

Application of Wavelet Transform Method for Textile Material Feature Extraction

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1. Introduction

During textile manufacturing processing, it is vital to inspect, detect, assess and rectify defects as soon as they emerge. This is particularly important for fabric engineering and finishing, as the fabric quality directly affects the quality of their final products. In textile industry history, visual inspection and classification were common practice. The nature of traditional manual inspection was very repetitive and slow, and defects could be missed due to inspector fatigue, misjudgement and neglect, not mentioning the costs of skilled labour for the task. Automated visual inspection of texture content in digital images plays an important role in detecting textile defects for quality control. A computer based inspection system can be designed to perform 100% defect inspection objectively and consistently. It eliminates inspection error due to human frailty, and saves the costs of skilled inspectors.

Ngan, Pang and Yung (2011) reviewed automated fabric defect detection methods developed in recent years. They summarised different approaches for texture defect automatic detection, where computer vision and image processing have been the key for success. Current technology of image acquisition has resulted in inexpensive, but high quality digital images, which can be conveniently streamed to a computer for information extraction. A general procedure for an automated inspection system, as shown in Figure 1, is to process the images to be inspected and extract the features of defects. Image processing should highlight texture defects, such as the location or extension of the defects using various properties of the textures. A classifier, trained and validated by history data and defect definitions, analyses the features to objectively classify the defects. Neural networks are commonly used to combine with texture features obtained from image processing for defect classification.

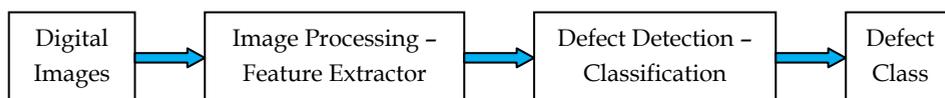


Fig. 1. A textile defect detection process

An industrial automated inspection system must operate in real-time, and produce a low false alarm rate. As computer technology develops, rapid image processing and pattern recognition can be performed quickly and inexpensively. It therefore becomes increasingly popular for computer aided feature extraction, defect detection, quality classification and decision making (Deng et al., 2011; Han & Shi, 2007; Liu et al., 2011a; Liu et al., 2011b; Mak & Peng, 2008; Mak et al., 2009; Wong et al., 2009; Zhang et al., 2010b) in the textile field. Thus, it is the trend that automated image-based inspection replaces human inspection, and improved feature extraction methods will accelerate the process. The region with a defect has a texture different from the background, which has a relatively consistent texture. Texture analysis has played an important role in the automatic visual inspection of textile surfaces. Among many methods, the wavelet transform tool has been studied for analysing images and extracting important information for improved pattern recognition (Deng et al., 2011; Han & Shi, 2007; Liu et al., 2011a; Ngan et al., 2005; Wong et al., 2009; Zhang et al., 2007, 2010b).

Human vision researchers have found that the visual cortex can be modelled as a set of independent channels, each with a particular orientation and spatial frequency tuning (Beck et al., 1987). This forms the basis for texture classification using the wavelet transform. The wavelet transform provides a solid and unified mathematical framework for the analysis and characterization of an image at different scales. It provides both time and frequency information, and has been successfully applied for textile image classification, including the application examples presented in this chapter. The wavelet transform approach appears to improve textile defect detection accuracy and real-time factory implementations.

This chapter presents some examples using wavelet transform for textile material feature extraction and classification. It first outlines how wavelet transforms together with other techniques were used in different textile defect feature extraction and classification. In particular, this chapter briefly summarises some applications examples in literature. It then presents a detailed application example to demonstrate wavelet transform feature extraction from knitted, woven, and nonwoven pilled fabric images for assessing the level of pilling. This approach is based on the multi-scale two-dimensional dual-tree complex wavelet transform to decompose the pilled fabric image with six orientations at different scales and reconstruct fabric pilling sub-images. For pilling objective rating, feature parameters are extracted from the pilling sub-images to describe pill (a small ball of fibres) properties. By using a classifier, the pilling grade can be accurately classified. Another detailed example is the use of the wavelet transform to extract animal fibre surface texture features for fibre identification. The complex wavelet transform decomposition and reconstruction are an effective way to extract cashmere and superfine merino wool fibre features, including cuticular scale height, scale shape and scale interval, which can be used for characterizing different animal fibres and subsequently classifying them.

2. Wavelet transform in textile applications

The hierarchical wavelet transform uses a family of wavelet functions and its associated scaling functions to decompose the original image into different sub-bands, providing both frequency and spatial locality. The wavelet transform method has been investigated in many situations where visual inspection is necessary in the textile industry; in particular, much research has been conducted on fabric defect automatic detection and classification.

A fabric can be seen as a manufactured planar structure made of fibres and/or yarns assembled by various means such as weaving, knitting, tufting, felting, braiding, or bonding of webs. Good quality fabric should have its designed appearance, and defects exist if the appearance was disrupted. Sari-Sarraf and Goddard (1999) described a vision-based on-loom fabric inspection system. The system processed images with a segmentation algorithm based on the concepts of 2-D discrete wavelet transform, image fusion, and the correlation dimension to attenuate the background texture and accentuate the defects. Fabric defects can be determined from the disruption of global homogeneity of the background texture of output images.

Kim and Kang (2007) used the wavelet packet frame decomposition to extract texture features followed by a Gaussian-mixture-based classifier for texture segmentation and classification. The wavelet packet frame decomposition produced texture information in all the frequency sub-channels, and the important texture was concentrated in the intermediate frequency sub-channels, which formed the feature vectors for classification. As a defect comprises a relatively small part of the fabric image, and has a texture different from the background, the advantage of this method is that homogeneous subregions can be regarded as non-defective. Each image was therefore divided into multiple non-overlapping regions for fabric texture/defect segmentation. Kim and Kang (2005) also evaluated fabric pilling based on the wavelet reconstruction scheme to attenuate the periodic background and enhance the pills using un-decimated discrete wavelet transform. Kim and Park (2006) conducted a further study on the quantification and evaluation of fabric pilling using two-dimensional and three-dimensional hybrid imaging methods. Each method was found to have its own merits.

