Textile Research Journal Article

Objective Pilling Evaluation of Wool Fabrics

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Abstract An objective pilling evaluation method based on the multi-scale two-dimensional dual-tree complex wavelet transform and linear discriminant function of Bayes' Rule was developed. The surface fuzz and pills are identified from the high-frequency noise, fabric textures, fabric surface unevenness, and illuminative variation of a pilled fabric image by the two-dimensional dual-tree complex wavelet decomposition and reconstruction. The energies of the reconstructed sub-images in six spatial orientations (±15º, ±45º, ±75º) are calculated as the elements of the pilling feature vector, whose dimension is reduced by principal component analysis. A linear discriminant function of Bayes' Rule was used as a classifier to establish classification rules among the five pilling grades. A new pilled sample with the same physical construction can then be automatically assigned to one of the five pilling grades by the classification rules. A general evaluation of the proposed method was conducted using the SM50 woven, non-woven, and SM54 knitted standard pilling test image sets. The results suggest that the new method can successfully establish classification rules among the five pilling grade groups for each of the three standard pilling test image sets and should be applicable to practical objective pilling evaluation.

Key words pilling, wool fabrics, objective evaluation, complex wavelet transform

Fabric surface pilling is a dynamic process combining two phenomena: fuzzing – the protruding of fibers from the fabric surface, and pills – the persistence of formed neps at the same surface [1]. It spoils the fabric surface appearance and touch, and thus reduces the value of the product. A key element in the control of fabric pilling is the evaluation of fabric pilling propensity. Normally, a fabric is treated to form pills in a process that simulates accelerated wear, and the pilled fabric specimens are then compared with standard pilling test images to determine the pilling grade on a scale from 1 to 5 (that is, from most severe pilling to no pilling). However, the pilling evaluation procedures, relying on photographic adjuncts and human rating, can be subjective and may lack reproducibility and repeatability. This has led to the need for new objective assessment methods for fabric pilling propensity. With advances in computer and digital image techniques, the ability to objectively evaluate the pilling intensity has become feasible.

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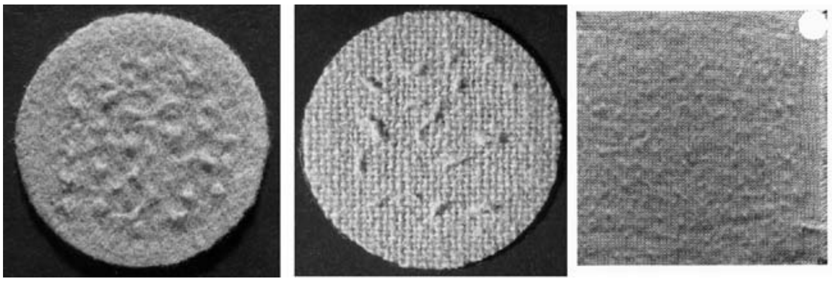


Figure 1 Standard pilling test images: WoolMark SM50 non-woven, woven, and SM54 knitted.

Many researchers have tried to identify the pills from the background texture by digital image techniques such as pixel-based brightness (or height) thresholding [2–10] and region-based template matching [11, 12].

From Figure 1, we can see that the pills exhibit fractal shapes and diverse sizes. It is impracticable to construct a matching template for the pills.

The brightness value of a single pixel actually depends upon the illuminative conditions, and pattern of fabrics. Although three-dimensional surface profiles obtained by using a laser-beam [10], stereovision systems [7], and projected light [2, 5] can reduce these disturbances, the initial roughness of fabrics (especially soft thick knitted fabrics), damages caused after pilling, and the presence of fuzz make the detection of the edge line (i.e. the height threshold) between pills and the fabric base complicated.

It is a common wisdom in computer vision and digital image techniques that the brightness variation is more informative than the brightness value. Also computer vision researchers had realized early that a multi-scale transform – that is, looking at images at different scales of resolution – is very effective for analyzing the information content of images. The wavelet transform measures the image brightness variations at different scales [13, 14]. It has been applied to objective pilling grading in recent studies [15–17].

Palmer and Wang [16, 17] suggest 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 matches the fabric texture frequency, the discrimination is the largest. However, the single scale wavelet transform can only measure the pilling intensity influence at that scale. In fact, for woven and knitted fabrics, most pilling information, which has a lower frequency than does the background period structure, is located at the higher decomposition scales (lower frequency bands).

