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Objective Grading of Fabric Pilling with Wavelet Texture Analysis

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Abstract A new objective fabric pilling grading method based on wavelet texture analysis was developed. The new method created a complex texture feature vector based on the wavelet detail coefficients from all decomposition levels and horizontal, vertical and diagonal orientations, permitting a much richer and more complete representation of pilling texture in the image to be used as a basis for classification. Standard multi-factor classification techniques of principal components analysis and discriminant analysis were then used to classify the pilling samples into five pilling degrees. The preliminary investigation of the method was performed using standard pilling image sets of knitted, woven and non-woven fabrics. The results showed that this method could successfully evaluate the pilling intensity of knitted, woven and non-woven fabrics by selecting the suitable wavelet and associated analysis scale.

Key words pilling, objective evaluation, wavelet transform, texture analysis

As one of the results of fabric abrasion, the unsightly appearance of pilling can seriously compromise the fabric's acceptability for apparel. Pills are formed in four stages: fuzz formation, entanglement, growth and wear-off [1]. The fabric type is one of the most important parameters that affect pilling. Due to their loose structure, knitted fabrics fuzz and pill more than woven fabrics, while fuzz is more common for non-woven fabrics because of the presence of bonds. Usually a non-woven fabric tears long before pills form (see Figure 1(1)). Normally, resistance to pilling is tested in the laboratory by processes that simulate accelerated wear, followed by a manual assessment of the degree of pilling by an expert based on a visual comparison of the sample to a set of standard test images [2]. As this subjective evaluation can be inconsistent and inaccurate, more reliable and accurate objective evaluation methods are desirable.

Digital image-processing techniques provide one of the best solutions for the objective evaluation of fabric pilling. Many researchers have tried to separate the pills from the background by image techniques, such as pixel-based brightness (or height)-thresholding [2–10] and region-based template matching [11, 12].

The brightness value of single pixel actually depends upon the illumination conditions, color and pattern of fabrics. It is a common wisdom in computer vision and image techniques that the brightness variation is more informative than the brightness value. Although three-dimensional surface profiles obtained by using a laser-beam [10], stereovision system [6] and projected-light [4, 9] conquer those influences, the laser-beam and stereovision system employ expensive and complicated equipment. As for the projected-light system, the initial roughness of fabrics, damage

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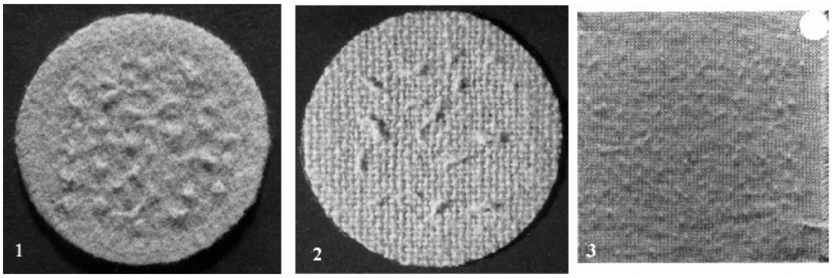

Figure 1 WoolMark® standard pilling test images from (1) SM 50 blanket set; (2) SM 50 plain set; (3) SM 54 lambswool set.

caused after pilling and the presence of fuzz make the detection of the boundary line (i.e. the height threshold) between pills and fabric base complicated.

Figure 1 shows test images with pilling intensity one (maximum pilling level) for three different fabric types – nonwoven (blanket), woven (plain) and knitted (lambswool) fabrics. The pills exhibit fractal characteristics, with features at multiple scales. It is difficult to define a priori an optimal template to match the diverse shape and size of pills.

It has been proposed in two recent studies [13, 14] that the pilling intensity can be classified by the standard deviation of the horizontal detail coefficients of two-dimensional discrete wavelet transform at one given scale. When the analysis scale closely matches the fabric texture frequency, the discrimination is the largest. This original method was based on a simple linear heuristic method, derived from observation, for the selection of the single best decomposition level on which to base future sample classification.

Here we propose a new method based on wavelet texture analysis to objectively classify fabric pilling intensity. The new method created a complex texture feature vector based on the wavelet detail coefficients from all decomposition levels and horizontal, vertical and diagonal orientations, permitting a much richer and more complete representation of pilling texture in the image to be used as a basis for classification. The use of principal components analysis (PCA) and discriminant analysis (DA) placed this method on a solid mathematical foundation.