Mak and Peng (2008), and Mak, Peng and Yiu (2009) presented a woven fabrics defect detection system, in which important fabric texture features were extracted optimally from a non-defective fabric image using a pre-trained Gabor wavelet network. The wavelet transforms were used to facilitate the construction of structuring elements in subsequent morphological processing to remove the fabric background and isolate the defects. This method does not need fabric defect information and hence is suitable for supervised defect detection.

Latif-Amet, Ertüzün, and Erçil (2000) reported a method for texture defect detection in fabric images by combining concepts from wavelet theory and co-occurrence matrices, which consider the relative occurrence frequency of pixels separated by a certain distance in a given direction. Detection of defects within the inspected texture was performed first by decomposing fabric images into sub-bands, then by partitioning the textured image into non-overlapping sub-windows and extracting the co-occurrence features, such as coarseness, contrast, homogeneity and texture complexity. They found that a particular band obtained by wavelet transformation has high discriminatory power to improve the detection performance. The wavelet transformation method extracted the particular band and discarding the others, which carried information with low discriminatory power. In general, the defect detection method that applied to the sub-band images is superior to the same method applied to the raw images.

Yang, Pang and Yung (2002) designed an adaptive wavelet-based feature extractor method to characterise fabric images with multi-scale wavelet features by using undecimated

discrete wavelet transforms. To minimise the error rate in fabric defect classification, Yang, Pang and Yung (2004) studied six wavelet transform-based feature extractors and classification methods. Compared to those commonly used wavelets, such as Haar wavelets and Daubechies wavelets, the adaptive wavelet designed with the discriminative feature extraction method largely enhanced the discriminant power of the wavelet features, which resulted in much better classification performance for the detection of fabric defects than the other discriminant training methods.

Using the wavelet transform method, Han and Shi (2007) decomposed fabric images with high frequency texture background at various levels to detect defects on images. By selecting an appropriate level at which the approximation sub-image was reconstructed, textures on the background were effectively removed. Together with an adaptive level-selecting scheme for analysing the co-occurrence matrices of the approximation sub-images, non-texture techniques can be used to resolve the texture defect detection problem. Compared with traditional frequency domain low and high pass filters, common wavelet transform methods appear to be much more effective in detecting defects due to the multi-scale analysis ability of wavelet transform.

Tsai and Hsiao (2001), and Tsai and Chiang (2003) proposed a wavelet transform method for the inspection of local defects embedded in homogeneous textured surfaces. Each wavelet decomposition level provided unique information about texture characteristics, and the energy value of the smooth sub-image was relatively low. By properly selecting the smooth sub-image or the combination of detail sub-images in different decomposition levels, backward wavelet transform constructed an efficient image with regular and repetitive texture patterns removed, and local anomalies enhanced for discriminating between defective regions and homogeneous regions. In addition, since this proposed method did not use an advance classifier such as a neural network to identify defects from textural features, it was simple and used less computational power. Tsai and Hsiao (2001) also pointed out that orthogonal wavelet bases captured local deviations in homogeneous textured surfaces better than biorthogonal bases for the application of defect detection in textured surfaces. Based on the energy distributions of wavelet coefficients, Tsai and Chiang (2003) further proposed an automatic band selection procedure to reconstruct images in the wavelet transform domain for automatically determining local defects. The band selection procedure determines the best decomposed sub-images and the number of multi-resolution levels to remove the global repetitive texture pattern, and reinstate image with local anomalies using the wavelet transforms for defect inspection in homogeneously textured images, including fabrics.

Liu *et al* (2010) combined wavelet texture analysis and learning vector quantization neural networks to classify nonwoven uniformity. Nonwoven images were decomposed to generate textural features from wavelet detail (sub-band) coefficients or sub-images at each scale with wavelet texture analysis. As the approximation sub-band coefficients usually represent the lighting or illumination variation, the high frequency sub-bands were used as the input features of the neural network for training and testing the classifier. The image classing system categorised five nonwoven uniformity grades with an overall identification accuracy of more than 87%. Liu *et al* (2011a) further studied combining wavelet energy signatures and robust Bayesian neural network for nonwoven uniformity classification. They found that when 18 features of the nonwoven images decomposed at level 3 with

wavelet transform were employed to describe the texture of nonwoven, the average accuracy was over 98% for all visual quality ratings. When 24 features of the nonwoven images decomposed at level 4 were used, the average recognition accuracy was over 99%.

Ngan *et al* (2005) applied the direct thresholding method based on wavelet transform detailed sub-images as an automated visual inspection method for defect detection on patterned fabric. They reported that the wavelet pre-processed golden image subtraction method, which can segment out the defective regions on patterned fabric effectively, provided an overall detection success rate of 96.7% from 30 defect-free images and 30 defective patterned images for one common class of patterned jacquard fabric. In this report wavelet based methods were used to extract detailed and approximation sub-images from a histogram equalized defective image. The sub-images were further processed for defect detection.

Wong *et al* (2009) presented a hybrid approach of stitching defect detection and classification in a fabric image using the wavelet transform and the back propagation neural network. The pyramid wavelet transform was employed to generate an approximation (smooth) image and detailed sub-images at a certain resolution level. The smooth sub-image has high energy concentration (more than 95%). It was further processed for image segmentation, attenuating the background texture and accentuating the anomalies. Through a neural network classifier, the combined method can identify five classes of stitching defects effectively.

Shin, Kim and Kim (2010) used a multi-level wavelet transform to extract pattern features from textile images. The pattern, colour and texture information were used as cues to predict the emotional semantics associated with the image. Although not relevant to defect detection, this work could be applied for efficient indexing annotating and searching/retrieving for diverse textile images on the Web to reduce the semantic gap between low-level features and the high-level perception of users.