Kim and Kang [15] suggest that the period background texture can be attenuated by the undecimated discrete wavelet transform. By using a simple thresholding proposed by Otsu [18], the pills can be separated from the background in the reconstructed smooth (approximation) sub-image at the appropriate decomposition level. However, the approximation sub-image comprises not only pilling information but also surface unevenness and illuminative variation, which will influence the detection of the threshold. Also, it is a single resolution analysis of the pills.

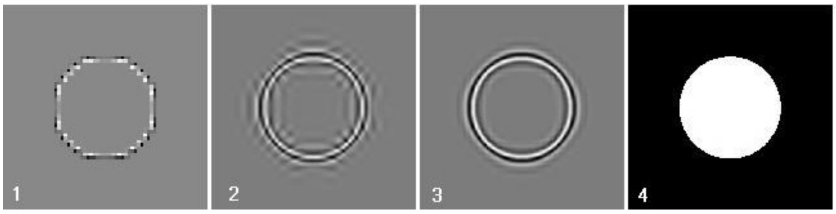
By using the advantage of a wavelet transform – the multi-resolution and directional selectiveness analysis – the diversity of fuzz and pills size and shape can be identified and characterized more accurately and effectively.

In this study, we use a multi-scale two-dimensional dual-tree complex wavelet transform (2DDTCWT) to remove the disturbance of high-frequency noise, fabric periodic texture, surface unevenness, and background illuminative variation of a pilled fabric image. The energies of the reconstructed six spatial orientated sub-images that capture the rest of the fuzz and pills information at given scales are proposed as elements of the pilling feature vector. We model each of the three standard pilling test image sets (see Figure 1) into 20 pilling feature vectors (four images for each of five grades of pilling). By using principal component analysis (PCA) to reduce the dimension of the pilling feature vector and linear discriminant function of Bayes' Rule as a classifier, classification rules can be established for each of the three sets and used to assign a similarly constructed real pilling image to one of the five pilling grades.

Dual-tree Complex Wavelet Transform

Compared to other multi-scale analyses, the wavelet transform has advantages such as: no redundant information because of the orthogonal wavelet basis; perfect reconstruction with compactly supported wavelets; and fast algorithms. However, the two-dimensional separable discrete wavelet transform (2DDWT) is only oriented vertically, horizontally, and diagonally, and fails to isolate the ±45º orientations (the reason for the checkerboard appearance as in Figure 2(1)). It is good at catching a point singularity, but is not suitable for a detecting line singularity (edge) of two-dimensional objects [19]. Perfect reconstruction is accomplished only if the detail and approximate coefficients remain unchanged. Also, there is substantial aliasing

Figure 2 Reconstructed scale-4 detail images: (1) by 2D DWT with wavelet DB1 (length 2); (2) by 2D DWT with wavelet COIF5 (length 30);(3) by 2D DTCWT with length 10 filters [20]; and (4) original image.



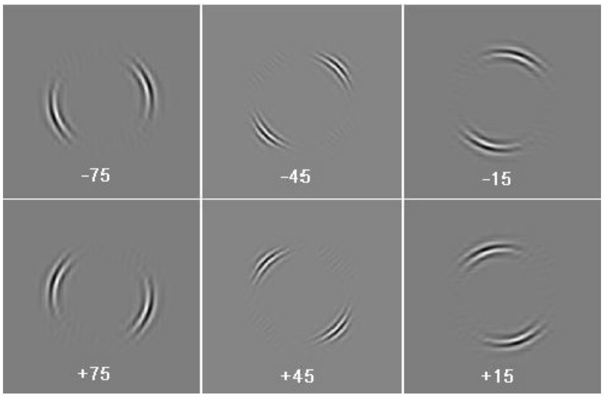


Figure 3 Reconstructed scale-4 detail sub-images with six orientations.

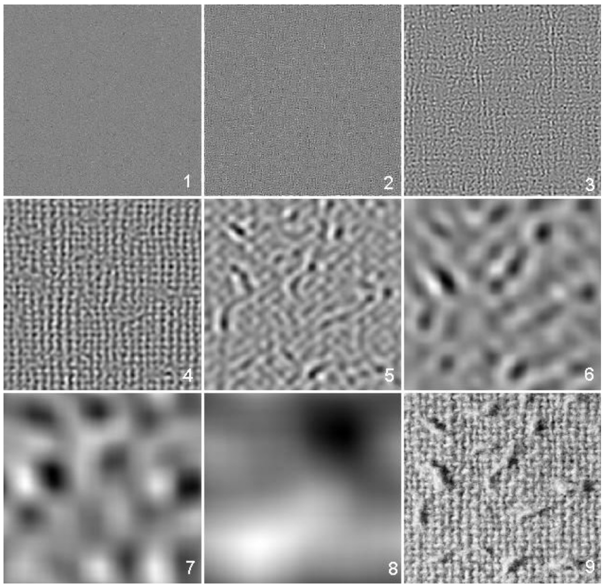


Figure 4 Reconstructed detail and approximation images ((1)–(8)) of WoolMark SM50 woven pilling grade 1 image (9) by 2DDTCWT.