In this paper, the theoretical basis of wavelet texture analysis is firstly explained. The choice of wavelet and analysis scale is discussed based on the analyzed images. PCA was used to find the significant components of the feature vector and then the pilling propensity of three fabric types was graded to degree 1–5 successfully by DA.

Two-dimensional Discrete Wavelet Transform

The two-dimensional discrete wavelet transform (2-D DWT) could be seen as the one-dimensional discrete wavelet transform applied sequentially along the horizontal (row) and vertical (column) axes.

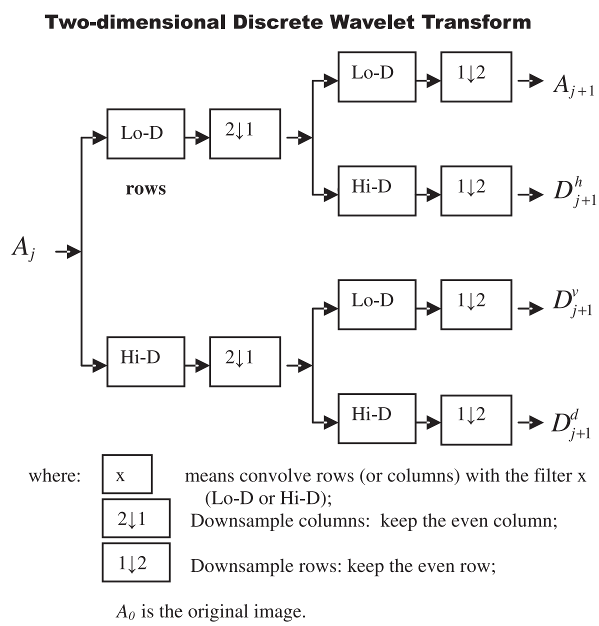

Figure 2 Decomposition of an image, A_j, into a coarser approximation sub-image, A_{j+1}, and detail sub-images D^h_{j+1}, D^v_{j+1} and D^d_{j+1}.

The algorithm is illustrated in Figure 2. We first convolved the rows of original image, A_j, with a one-dimensional low-pass filter Lo-D or band-pass filter Hi-D, retained every other column, then convolved the columns of the resulting images with Lo-D or Hi-D and retained every other row. From the discrete filters Lo-D and Hi-D, we could construct the corresponding mother wavelet function, ψ, and vice versa.

At each scale, the finer approximation sub-image, A_j, was decomposed into a coarser approximation sub-image, A_{j+1}, and detail sub-images D^h_{j+1}, D^v_{j+1} and D^d_{j+1}. For any decomposition scale number $J > 0$, an image, A_0, was completely represented by the $3J + 1$ sub-images A_J, $(D^h_j)_{-J \le j \le 1}$, $(D^v_j)_{-J \le j \le 1}$, $(D^d_j)_{-J \le j \le 1}$. A_J was the coarse approximation at scale J and corresponded to the lowest frequencies. $(D^h_j)_{-J \le j \le 1}$, $(D^v_j)_{-J \le j \le 1}$ and $(D^d_j)_{-J \le j \le 1}$ were called horizontal, vertical and diagonal detail sub-images, respectively. D^h_{j+1}, D^v_{j+1} and D^d_{j+1} were the different information between the approximation sub-images A_j and A_{j+1}. D^h_{j+1} gave the vertical high frequencies (horizontal edges), D^v_{j+1} gave the horizontal high frequencies (vertical edges) and D^d_{j+1} gave the high frequencies in both directions (diagonal edges). The wavelet decomposition measured the image brightness variations at different scales and orientations. By using a wavelet orthogonal base, this set of sub-images could be interpreted as a set of independent spatially oriented frequency channels. There was no redundant information between each scale detail sub-image [15].

Wavelet Texture Analysis

Multiscale wavelet transform methods of textural feature extraction are called wavelet texture analysis (WTA) and have been used to characterize texture and to treat the problem of texture segmentation and classification [16–19].

