibility of wavelet texture analysis for objective assessment of composite surface finish, two CFRP sample panels (150 mm x 150 mm) were created. The CFRP panels comprised two 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 standard - supplied by Fibre Glass International, FGI). The carbon fibre cloth was placed on a pre-released flat glass mould surface and resin and hardener mix was introduced by hand using brushes. The panels were backed with a plywood base for flexural stiffness and then vacuum bagged. To create two different surface finishes (‘good’ and ‘bad’), the carbon fibre cloth on the ‘bad’ panel was not fully wet-out. Insufficient resin resulted in dry areas that were clearly evident at the intersection/cross-over between the warp and weft of the weave. A significantly better finish (less dry spots) could be observed on the ‘good’ panel when compared to the ‘bad’ panel. Curing occurred under atmospheric conditions. We purposefully elected to use an un-coated composite in the work presented here; the combination of the visible textile weave construction and the surface finish properties presents a more challenging image analysis/classification task for the proposed WTA method than a coated surface, which removes/hides the potentially confounding visual element of the weave structure.

The two 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. These high resolution scans where then separated into 16 sections each with some overlap, yielding 32 sample images – 16 each of good and bad. All numerical analyses described hereafter was performed using the Matlab computing environment [22]. The wavelet analysis method is expedited by images that have linear dimensions of an integer power of two. To this end, all 32 sample images were sized to be 1024 by 1024 pixels for testing. Fig. 1 and Fig. 2 show typical ‘good’ and ‘bad’ sample test images produced in this manner.

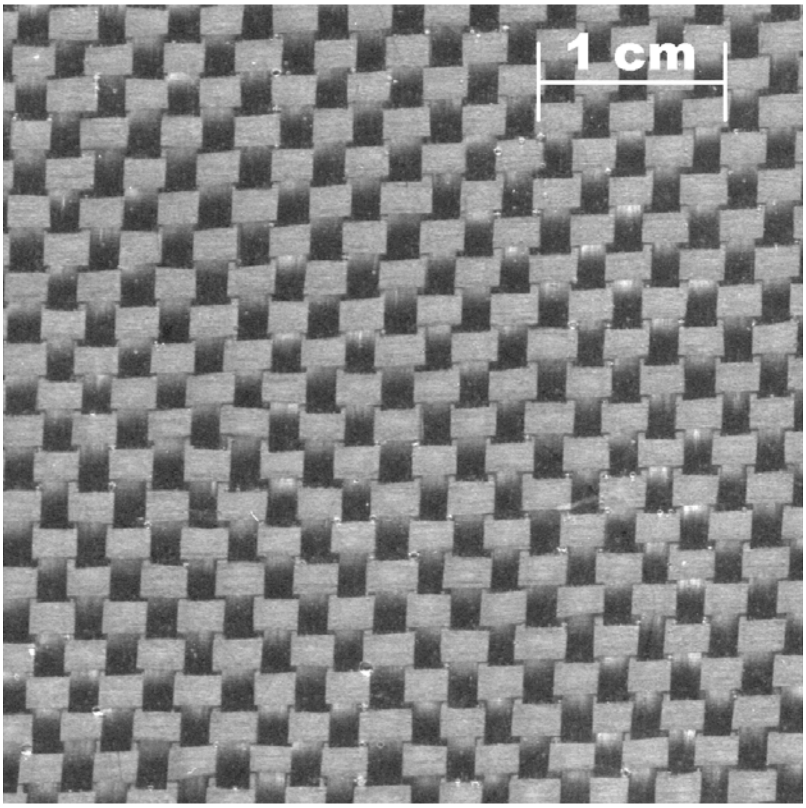


Fig. 1. A typical ‘good’ sample.