(ringing artifacts in the vicinity of edges) in the one-scale reconstructed detail images (see Figure 2(2)) because of the finite impulse response filters' approximation to ideal analytic filters.

The dual-tree complex wavelet transform (DTCWT) [20] is an enhancement to the discrete wavelet transform, which yields nearly perfect reconstruction, approximate analytic wavelet basis, and directional selectiveness (±15º, ±45º, ±75º) in two dimensions (see Figure 3). The analytic wavelet is supported on only the positive half of the frequency axis, and that results in no aliasing in the one-scale reconstructed detail images (see Figure 2(3)). The six directional detail sub-images in Figure 3 form an orthogonal representation of the scale-4 detail image in Figure 2(3) and represent the edge of a two-dimensional object more efficiently.

Pills and Fuzz Identification in the Spatial Frequency Domain

A pilled fabric image consists of multi-scale brightness variation information. Figure 4 shows a pilling grade 1 (highly pilled) fabric image (Figure 4(9)) and the reconstructed detail images at scales 1–7 (Figures 4(1)–(7)) and approximation image at scale 7 (Figure 4(8)) by 2DDTCWT. The first and second scale detail images are the highest frequency noise that is normally produced in the image capture process (see Figures 4(1) and 4(2)). The last scale detail and approximation images usually include the lowest frequency parts, i.e. the fabric surface unevenness and the background illuminative variation (see Figures 4(6) and 4(7)). Scales 3–4 detail images are mainly the fabric texture edges (brightness variation) at those scales (see Figures 4(3) and 4(4)), while scales 5–6 detail images capture the edges of different size fuzz and pills (see Figures 4(5) and 4(6)). The reconstruction image without the first two scale detail images and last scale detail and approximation images (see Figure 5(2)) is almost identical to the original image (see Figures 4(9)), except its even background gray values. The reconstructed image from scales 5–6 (see Figure 5(1)) shows that it includes almost all the pilling information and excludes nearly all other disturbance information. So, the fuzz and pills are separated from the high-frequency noise, fabric texture, surface unevenness, and illuminative varia-

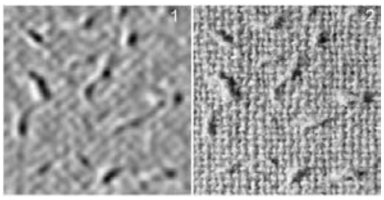


Figure 5 (1) Identified surface fuzz and pills at scales 5–6. (2) Reconstructed image at scales 3–6.

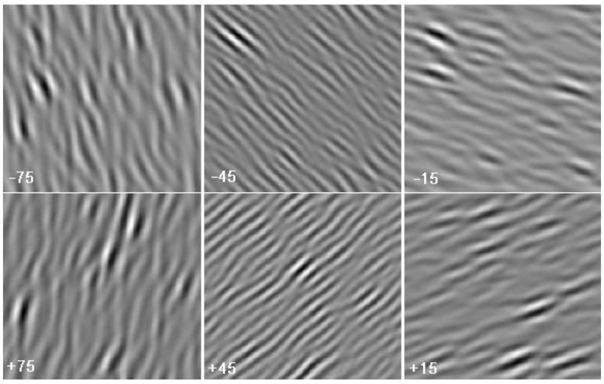


Figure 6 Reconstructed scale-5 detail sub-images in ±15°, ±45°, ±75° spatial orientations.

tion of the pilled fabric images by the scales 5 and 6 detail images.

At each of scales 5 and 6, the 2DDTCWT also measures the edges of fuzz and pills in the ±15º, ±45º, and ±75º directions on a fused and smoothed background. Figure 6 shows the six directional detail sub-images that compose the scale-5 detail image in Figure 4(5).

So, the different size fuzz and pills could be identified by the 2DDTCWT decomposition and reconstruction with six (±15º, ±45º, ±75º orientated) detail sub-images at several scales.

Pilling Feature Vector Extraction

Pilling is a dynamic process that starts with the formation of fuzz, and then the entanglement of fuzz forms pills. Both pills and fuzz should be considered in the pilling rating procedure. We propose to extract the pilling features from the sub-images that capture the fuzz and pills at different scales.