The basic idea of WTA is to generate textural features from wavelet detail coefficients or sub-images at each scale. The approximation sub-image usually represents the lighting or illumination variation, so it is generally not included as a textural feature. The normalized energy of the wavelet detail coefficients is defined as:

$$E_{jk} = \frac{1}{M \times N}\sum_{m,n}^{M,N}(cD_j^k(m,n))^2 \quad (-J \le j \le 1, k = h, v, d) \quad (1)$$

where $M \times N$ is the size of the sub-image. When these energies are employed as elements of the textural feature vector, it is called the wavelet energy signature [19]. As the mean values of detail coefficients are equal to zero [18], the normalized wavelet energy signatures are equal to the variances of the wavelet detail coefficients.

The wavelet packet energy signature is also used in texture classification [17, 20]. However, the wavelet packet transform is more natural and effective for textures which have a dominant middle frequency channel. For pilling images with energy concentrated in the low frequency channels, the conventional wavelet transform is more suitable.

Application to the Pilling Image Grading

In the visual evaluation, observers rated the pilling of a fabric by comparing pill properties, such as pill numbers, area and density, to those of the visual standard. The intensity of fuzz and pills, which was related to the five degrees of observer-assessed pilling intensity, changed the fabric surface texture correspondingly. The fabric texture (in non-woven fabrics, the fuzz and pills appeared to be the main texture), fuzz, pills and background intensity variation usually had different space-frequency distributions.

Therefore, with the appropriate wavelet and decomposition scale, we separated the fabric texture, fuzz, pills and background intensity variation into independent sub-images by 2-D orthogonal DWT. Then the wavelet energy signature, E_{jk} $(1 \le j \le J, k = h, v, d)$, which characterized the distribution of the fabric texture, fuzz, pills and background intensity variation along the scale axis over three orientations, could be used by multivariate analysis to classify the observations. Principal components analysis transformed a set of correlated variables into a smaller set of uncorrelated variables called principal components. It is recommended as a first step prior to performing any other kinds of multivariate analysis. It can help to assess the actual dimensionality of the data [21]. Then the principal components were used as new observation variables of each pilling image. The principal component scores were used as observation vectors of DA to classify the pilling images.

Choice of Wavelet and Decomposition Scale

The feature vectors extracted from the pilling images were determined by two parameters: the analyzing wavelet and the decomposition scale. The 2-D DWT was an inner product between the image data and the wavelet; therefore, wavelet coefficients combined information about the image and the wavelet. Hence, the choice of those two parameters mainly depended on the pilling image data profiles we wanted to analyze.

In selecting a wavelet function, there were several criteria which were considered:

1) Orthogonal or Non-orthogonal

If the data at separate scales were correlated, it was difficult to know whether a similarity between the detail sub-images at different scales was due to the property of the image itself or to the intrinsic redundancy of the wavelet representation. In orthogonal wavelet analysis, the information in each detail image was independent, which was consistent with the assumption that each texture had its unique distribution of features at all scales. Orthogonal wavelet families included Daubechies (dbN), Symlets (symN) and Coiflets (coifN).

2) Shape

A common pitfall in transform analysis is to forget the presence of the transform function [22]. In order to reduce the risk that the structure of the analyzing wavelet function