Liang *et al* (2012) employed wavelet transform analysis and statistical measurement for objective and automatic evaluation of yarn surface appearance, which is related to yarn quality and traditionally was subjectively performed by visual inspection of the yarn board (parallel yarns on a black background board) in the textile industry. The wavelet transform algorithm (Discrete Wavelet Transform) was used to remove the yarn hairiness (the fibres on the periphery layer of yarn) as noise and separate yarn lines from the background during pre-processing of the yarn board images. The yarn hairiness image, on the other hand, can be reconstructed by subtracting the detected yarn lines from the original yarn image. The extraction of hairiness characteristics from a yarn surface appearance image was carried out by calculating wavelet energies under a certain decomposition level using four types of mother wavelets. Furthermore, statistical measurements extracted other important yarn quality statistics features, such as yarn diameter variation and distribution, yarn faults (neps, thin/thick places) and hairiness from the texture images. Depending on the classification tool, their experimental validation results showed their yarn grading system achieved over 90% classification accuracy for the individual yarn category and 87% for global yarn database.

Qu and Ding (2010) used 2D wavelet transform to extract the edge features of foreign fibres in lint cotton within a complex background. The wavelet transformed the original cotton luminance image to the morphology component and three detail components. By removing

the background and noise, the contaminant edge features were obtained from the detail components. Further morphological analysis differentiated the gray and colour features between foreign fibres and cotton.

3. Fabric pilling feature extraction and rating

3.1 Background

Fabric pilling refers to the formation of fibrous balls on the surface of a fabric. The pills, balled or matted particles of fibre that remain attached to the surface of the fabric, spoil the original appearance of the fabric and can cause premature wear. Normally, resistance to pilling is tested in the laboratory by standard methods that simulate accelerated wear, followed by a manual assessment of the degree of pilling based on a visual comparison of the sample with a set of standard pilling images. The degree of pilling is determined on a level ranging from 1 (very severe pilling) to 5 (no pilling). This subjective evaluation can be inconsistent and inaccurate, and pill rating may vary from one laboratory to another. Reliable and accurate objective evaluation methods are desirable for the textile industry.

Current pilling image processing methods cannot effectively eliminate the influence of fabric texture for accurate pilling prediction (Deng et al., 2011). A pillied fabric image consists of brightness variations caused by high frequency noise, randomly distributed fibres, fuzz and pills, fabric surface unevenness, and background illumination variance. Interference from fabric background texture affects the accuracy of pilling rating by directly computer-aided image classification. A pillied fabric often has distinct pills as well as ambiguous fuzz and small pills that are difficult to classify. In addition, the fabric surface ruggedness may add further difficulty to fabric pilling feature extraction and assessment. Many researchers have tried to separate the pills from the background by image analysis techniques, such as pixel-based brightness threshold (Kim, S. & Park, 2006; Konda *et al.*, 1988; Xin *et al.*, 2002) and region-based template matching (Xin et al., 2002). However, these methods can not eliminate the influence of fabric texture.

The two-dimensional discrete Fourier transform (DFT) has been used (Palmer & Wang, 2004; Tsai & Chiang, 2003; Zhang et al., 2007) to separate periodic structures in fabric image from non-periodic structures in the image (the pills) in the frequency domain. The DFT can provide only gross summary of spatial frequency information about the entire image, not location information since localized pills in nature cannot be easily identified directly by Fourier transform (Xu, 1997). The multi-scale transform can effectively analyse the images at different scales of decomposition. For example, the wavelet transform measures the image brightness variations at different scales (Kim & Kang, 2005). It has been applied to objective pilling grading in recent studies. Palmer and Wang (Palmer & Wang, 2003, 2004) suggested that the pilling intensity can be classified by the standard deviation of the horizontal detail coefficients of a two-dimensional discrete wavelet transform at one given scale. When the analysis scale closely matched the fabric texture frequency, the discrimination was the largest. More pills and fuzz on the fabric surface gave higher standard deviation of the horizontal detail coefficients. However, the energy method for pilling analysis can only give frequency information, not the location information.

Otsu (1979) proposed a simple threshold to separate pills from the background in the reconstructed smooth (approximation) sub-image at an appropriate decomposition level.

However, the approximation sub-image comprises not only pilling information but also surface unevenness and illuminative variation, which will influence the determination of the threshold.

Using the two-dimensional dual-tree complex wavelet transform, the pilled nonwoven fabric image can be decomposed to sub-images of different frequency components, and the fabric texture and the pilling information are presented in different frequency bands. The energies of the six direction detail sub-images, which capture brightness variation caused by fuzz and pills of different sizes, quantitatively characterised the pilling volume distribution at different directions and scales. By extracting the pilling sub-images, a pilled image can be reconstructed for objective pilling evaluation by the combination of pilling identification, characterization method and an appropriate neural network supervised classifier (Zhang et al., 2010b).

3.2 The complex wavelet transform

The complex wavelet transform (CWT) is an enhancement to the two-dimensional discrete wavelet transform (DWT), which yields nearly perfect reconstruction, an approximately analytic wavelet basis and directional selectiveness in two dimensions. The most important property of CWT is that it can separate more directions than the real wavelet transform. The CWT can provide six sub-images in two adjacent spectral quadrants at each level, which are oriented at angles of $\pm 15^\circ$, $\pm 45^\circ$, $\pm 75^\circ$. The orientation selectivity is clearly shown in Figure 2. The strong orientation occurs because the complex filters are asymmetric responses. They can separate positive frequencies from negative ones vertically and horizontally without aliasing positive and negative frequencies.