Pill density, average size, and height are the main pill properties that visual observers use to rate the pilling grade of a fabric [12]. The density, size, and height have a decreasing trend when the pilling grade increases, and linear and non-linear relationships have been observed in woven and knitted fabrics [3, 12, 15, 21].

We define the energy of a detail sub-image as

$$E_{jk} = \frac{1}{M \times N}\sum_{m,n}^{M,N}\left(D_j^k(m,n)\right)^2 \qquad (1)$$

$$(-J \le j \le 2, \quad k = \pm15°, \pm45°, \pm75°)$$

where $M \times N$ is the size of the detail sub-image, $D_j^k(m,n)$ is the pixel gray-scale value of the detail sub-image at scale j in direction k. Because the mean value of each detail sub-image is zero, the energy is equal to the standard deviation of the detail sub-image.

Most standard photograph adjuncts are taken under lateral illumination so that pills can be easily noticed from the pill (bright) shadow (dark) gray value variation. This local contrast between a pill and its surrounding region that represents the size and height of the pill is captured in the sub-images of Figure 6. The fuzz and pills introduce peak (positive) and trough (negative) gray values into the fused and smoothed background. When the number and height of the given fuzz and pills in the detail sub-image at scale j in direction k increase, the energy will also increase. The square of the gray value measures the difference between small and large pills of the same area ratio, which frequently exists between the most severe two pilling grade samples. That is, larger pills lead to higher energy.

Based on the above analysis of the reconstructed detail sub-images of the SM50 woven standard pilling images, we assume that the energy is a quantitative measurement of the pill number and height at scales 5–6. We extract the energy of each detail sub-image at scales 5 and 6 in six directions as the element of the pilling feature vector to characterize the pilling intensity. Using the same method, pilling feature vectors can be extracted from knitted and non-woven standard pilling images. For the non-woven fabric pilling image, the only difference from the woven and knitted fabrics is that there is no periodic texture as a background.

Sample Preparation

To evaluate the new method, WoolMark standard woven, knitted, and non-woven pilling test image sets were used. Figure 7 shows the original standard woven pilling test images and the 512 × 512 pixel samples cropped from them. The circular pilling area is tangential to the outside square of the sample image so that it includes all the pilling information.

For each pilling grade (1 to 5), it is desirable to have four sample images. The WoolMark SM50 woven and non-

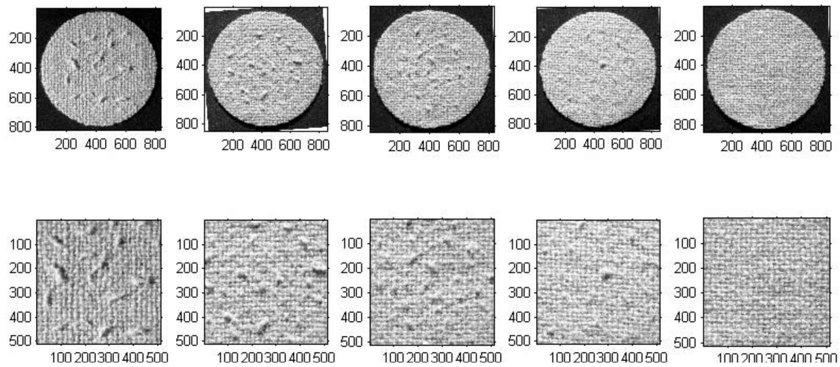


Figure 7 WoolMark SM50 woven pilling standard test images and prepared sample images.

woven pilling test images provide four images for each pilling grade. The WoolMark SM54 knitted pilling test images have only one image for each pilling degree. These standard images were cut into four samples without over-lapping, assuming that the distribution of pills is random.

Pilling Assessment

After extracting a pilling feature vector from a pilled fabric image, we can model each pilling test image set into 20 pilling feature vectors. The number of elements of a pilling feature vector represents the dimension of the data set. By principal component analysis, which is often referred to as the Karhunen–Loeve expansion in pattern recognition, new reduced dimensions or directions can be found. The reduced directions are principal components that maximize the spread of the data.

Figure 8 is a plot that compares the explained variance versus the number of principal components. We can see that the first two principal components account for 92% of the variance of the original variables. This means that the 12-dimensional data set can be projected onto the two-dimensional sub-space at the cost of losing only 8% of the information, which is probably nothing but random noise [22].