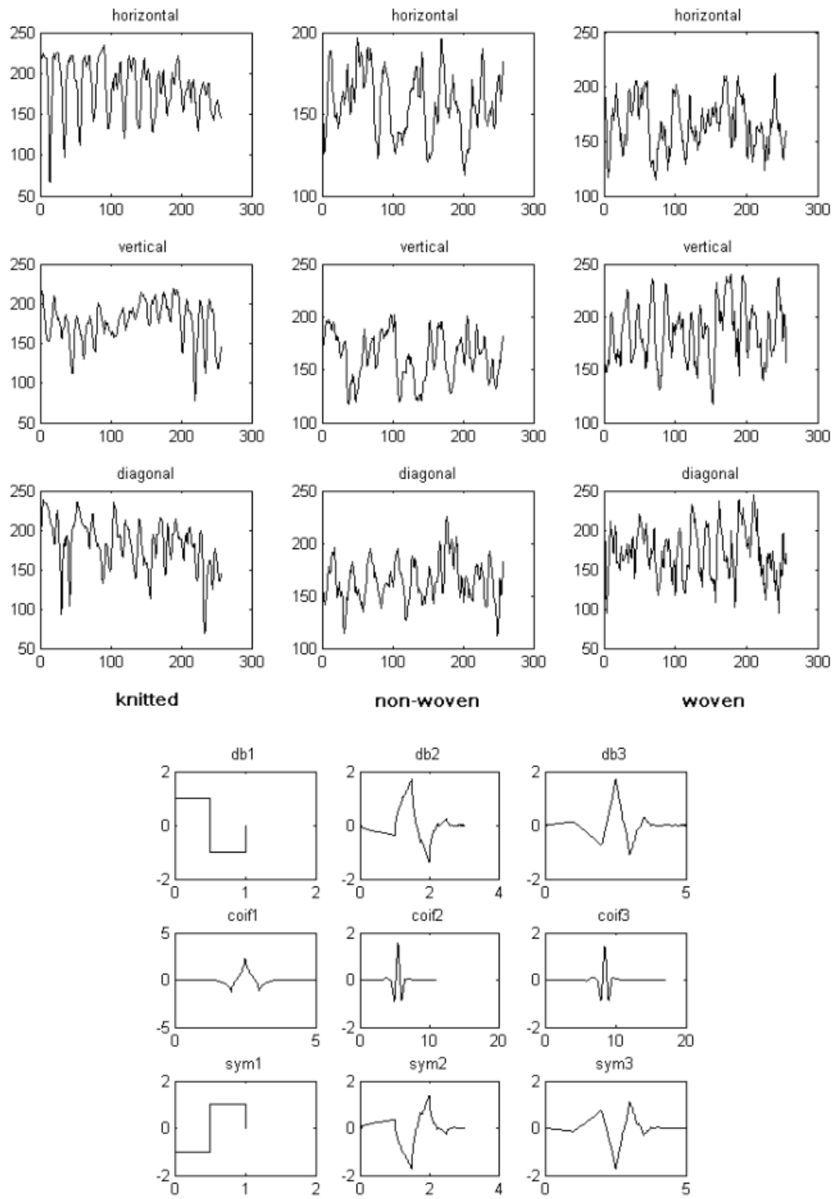

Figure 3 Typical shapes of data and analysis wavelets.

was misinterpreted as a characteristic of the image, we chose the wavelet in accordance with the intrinsic structure presented in the data. Figure 3 presents examples of the pixel data profiles (horizontal, vertical and diagonal) from three standard pilling test images and a range of wavelet function profiles. From Figure 3 we can see that horizontal, vertical and diagonal intensity profiles of non-woven, knitted and woven pilling images had a sharp peak with two nearly symmetric troughs at either side. The coifN wavelet family had shapes similar to this.

3) Decomposition Scale and Wavelet Width

The Matlab function WMAXLEV (S, Wname) calculates the maximum decomposition scales for an image of size S using wavelet Wname. The rule gives the last scale for which at least one coefficient is valid. It is given by:

$$(LW-1)*(2^{level}) < LS \tag{2}$$

where LW = the length of wavelet filter coefficients and LS = the length of image row/column [23]. When the size of an image is fixed, the shorter the filter coefficients' length, the larger the decomposition scale.

According to this rule, for a pilling image of 512×512 pixels, if the analyzing wavelet function is coif1 whose filter length is 6, the maximum decomposition scale is 6, while for coif5 whose filter length is 30, the maximum scale is only 4.

To evaluate this rule, we decomposed the pilling image taken from Figure 1(2) (see the Experimental Material section) and reconstructed the detail-only images (Figure 4(2), (4), (6) and (8)) and the corresponding last scale approximation images (Figure 4(1), (3), (5) and (7)) with wavelet coif1 and coif5. The coif5 scale 4 approximation sub-image (Figure 4(5)) still contained most pill information and background intensity change while the fabric texture has been separated (see Figure 4(6)). The coif1 scale 6 approximation image (Figure 4(1)) contained only a little pill information, which could be detected by the difference of the maximum pilling gray value between Figure 4(2) and Figure 4(4). In the case of the 512×512 pixels pilled woven fabric image, we needed to decompose it to scale 7, so that the detail coefficients could completely represent the pilling texture and the scale 7 approximation image represented the background intensity variation (see Figure 4(3) and 4(7)). The decomposition level at which the background features (intensity variation) became apparent was relative to the size/magnification of the original image. To reduce the invalid coefficients, coif1 should be selected as analysis wavelet.