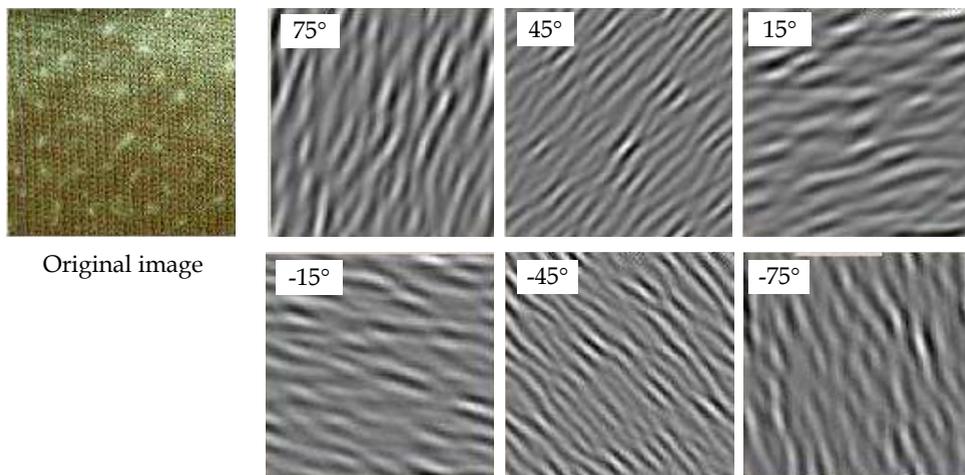


Fig. 2. 2-D impulse responses of the complex wavelets at scale 4 (6 bands at angles from $+75^\circ$ to -75°)

Figure 3 illustrates the difference between DWT and CWT. The orientation selectivity of CWT method is much clearer under each scale in comparison with the classical wavelet

DWT. There is an obvious mosaic phenomenon for Scales 5-6 sub-images from the DWT method. As a result, the reconstructed pilling image is not as clear as that from the CWT method.

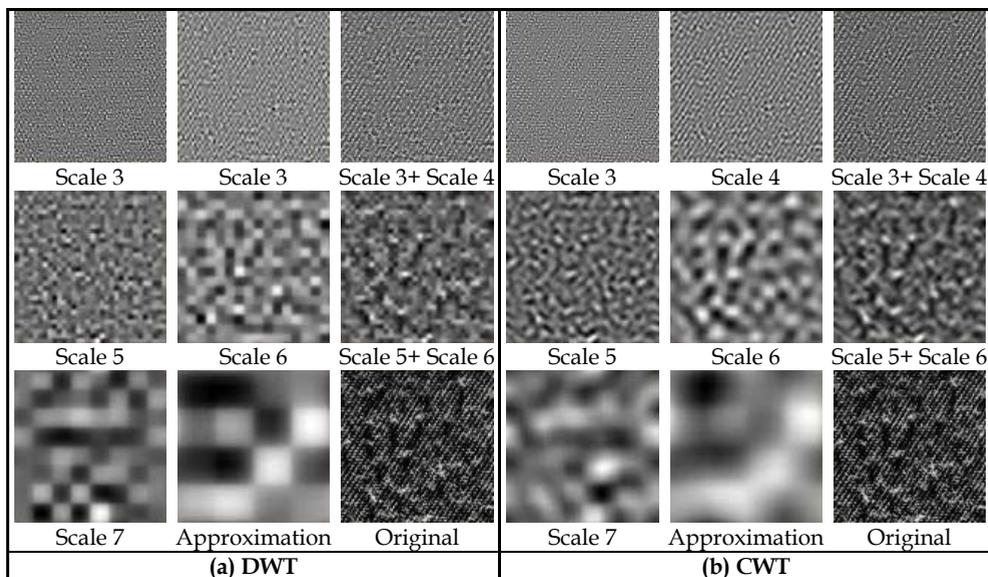


Fig. 3. Decomposition and reconstruction effects from DWT and CWT

3.3 Separate pilling from fabric background texture and wavelet reconstruction

Pills and fuzz are the vital features in the pilling rating procedure. Extracting them from the fabric image is the most important task for objective pilling assessment. To achieve this, the pilled fabric image has to be decomposed and reconstructed at different scales (see Figure 3 and Figure 4). After a fabric image is processed by CWT, the frequency band in each sub-image decreases with the decomposition scale. The attenuation of fabric patterns by CWT reconstruction is simple and effective since it can be attained by simply setting the relative detail coefficients to zero and reconstructing the image (Figure 4) without the delicate selection of the threshold and filter design. The sub-images contain information of high frequency signals, the fabric textures and the low frequency signals such as the background illuminative variation and the fabric surface unevenness, which are normally irrelevant to fabric pilling. The sub-images also contain information of fuzz and different size pills, which are the features for pilling classification. The key to pilling image reconstruction is to determine the decomposition level of original image and select appropriate Scales (sub-images) for invert complex wavelet transform (Figure 4).

The pilling feature can be determined by examining the relationship between energy and the decomposition scales. The energies of the wavelet coefficients distributed in different frequency channels at various decomposition levels provide unique information about texture characteristics. The choice of a proper decomposition scale is based on the energy relative gradient of detail sub-images in two consecutive scales. The decomposition scale for