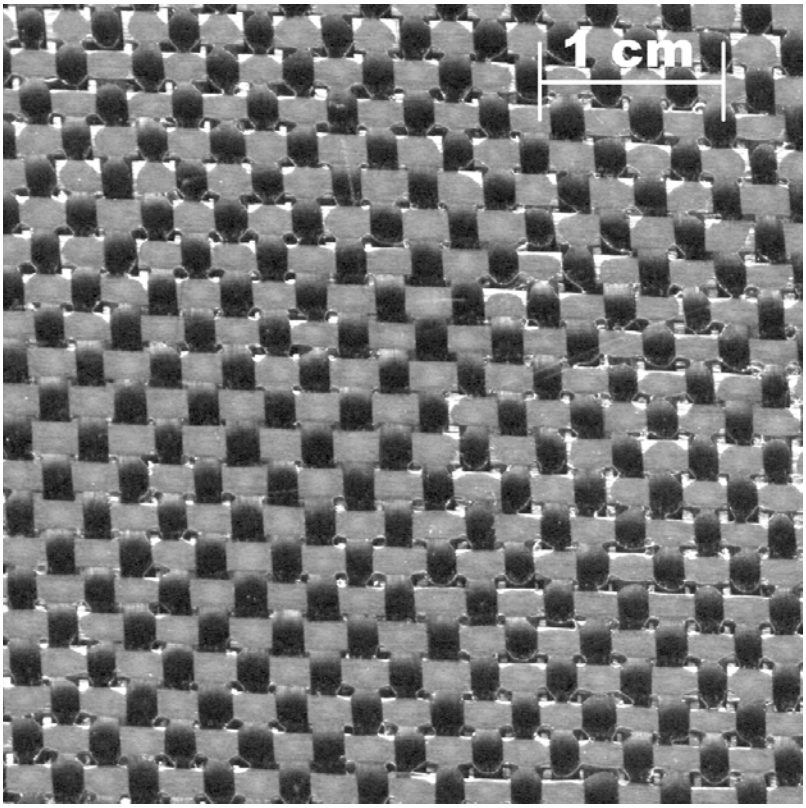


Fig. 2. A typical ‘bad’ sample.

Fig. 3 shows a typical horizontal data cross section from a ‘good’ sample. Higher data values represent lighter (whiter) elements in the sample image. The fibre plain weave ‘under and over’ warp and weft structure is readily apparent. Fig. 4 shows a typical horizontal data cross section from a ‘bad’ sample. The same basic weave structure is apparent in the data, but overlaid on this, at points in the horizontal cross section, are extreme (both high and low) pixel values caused by the dry spots on the bad panels.