Generally, when the row/column pixels of sub-images were near or equal to the number of the wavelet filter coefficients, the decomposition stopped. The size of scale 7 sub-image was 8, which was still larger than the coif1 filter length 6.

Therefore, in order to separate the pills from the background intensity variation caused by lateral illumination or fabric surface unevenness, which had a lower frequency than the pills and fabric texture, we selected coif1 and 7 as analyzing wavelet and scale.

Experimental Material

To evaluate the new method, woven, knitted and nonwoven pilling test images were used. Figures 5–7 show the 512×512 pixel samples taken from them.

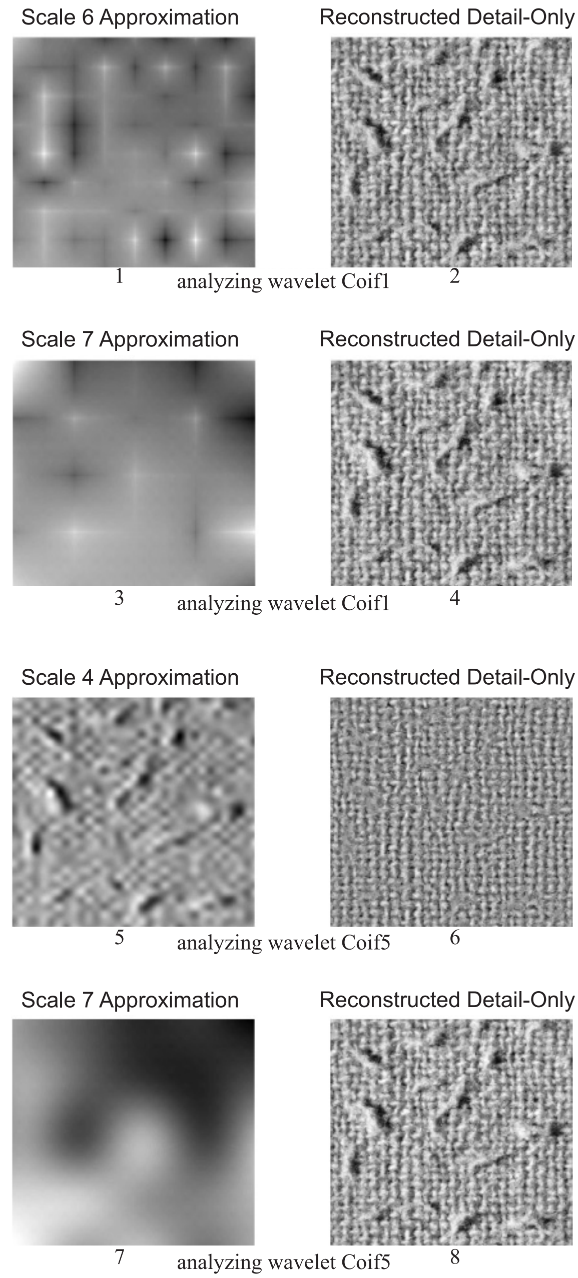

Figure 4 Approximation, reconstructed detail-only images.

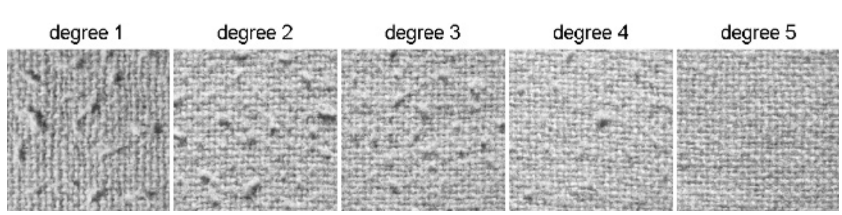

Figure 5 Woven fabrics: WoolMark SM 50 plain.