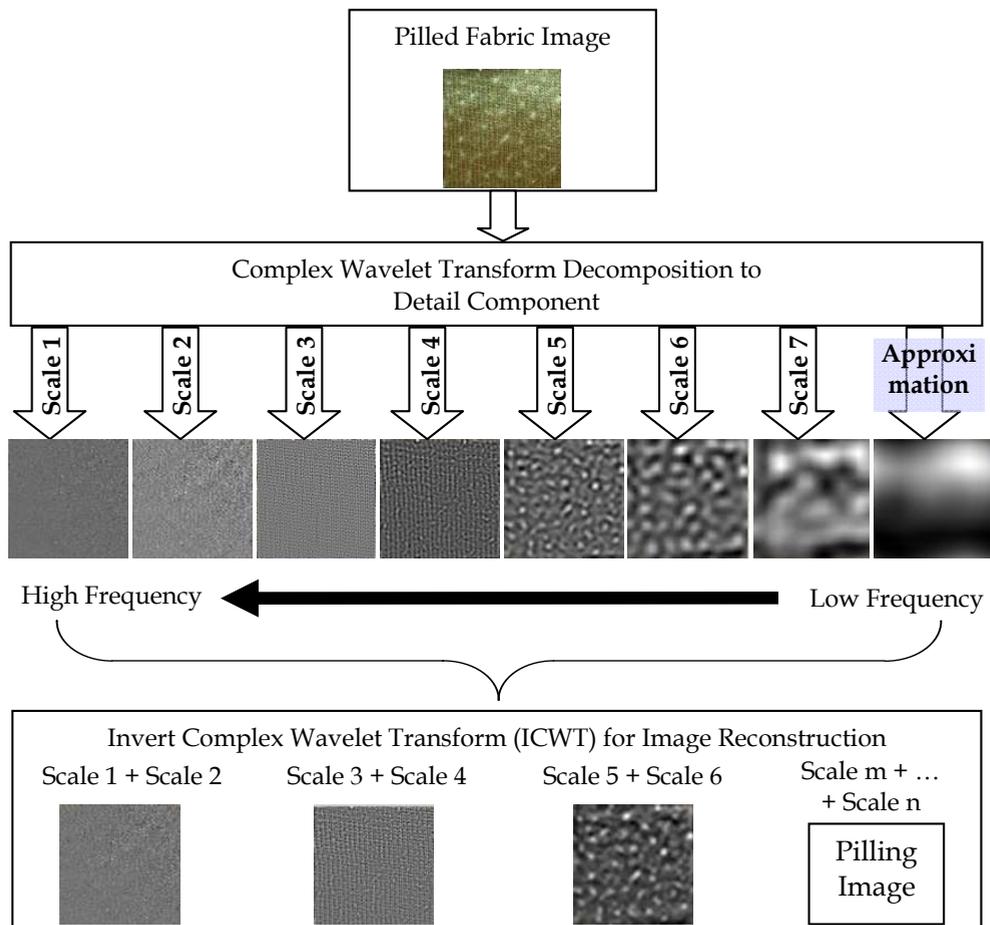


Fig. 4. Block scheme of extracting pilling image from pilled fabric image with CWT

obtaining an optimum pilling image is different for different frequency backgrounds. In general, fabrics with a rough background have more low frequency components and a greater decomposition scale than those with a fine background. By the optimum scales, the pilling information can be separated from the high-frequency noise, fabric texture, surface unevenness, and illuminative variation of the pilled fabric images (Deng et al., 2011). The examples in Figure 5 indicate that a pilled fabric can be successfully decomposed into pilling image and background image after filtering out disturbance information. The pilling image can be further converted to a binary image for feature extraction and classification.

3.4 Extraction of pilling features

Pilling features can be extracted in the spatial domain, in the frequency domain, or a combination of both frequency and spatial domains. In this example, the combination method was used.

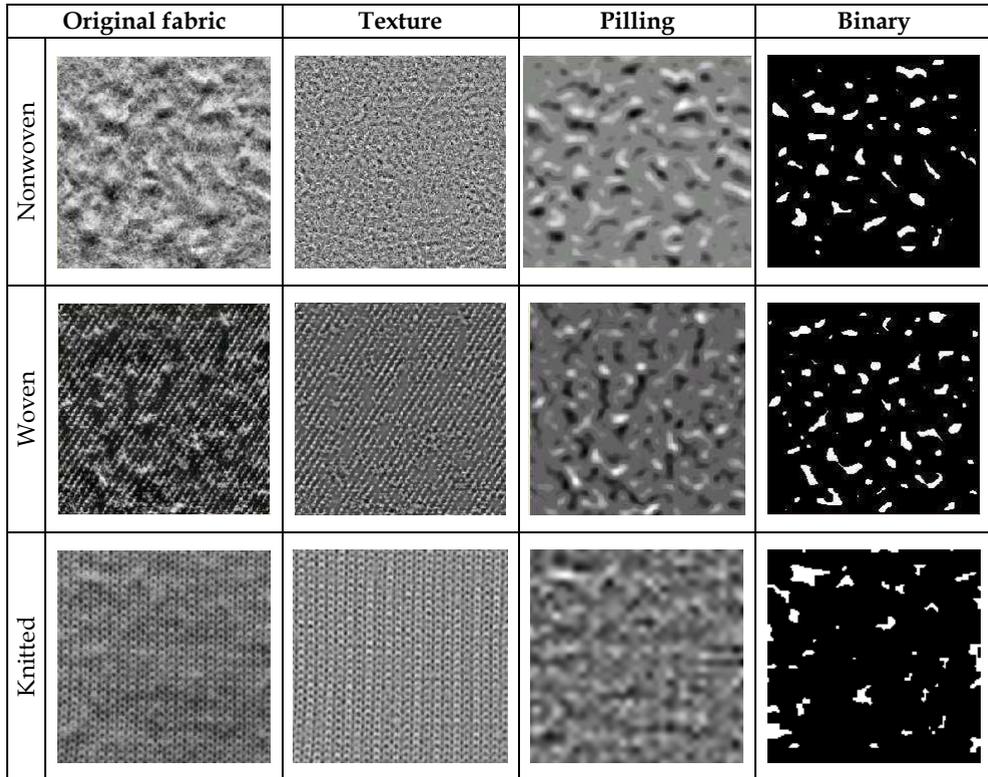


Fig. 5. Original, texture, pilling and binary images

3.4.1 Energy feature of pilling

Under lateral illumination specified in the testing standard (determination of the resistance to pilling and change of appearance of fabrics), pills can be easily differentiated from the bright (pills) to dark (background) gray value variation. This local contrast between a pill and its immediate surrounding region highlights the size and height of the pill as shown in the reconstructed images of Figure 3 and Figure 5. Larger pills lead to higher energy (the sum of the gray value squared), which must be used as one of elements of the pilling feature vector to characterize the pilling intensity and differentiate samples of different grades.