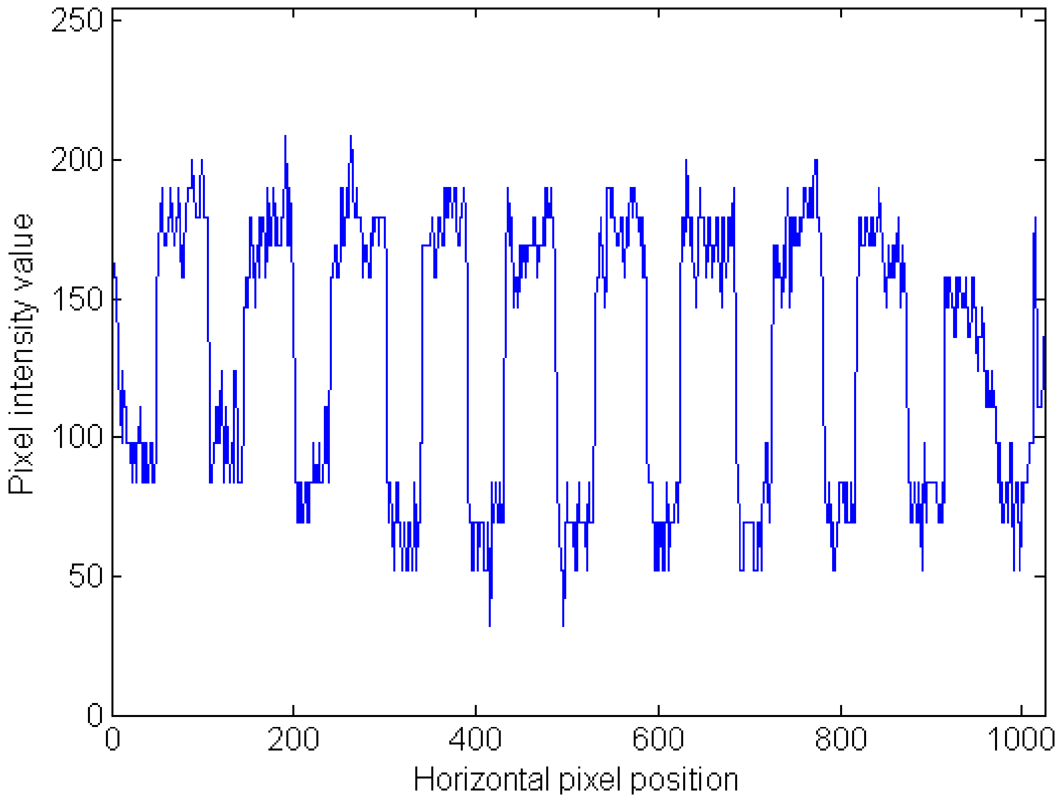


Fig. 3. A typical horizontal image data cross section from a ‘good’ sample.

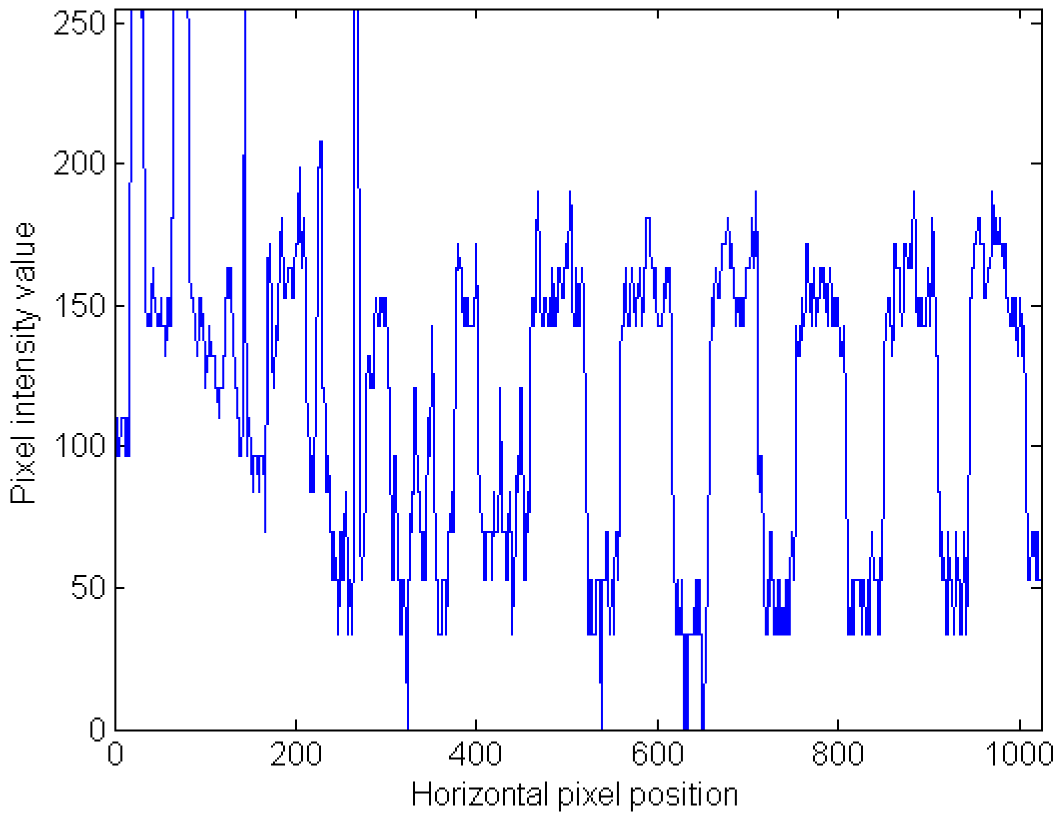


Fig. 4. A typical horizontal image data cross section from a 'bad' sample.