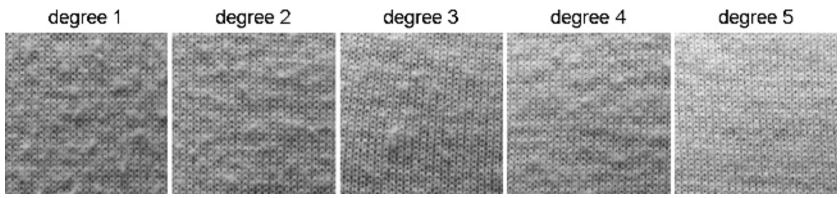

Figure 6 Knitted fabrics: WoolMark SM 54 lambswool.

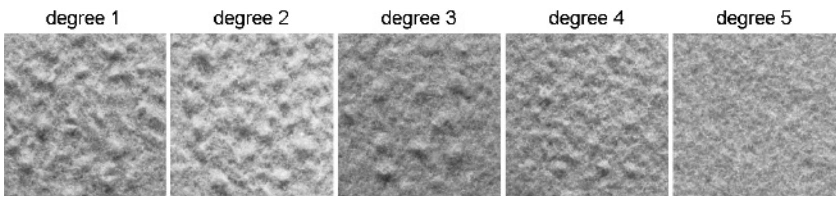

Figure 7 Non-woven fabrics: WoolMark SM 50 blanket.

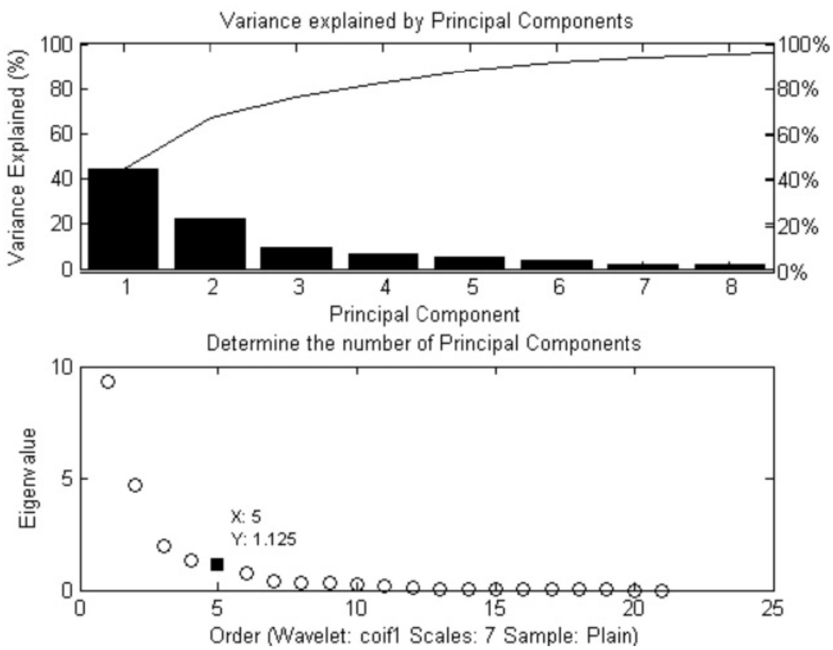

Figure 8 Determine the principal components of the wavelet energy signature.

For each pilling degree (1 to 5), we desired four sample images. The WoolMark SM 50 blanket and plain pilling test image sets provided four samples for each pilling degree. The WoolMark SM 54 lambswool pilling test image set had only one image for each pilling degree. We cut the standard image of this set into four samples without over-lapping (it was assumed that the distribution of pills was random).

Experimental Procedure

1. Each image was decomposed to 7 scales and 21 detail sub-images using the coif1 wavelet. The normalized energy of each detail sub-image became an element of the texture feature vector. There were four images of each of the five pilling intensities, so there were 20 texture feature vectors, each containing 21 elements for each set pilling test images. As noted above, each sub-image was the measurement of image gray value variants at that scale i.e. the edges of pills were distributed amongst all of the detail sub-images, so each element of the feature vector was equally important. The variance of each element was not comparable, so the raw data were standardized by dividing each element by its standard deviation.

2. By PCA, the principal components of the texture feature vector were determined. As the PCA was based on the standardized data and correlation matrix, components whose eigenvalue was greater than 1 were selected as principal components, as shown in Figure 8.

3. The principal component scores of all the 20 images were used as observation vectors of DA. Classification was performed first with all four samples used as the training set and then three of the four samples used as the training set (the remaining one was used as the observation sample). As the observation number of each class was less than the number of observation variables, we analyzed the data by pooling the variance-covariance matrices.