3.4.2 Shape feature of pilling

Pill density, size, and height are the main pill properties that observers use to rate the pilling grade of a tested fabric. They have a decreasing trend when the pilling grade increases, and linear and non-linear relationships have been observed in woven and knitted fabrics respectively (Kang et al., 2004; Konda et al., 1988). Therefore, pill shape feature (Figure 6a) should be used as a pilling feature vector to characterize the pilling degree. The total volume, height of pills, and standard deviation of height of pills, which can be calculated directly from the extracted gray pilling images shown in Figure 6, indicate the gray value

magnitude and deviation of sample images and thus reflect the 3D pilling information of the pillared fabric surface. The greater the value of magnitude and deviation, the more severe the fabric pilling will be. The pill number and pill area show the pilling 2D information and they can be calculated from the binary images shown in Figure 5 and Figure 6b. These feature indexes increase when fabric pilling becomes more severe, and also should be used for objective pilling rating.

3.4.3 Pill binary image

In Figure 6c, the semi-binary images are obtained by replacing those pixel gray values that are lower than a threshold with 0, but keeping the other original gray values. The binary images, however, are developed by substituting the gray value higher than the threshold with 1 and those lower than the threshold with 0. Every small area of the white region in the binary image in Figure 6b represents a pill. The pilling area parameters, including total area, standard deviation of each pill area, and the pill location deviation coefficient of pills can be used for indexing the pill shape features.

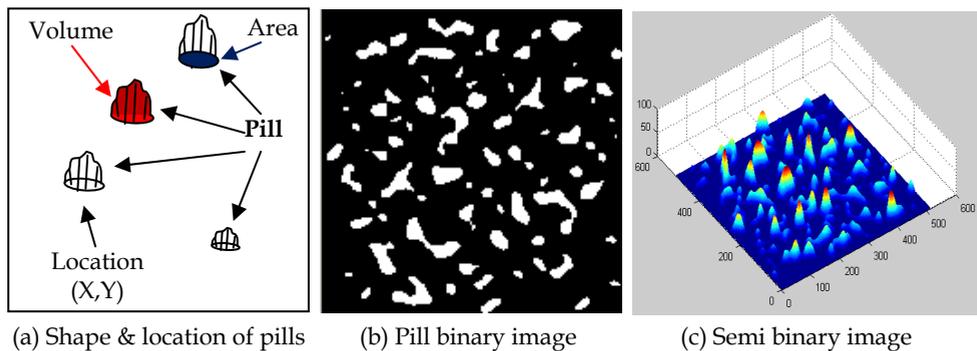


Fig. 6. Pill features and binary image

3.5 Neural network pilling objective classification

To objectively rate fabric pilling, an artificial neural network was trained to establish and generalize the relationship between pilling grade and objective pilling assessment parameters obtained through image processing. There are six input neurons corresponding to six feature indexes and five output nodes representing five pilling grades. Pilled fabric samples including woven, nonwoven and knitted fabrics were rated for fabric pilling rating according to their respective standards. All pilled fabric samples were digitised with a digital camera in the same way. Each fabric image was cropped to a 512×512 pixel 256 colour image or 512×512 pixel 8 bit gray scale image for feature extraction with wavelet transform. The features obtained included the pilling intensity and location, the energy ratio of pilling sub-image to background texture sub-image, the ratios of total pill area, the height standard deviation and volume to the image size, standard deviation of area and volume, and location deviation of pills. Information from forty different kinds of pilled fabric images was used to train the neural network and information from additional twenty pilled fabric images was used to test the trained model. The results indicated that, once the classification

rules have been established, they can be used as a tool for objective classifying pilling grades (Deng et al., 2011).

In another attempt at objective pilling rating (Zhang et al., 2010a), a large set of 203 commercially rated pilled fabric samples were imaged using a digital camera. The two-dimensional dual-tree complex wavelet transform was used to decompose and reconstruct the sample images into their single-scale detail and approximation images. From each of the 203 fabric images, a texture feature vector consisting of 12 energy features was developed. Principal component analysis revealed that 87% of the variation in the texture feature vector accounted for the first principal component, and only minor proportions of the variation distributed amongst the remaining components. Based on this result, the single transformed first principal component consisting 12 pilling texture features was used as the basis for classification. Two thirds of the fabric image sample sets were used to train the neural network. Following training, the remaining 68 image samples were presented to the neural network as test samples for automatic pilling classification. Figure 7 shows the test sample rating results from the neural network classifier and paired with the original human expert rating for the same fabric sample, ranked according to the expert pilling ratings from 1 to 5.