Detailed mathematical treatments of the wavelet transform are available elsewhere [23], but, in principle [24], the one-dimensional continuous wavelet transform (1DCWT) involves the comparison of a small waveform (wavelet – a time-limited waveform with particular mathematical properties) with a section of the data under test. The process produces a coefficient that represents the 'match' between the data and the wavelet. The wavelet is translated by a small distance, and the comparison is repeated, in this way, the 1DCWT provides characteristic information about the data that is localised in position. Then, the wavelet is dilated (scaled up) and the process is repeated over a range of scales. Each different scale produces characteristic information about the image localised in scale (which can be related to spatial frequency). Rather than calculating the 1DCWT at every possible scale and position, if we choose a wavelet basis function that is orthonormal and compactly supported (bounded in time), as well as choosing scales and positions based on powers of two, we have the commonly used orthogonal form of the discrete wavelet transform (DWT). At each analysis scale the DWT yields ‘approximation’ coefficients that represent low frequency (high scale) components of the data/signal, as well as ‘detail’ coefficients that represent high frequency components of the signal. The approximation forms the input to the analysis for the next successive scale decomposition, and the detail is a measure of the match between the signal and the wavelet at the current analysis scale. The multi-scale decomposition of the source data by iterative DWT analysis is known as ‘multiresolution analysis’. The DWT can be extended into two dimensions for the analysis of 2D data, such as surface profile data or images. Here, the analysis at each scale yields an approximation of the original image and three sets of details that represent the horizontal, vertical and diagonal details in the original image. This is the two dimensional discrete wavelet transform (2DDWT).

Wavelet analysis requires the selection of a wavelet basis for the multiresolution decomposition. There are no definitive rules for selecting the ‘best’ wavelet for a particular analysis application [25, 26], though shape similarity between the wavelet function and the features in the data to be analysed is one of the selection criteria noted in the literature [27]. A heuristic technique of analysing sample data with a range of candidate wavelets and applying selection criteria to identify the optimal analysis wavelet is also described [26, 28]. In the application described here, we use the Daubechies wavelet with three vanishing moments (db3). Other wavelet bases produced essentially similar results, but the db3 wavelet basis yielded the best classification results.

Wavelet texture analysis (WTA) creates a texture feature vector based on the wavelet detail coefficients (*cD*) from all decomposition levels and 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. The final approximation coefficients resulting from a 2DDWT multiresolution decomposition usually represent the background lighting or illumination variation and hence are generally not included as a textural feature. 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 [12]; 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 contains $3J$ elements. In the application described here, five levels of wavelet decomposition were sufficient, so each texture vector used contained 15 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 features 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 is often used as an initial step in multivariate analysis, and can help to assess the actual dimensionality of the data [29]. PCA uses linear matrix algebra to generate the principal components 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 [30]. The PCA transformation results in the first principal component having the highest variance possible (i.e., accounting for as much of the variability in the original data as possible). Each succeeding principal component subsumes as much of remaining variance in the data as possible, under the condition that it is orthogonal (not correlated) with all the preceding principal components. 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. This relationship is typically visualised in a ‘scree plot’ of the form shown in Fig. 5. The principal components thus developed can be used as a new set of observation variables for each sample image, but with reduced dimensionality, and hence, simplified subsequent processing. The principal component scores are used as observation vectors in discriminant analysis (DA) to classify the sample images. DA is a conventional probabilistic classifier that allocates each observation to the class with which it has the highest posterior probability of membership. In the example presented here, a simple linear classifier is used. It presumes that the each element of observation vector has a normal/Gaussian distribution. Based on a number of 'training' samples of each class of input type (here 'good' and 'bad'), linear partitions (here a single partition) are developed in the multi-dimensional space of the observation vector elements that are/is then used to automatically classify further 'unknown' samples into input class types. The performance of the classification method can be assessed by using a sub-set of the samples to 'train' the classifier, and the remainder of the samples as test candidates for classification.

3. Results and discussion

The texture feature vectors for all 32 sample images were computed and combined as the input data for PCA. Following PCA transformation, Fig. 5 is a scree plot of the variance in the original image data that is explained by the first three principal components. It can be seen that first principal component explains more than 96 percent of the variance in the original texture feature vector set, and together the first and second principal components account for in excess of 99 percent of the variation in the data. The PCA transformation has reduced the effective dimensionality of the texture feature vectors from 15 to two; in fact, the first principal component alone may be sufficient for classification.