The image preparation, 2-D DWT, and PCA and DA were performed using the Matlab Image Processing Toolbox, Wavelet Toolbox, Statistics Toolbox, respectively [23–26].

Results and Discussion

Figure 9 shows that the scale 7 approximation sub-image reflected the background intensity variation, and the reconstructed image without the scale 7 approximation contained all the pilling/texture information of the original image, except for the uniform background lighting. The fabric texture information was mainly concentrated in the scale 1–4 detail images and the pilling information in the scale 5–7 detail images. The results in Table 1 show that sub-images that had strong relationships with the nth principal component were scale 1–4 horizontal and scale 3–5 vertical with the first principal component, scale 1–2 vertical and scale 5–6 horizontal with second, scale 1 vertical and scale 7 horizontal with third, scale 4 diagonal and scale 7 vertical with fourth, and scale 6 vertical and scale 7 horizontal with fifth. In the scale 1–4 sub-images, as the pilling intensity increased, the variance (energy) of sub-image increased as the pills introduced variations that broke the background uniform fabric structure [13]. In the scale 5–7 sub-images, the background fabric structure was filtered out and there remained the pills' information which was reflected by the energy, as shown in Figure 9. Therefore, the wavelet energy signature measured the pilling information in different scales and orientations.

In the case of Figure 8 i.e. WoolMark SM 50 plain pilling test images analyzed by coif1 wavelet to 7 decomposition scales, the first five principal components accounted for about 90 % of the variation of the original variables. PCA could effectively assess the actual dimensionality of the wavelet texture feature vector and helped the DA to produce a discriminant rule for classifying the fabric pilling in this application.

The results in Table 2 show that the 20 pilling images were successfully classified into 5 pilling degrees. The training misclassification error ratio was the percentage of observations in the training set that were misclassified. By using one sample of each pilling intensity group as an observation and the remaining three as the training set, we also got high classification accuracy, as shown in Table 3.

Table 1 PCA eigenvectors of wavelet energy signature (PCn: principal component n; Sn: scale n; H: horizontal, etc.).

	PC1	PC2	PC3	PC4	PC5
S1-H	–0.28	–0.09	0.15	–0.23	–0.23
S1-V	–0.01	–0.35	0.37	0.06	0.27
S1-D	–0.23	–0.25	0.22	0.01	–0.04
S2-H	–0.30	0.02	0.08	–0.20	–0.18
S2-V	0.18	–0.31	0.25	–0.01	0.26
S2-D	–0.22	–0.25	0.31	–0.12	–0.04
S3-H	–0.29	0.16	–0.00	–0.11	–0.09
S3-V	0.28	–0.20	0.07	–0.05	0.12
S3-D	–0.22	–0.22	0.16	–0.27	–0.02
S4-H	–0.27	0.20	0.10	0.01	0.02
S4-V	0.30	–0.13	0.01	–0.07	–0.07
S4-D	0.04	0.26	0.19	–0.41	0.38
S5-H	–0.08	0.40	0.22	–0.02	0.10
S5-V	0.30	–0.04	0.06	–0.21	0.00
S5-D	0.15	0.28	0.22	–0.45	0.05
S6-H	0.14	0.30	0.27	0.18	–0.01
S6-V	0.22	0.01	–0.00	–0.19	–0.59
S6-D	0.24	0.14	0.26	–0.07	–0.18
S7-H	0.03	–0.03	0.40	0.32	–0.40
S7-V	–0.10	0.23	0.29	0.46	0.15
S7-D	0.24	0.04	0.25	0.03	–0.16

Table 2 All four samples used as training set.

Sample type	Training set	Training misclassification error ratio
WoolMark SM50 blanket	4/each degree	0
WoolMark SM54 lambswool	4/each degree	0
WoolMark SM50 plain	4/each degree	0

Discriminant analysis is a conventional probabilistic classifier that like the maximum-likelihood classifier allocates each observation to the class with which it has the highest posterior probability of membership. Studies have shown that the accuracy of DA classification increases with training set size [27].