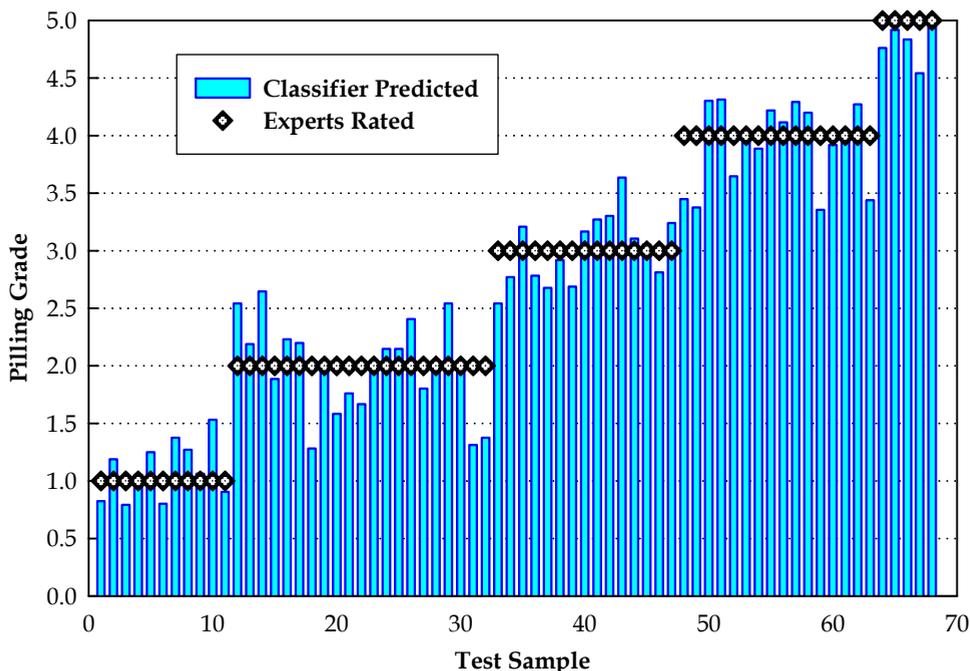


Fig. 7. Artificial neural network pilling classification results (not to a pilling grade) VS expert ratings (Data source: (Zhang et al., 2010a))

It can be seen from Figure 7 that the difference between the classifier test results and the expert measured grades for the test subset samples ranges ± 0.7 pilling grades. When the classifier test results are converted to integer values and compared to the expert ratings, only a handful of test samples were misclassified. Re-examining the misclassified samples

revealed that it was difficult to visually discern the difference between the pilling ratings of the fabric samples in question. This perhaps raises as many questions about the human expert rating ability as it does about the accuracy of the automatic classification. Many human experts of pilling rating claim the ability to interpolate half-interval pilling intensity ratings based on comparisons of fabric samples to a standard pilling image set. The ability of the neural network classifier to produce a floating point output rating can match this purported precision rating precision.

4. Identification of animal fibres with wavelet texture analysis

Cashmere is fine, downy wool growing beneath the outer hair of the Cashmere goat. Cashmere products are soft, luxurious and expensive. Cashmere and fine sheep's wool blends produces a lower cost product while exploiting the positive market perceptions associated with the luxury cashmere content. Correct labelling cashmere composition in such blends is required by law in most countries. Though cashmere and wool fibres have similar scaly surface morphology as shown in Figure 8, they may be classified through the following main cuticular scale features (Wildman, 1954):

- the form of the scale margins, e.g., smooth, crenate (scalloped) or rippled;
- the distance apart of the external margins of the scales, e.g., close, distant or near;
- the type of overall pattern, e.g., regular, irregular mosaic, waved or chevron; and scale height.

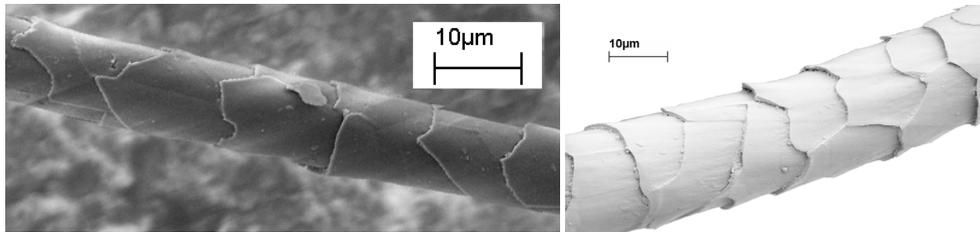


Fig. 8. SEM images of an Australian cashmere fibre (Left) and Merino wool fibre (Right)

To visually identify cashmere and sheep's wool in their blends, International Wool Textile Organisation test method (IWTO-58-00) uses scanning electron microscopic (SEM) analysis, while both American Association of Textile Chemists and Colorists Test method (20A-2000) and American Society for Testing and Materials method (D629-88) use light microscopy. However, the test accuracy that can be achieved depends largely on the operator's expertise with the microscopic appearances of different fibres. The operator-based assessment is subjective, tedious and costly. An automatic method is desirable to objectively identify animal fibres.

A computer based classification method for animal fibre identification may use combinations of microscopy and image analysis together with statistical and feature classification techniques (Robson, 1997, 2000; Robson et al., 1989; She et al., 2002). However, it is believed that wavelet texture analysis provides a reliable fibre classification system for the discrimination between cashmere fibre and the superfine merino fibre (Zhang et al., 2010a).

To demonstrate this, 13 cashmere fibre images and 15 superfine merino wool fibre images were scanned from the reference collection Cashmere Fibre Distinction Atlas (Zhang, 2005). By using the two-dimensional dual-tree complex wavelet transform, a scanned fibre image was decomposed and reconstructed into single-scale only detail and approximation images as shown in Figure 9. The lowest frequency approximation image represents the brightness variation, the lighting or illumination variation, so it is not used to generate a textural feature. The Scales 1 to 4 detail images measure the brightness variations of the cuticular scale edges at different scales/frequencies. The cuticular scale's height, shape and interval are directly related to the brightness variation at scale edges. Therefore, the texture features extracted from these detail images are intended to be a comprehensive measurement of the scale height, scale shape and scale interval.