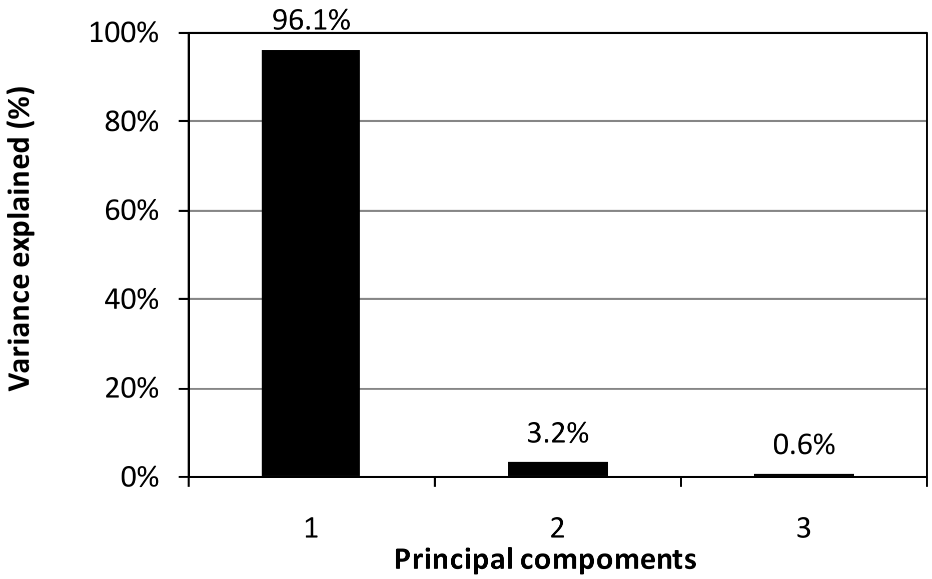


Fig. 5. Scree plot of first three principal components showing proportion of the variance explained.

Fig. 6 shows the location of all 32 samples, following PCA transformation, plotted on axes of the first two principal components that have been normalised against their variance. It is clear that the samples separate out into two distinct groupings. The 16 points on the left represent the good samples and the 16 points on the right represent the bad samples.