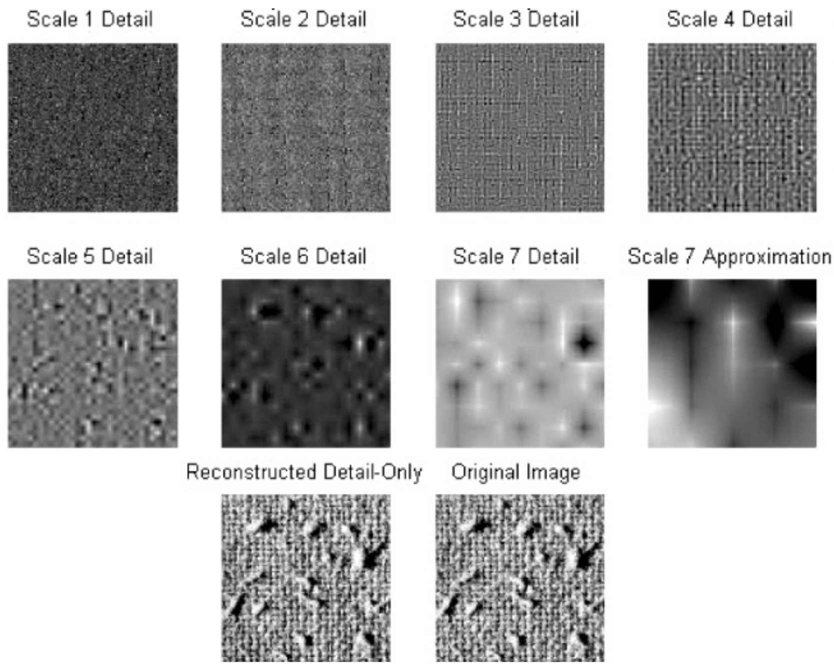

Figure 9 The reconstructed scale 1–7 detail sub-images, the scale 7 approximation image, the reconstructed detail-only image using wavelet coif1 and the original WoolMark SM 50 plain degree 1 standard pilling test image.

Table 3 Three of four samples used as training group (samples 1–4: degree 1, 5–8: degree 2, etc.).

Sample type	Training set	Samples	Training misclassification error ratio	Samples classification result
WoolMark	Remaining 3	[1 5 9 13 17]	0	[1 2 3 4 4]
SM50		[2 6 10 14 18]	0	[1 2 3 5 5]
blanket		[3 7 11 15 19]	0	[1 2 3 4 4]
		[4 8 12 16 20]	0.0667	[1 2 3 4 5]
WoolMark	Remaining 3	[1 5 9 13 17]	0	[1 2 3 4 5]
SM54		[2 6 10 14 18]	0	[1 2 3 4 5]
lambswool		[3 7 11 15 19]	0	[1 2 3 4 5]
		[4 8 12 16 20]	0	[2 2 3 2 5]
WoolMark	Remaining 3	[1 5 9 13 17]	0	[1 3 4 4 5]
SM50		[2 6 10 14 18]	0	[1 2 2 4 4]
plain		[3 7 11 15 19]	0	[3 2 2 3 5]
		[4 8 12 16 20]	0.0667	[1 3 3 4 4]

We propose that the WTA analysis method described here simulated the human visual evaluation process, in which experts observed and separated the background texture, background intensity change, fuzz and pills of a fabric, then the fuzz and pill properties were evaluated, and then after comparing with the standard images, the fabric pilling intensity was rated.

Conclusions

We have developed a new method based on wavelet texture analysis and multivariate analysis to objectively grade the pilling intensity of standard pilling test images. The grading process simulated the human visual pilling evaluation. We discussed how to select the wavelet and decomposition scale that was optimal for this application. With coif1 wavelet and decomposition scale 7, the fabric texture, fuzz, pills and background intensity variation information could be separated into horizontal, vertical and diagonal detail sub-images and approximation sub-images at different scales. The wavelet energy signature extracted from the detail sub-images gave a much richer and more complete representation of pilling texture in the image than the original published method [13]. Principal components analysis and discriminant analysis could derive the representative description of each pilling grade and use it as a discriminant rule, and the standard 20 samples could be successfully classified into 5 degrees of pilling intensity. The combination of principal components analysis and discriminant analysis permitted a sophisticated basis for classification and placed this method on a solid mathematical foundation.

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