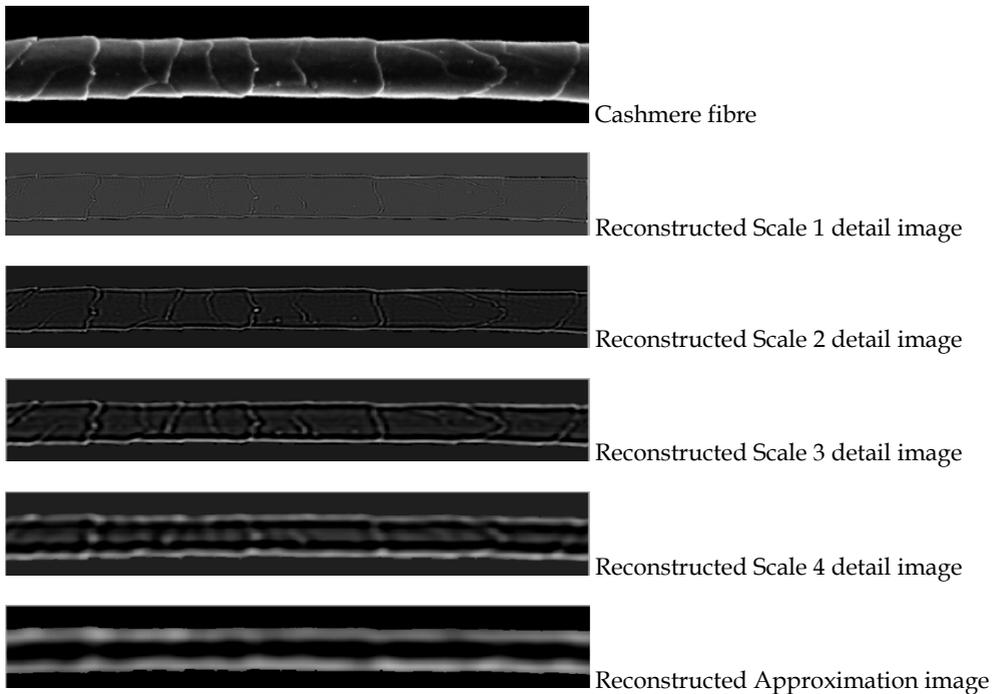


Fig. 9. Reconstructed Scale 1 to 4 detail images and approximation image

From each of the 28 fibre images, textural features were generated from the six directional detail sub-images at scales 1 to 4. A texture feature vector consisting of 24 (6 orientations \times 4 scales) energy features was developed. Principal component analysis (Krzanowski, 1988) was used to reduce the dimension of the texture feature vector, and generate a new set of variables, called principal components. Each principal component was a linear combination of the original variables. All the principal components were orthogonal to each other, so there was no redundant information. The principal components, as a whole, formed an orthogonal basis for the space of the data. Eight principal components represented more than 99.8% the actual dimensionality of the 28×24 texture feature vector data, which were used as the input of a classifier. When using 24 or 26 fibre samples as training data, the rest

as testing sets, 27 samples out of the 28 samples were correctly classified, suggesting that wavelet transform based features contained vital information for fibre identification. Visual comparison revealed that the misclassified cashmere fibre has the same range diameter of a wool fibre, and their scale characteristics such as scale frequency and scale length are difficult to discern. If a large sample size was used for classifier training, it might be possible for the classifier to pick up small details of fibre surface feature; hence the accuracy of fibre classification could improve. With the enhanced classifier, this method could be further developed to a completely automated and objective system for animal fibre identification.

5. Summary

This chapter presents selected examples of textile related applications using the wavelet transform method, which extracts surface texture features for objective defect identification and quality classification. Wavelet transform is often used together with other methods to create a process that can best identify the required features. The general procedure for an automated inspection/classification system is to first process the digital images to be inspected and extract the features of significant for highlighting defects in the original image or key identification parameters. Then, a classifier, trained and validated by history experimental data and vector definitions, analyses the features to objectively classify the defects. Neural networks are commonly used to combine with texture features obtained from image processing for defect classification.

The multi-scale two-dimensional dual-tree complex wavelet transform method can effectively decompose a textile image with six orientations at different scales and reconstruct the textile background texture and defect sub-images. An energy analysis method provides important information of sub-images, which can be used to dynamically search for an optimum image decomposition scale and dynamically discriminate different features from the textile image. It has been proved that this method is an effective way to extract pilling features from pilled fabric images, which consist of noise, fabric texture, surface unevenness, and background illuminative variation. Normally, the fabric texture information is obtained from high frequency detail images and the pilling information from low frequency images. Using the complex wavelet transform, pills of different sizes can be identified by the reconstructed detail sub-images with six orientations at different scales. With the energy analysis method, the optimum decomposition scale can be obtained for the distinction between pilling and fabric texture. The energy of the sub-image is coherent with the given size and pill height that describe the pilling intensity. By using the pilling parameters and an artificial neuron network method, classification rules can be established to comprehensively evaluate knitted, woven and nonwoven pilling test images for fabric pilling, and successfully classify them into the five pilling ratings.

This chapter also demonstrates the feasibility of using wavelet texture analysis in classifying cashmere and superfine merino wool fibres. The two-dimensional dual-tree complex wavelet provides an effective way to extract features that represent cuticular scale height, scale shape and scale interval. This may provide the essential foundations to develop an objective automated system for animal fibre distinction.

It is evident that the wavelet transform method is a robust and adaptable tool that is able to produce enhanced results when integrated with other feature extraction processes. Already,

wavelet transform has been used for a number of practical purposes in the textiles industry for defect identification and surface characteristic classification, but there is still much potential for further development of more accurate detection methods and new areas of application.

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Wavelet Transforms and Their Recent Applications in Biology and Geoscience

Edited by Dr. Dumitru Baleanu

ISBN 978-953-51-0212-0

Hard cover, 298 pages

Publisher InTech

Published online 02, March, 2012

Published in print edition March, 2012

This book reports on recent applications in biology and geoscience. Among them we mention the application of wavelet transforms in the treatment of EEG signals, the dimensionality reduction of the gait recognition framework, the biometric identification and verification. The book also contains applications of the wavelet transforms in the analysis of data collected from sport and breast cancer. The denoting procedure is analyzed within wavelet transform and applied on data coming from real world applications. The book ends with two important applications of the wavelet transforms in geoscience.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Lijing Wang, Zhongmin Deng and Xungai Wang (2012). Application of Wavelet Transform Method for Textile Material Feature Extraction, Wavelet Transforms and Their Recent Applications in Biology and Geoscience, Dr. Dumitru Baleanu (Ed.), ISBN: 978-953-51-0212-0, InTech, Available from:
<http://www.intechopen.com/books/wavelet-transforms-and-their-recent-applications-in-biology-and-geoscience/application-of-wavelet-transform-method-for-textile-material-feature-extraction>

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