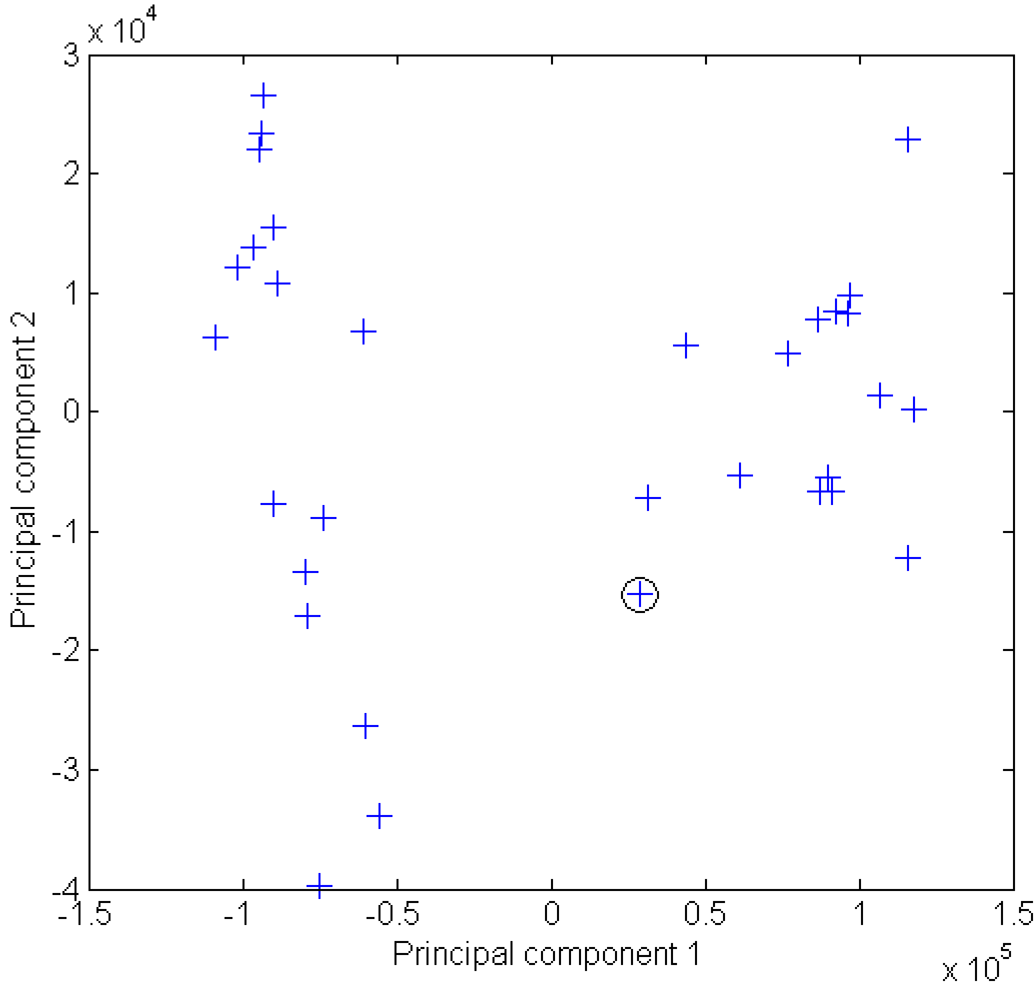
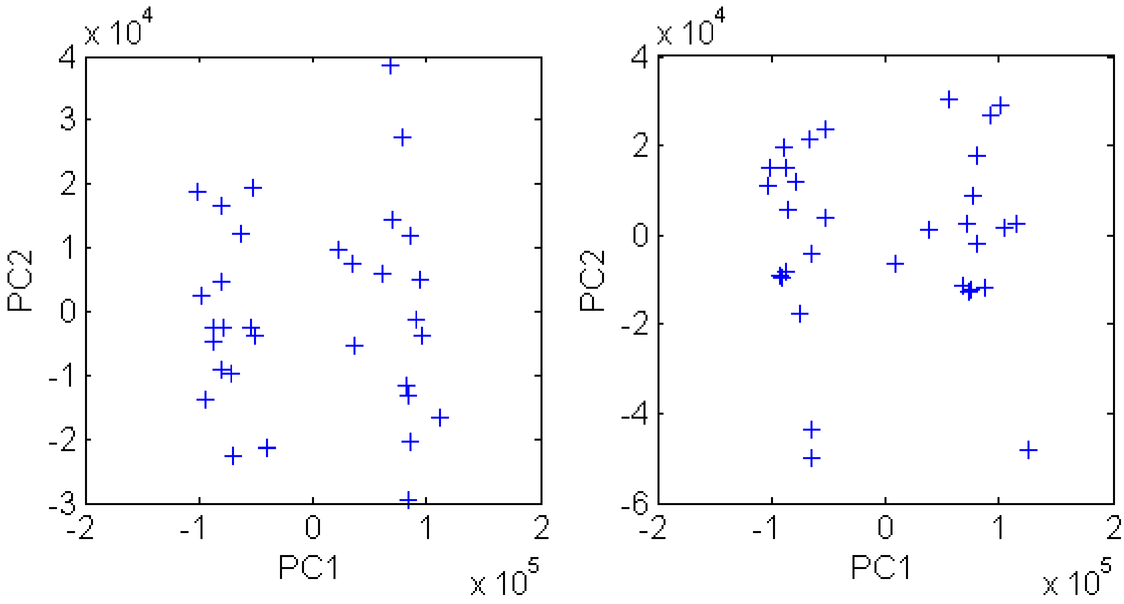
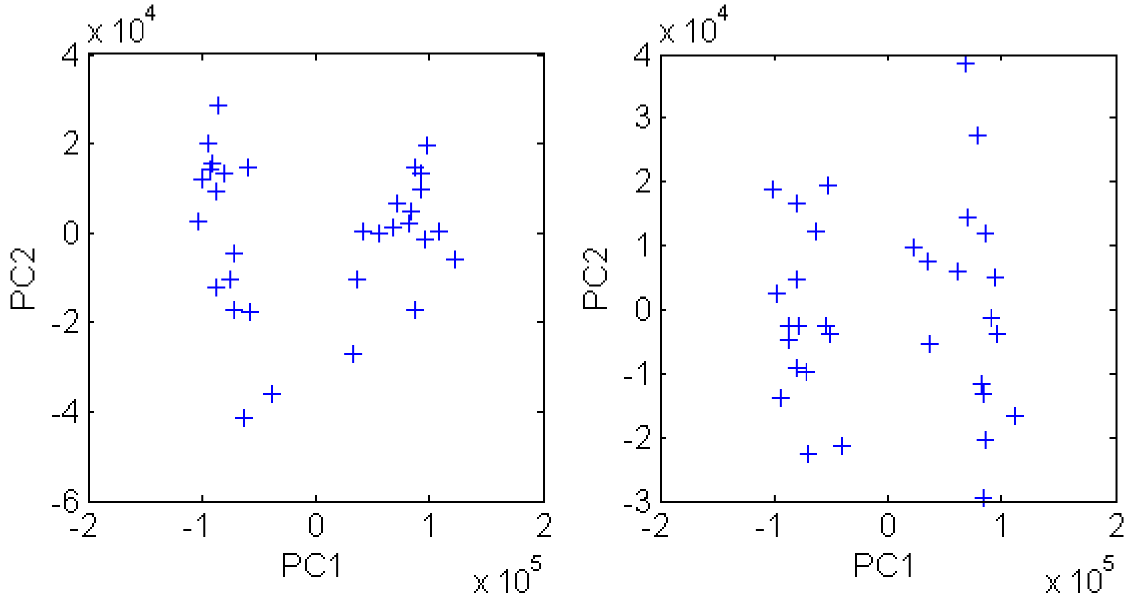


Fig. 6. Plot of first two principal components showing the location of all samples. (The circled sample point is the only misclassified sample – see explanation below)

As noted previously, a common approach to the selection of an optimal wavelet basis for analysis is to trial a range of candidate wavelets and to use the one that provides the best results. In this case, the db3 wavelet yielded the best results. Fig. 7 shows the outcomes of the analysis above repeated for a range of other common wavelet bases, including the Daubechies wavelet with one vanishing moment (db1), the Daubechies wavelet with four vanishing moments (db4), the Coiflet wavelet with two vanishing moments (coif1) and the Biorthogonal spline wavelet of order 1.1 (bior1.1). In the same fashion as Fig. 6, Fig. 7 shows the resultant plots of the first two principal components for the four additional wavelet bases, and indicates that, while there are differences, the same general results are obtained for all five wavelet bases. That is, while there is some sensitivity in the analysis to the wavelet basis chosen, the good and bad samples separate into two distinct groupings with a clear division between them, suggesting that automatic classification of the groupings will be possible for a range of wavelet bases.



(a) (b)



(c) (d)

Fig. 7. Comparison plots of first two principal components showing the location of all samples, as derived from wavelets (a) db1, (b) db4, (c) coif1 and (d) bior1.1.

As noted above, the PCA process transforms a set of variables into a reduced number of ‘principal components’, which are linear combinations of the original variables. Based on the main analysis presented in Fig. 6, Table 1 shows the component loadings for each of the five wavelet analysis scales and each of the three analysis orientations for the first two principal components. For example, the first principal component of a sample image is composed of 0.0005 x the energy measure of the scale 1 horizontal wavelet coefficients + 0.0002 x the energy measure of the scale 1 vertical wavelet coefficients + … + 0.0909 x the energy measure of the scale 5 diagonal wavelet coefficients. It can be seen that the main/largest loading, and therefore main discriminating ability, occurs at the fifth analysis scale.

Table 1

Wavelet analysis component loadings for first two principal components

Wavelet analysis scale	Orientation	Principal Component 1	Principal Component 2
1	Horizontal	0.0005	0.0005
1	Vertical	0.0002	0.0002
1	Diagonal	0.0001	0.0001
2	Horizontal	0.0047	0.0026
2	Vertical	0.0020	0.0010
2	Diagonal	0.0006	0.0004
3	Horizontal	0.0379	0.0146
3	Vertical	0.0199	0.0090
3	Diagonal	0.0058	0.0029
4	Horizontal	0.1624	-0.0236
4	Vertical	0.1280	0.1063
4	Diagonal	0.0376	0.0051
5	Horizontal	0.4319	-0.8865
5	Vertical	0.8713	0.4377
5	Diagonal	0.0909	-0.1019

Given that virtually all of the variance in the original texture feature vector set is explained by the first principal component (PC1), it was decided to use PC1 solely as the basis for automatic classification by DA. Fig. 6 visually confirms that PC1 should be a good basis for classification, and that a simple linear discriminant function should be adequate to classify between good and bad samples. The DA process takes some of the samples as a training set to develop a discriminant function, which forms the basis for automatic classification of subsequent samples from a similar population. The basic linear classification function in Matlab requires that the number of training samples be greater than the number of groups to classify. In this case, there are two classification groups (good and bad), so at least three training samples are required. It was decided to make the classification task as challenging as possible, and to use the minimum training sample size while retaining balance in the representation of the groups to be classified. This leads to a training set based on two good and two bad samples, with the balance of the 28 samples submitted for DA for classification.

To explore the performance of the DA, all combinations of two-from-sixteen (120) good and two-from-sixteen (120) bad training samples were constructed. The total number of unique training set combinations is 14400 (= 120 x 120). In the 14400 trials, representing 403200 (14400x28) individual sample classification attempts, only four misclassifications of a single sample occurred – the remaining 403196 samples submitted for classification were correctly assigned to either good or bad. In all four occurrences of misclassification, the training set was constructed from samples at the extreme right edge of good and bad sample clusters in Fig. 6, placing the linear classification boundary on top of the sample circled in Fig. 6, which was the misclassified sample, being classified as good instead of bad. In the case presented here, all but the most extremely unrepresentative training sets resulted in 100 percent correct classification of all samples. To further explore the performance of the DA and its sensitivity to the size of the training set, all combinations of three-from-sixteen (560) good and three-from-sixteen (560) bad training samples were also constructed and tested. The total number of unique training set combinations is 313600 (= 560 x 560). In the 313600 trials, representing 8153600 (313600x26) individual sample classification attempts, no misclassifications of a single sample occurred. Hence, with a modest proportion of the total sample set used for training, excellent DA classification is obtained.

While many applications for composites with visible surfaces involve painting, gel coating, lacquering or other coatings to hide the textile construction and/or improve the quality of the surface finish, this is not universally so. Techniques have been developed for the production of composites achieving high-quality surface finish with no coating at all [31]. As noted above, WTA has been successfully applied to the task characterisation of a wide range of engineering surfaces including metals, textiles and composites [12, 14-17]. Specifically in the case of visual assessment of the quality of composite surface finish, the ability of WTA to characterise surface texture in a way analogous to the human visual system holds great promise that it will work equally well applied to a range of composite surface finish types. The essential method of orthogonal decomposition of an image into separate planes containing the information relating to different scales and orientations present in the original image has the ability to isolate different types of visible surface flaws. This means that it is largely agnostic to the underlying composite construction (i.e., woven or non-woven), or even to whether it is a plain painted/coated surface. While the initial application presented here is based on the assessment of a composite with a woven construction and untreated surface, planned future work will include the objective assessment of graduations of finish quality for a range composite construction types and surface finishes.

4. Conclusions

This paper describes the application of wavelet texture analysis (WTA) to the task of automatically classifying the surface finish properties of CFRP samples into two quality grades. WTA creates a rich visual texture representation of the sample, capturing image features at different scales and orientations, which, following dimensional reduction via principal components analysis, is used as an input for discriminant analysis using a simple linear classifier. Automatic classification was successful for all but four samples out of 14400 classification trial configurations, representing 403200 sample classification attempts. This work establishes the principle of WTA as a basis for automatic classification of CFRP surface finish. These initial results, plus prior experience in the related application of classification of textile surface finish into five grades using WTA, suggest that WTA can be a practical tool for composite material surface finish evaluation. Planned future work will extend the evaluation of the performance of WTA to the classification of sample surface finish into additional grades of quality.

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