With the groups and the principal component scores as input, the "linear discriminant" function of Bayes' Rule was used as a classifier to separate the five pilling grade groups of 20 samples. The principal component scores are the pilling feature vectors' projection onto the reduced directions – the first two principal components.

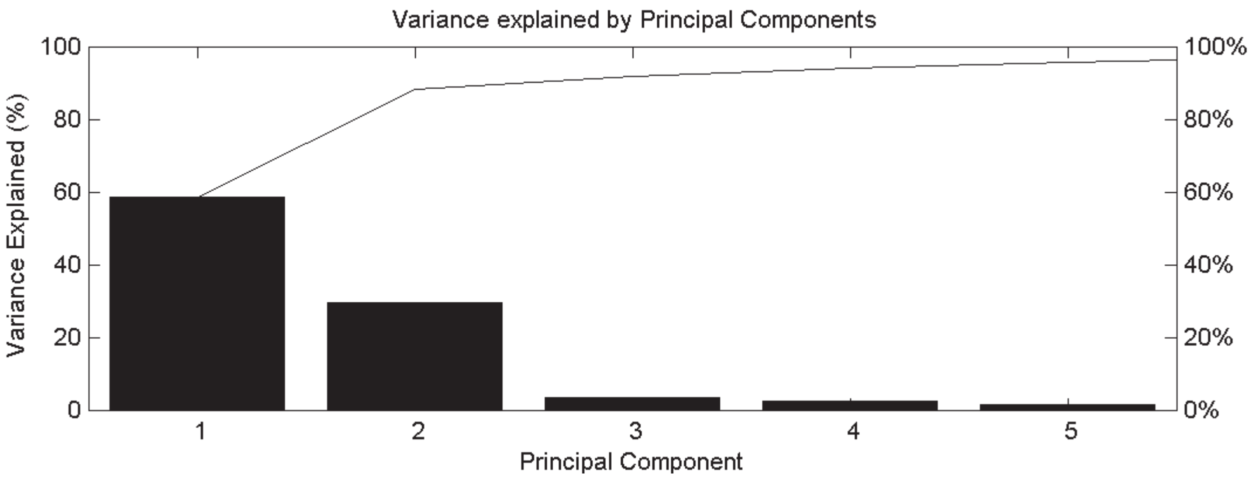


Figure 8 Variance explained versus the number of principal components.

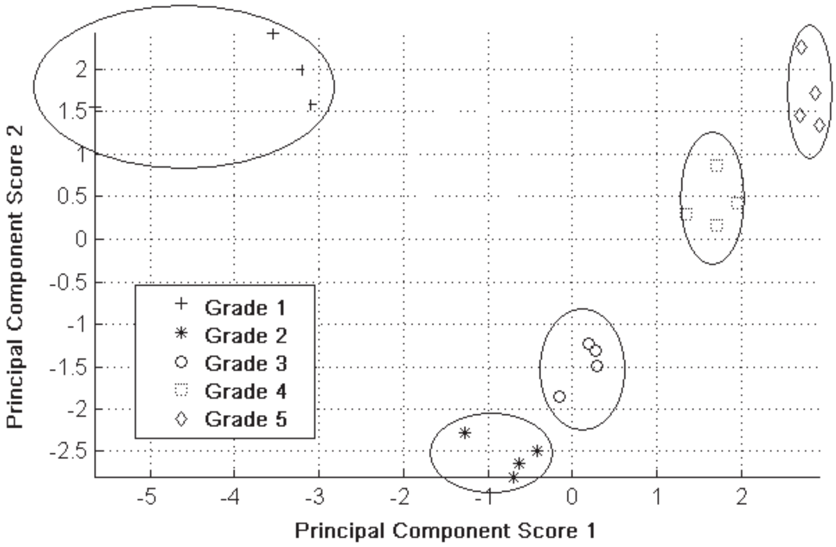


Figure 9 Plot of principal component score 1 versus 2 of the woven pilling image set.

Results

Figure 9 shows a plot of the first two principal component scores of the SM50 woven pilling test image set. It shows clear separation lines among the five pilling propensity groups and a progressive trend between the no pilling (grade 5) and the most severe pilling (grade 1) samples. The results in Table 1 show that the 20 pilling images in each standard test set are successfully classified into five pilling grades with zero training misclassification error ratio. The training misclassification error ratio is the percentage of observations in the training set that are misclassified. By using one sample as an observation and the remaining 19 samples as the training set, we also get high classification accuracy. The woven pilling set can also be successfully graded. The non-woven sample 15 of grade 4 is assigned to grade 3. The knitted sample 4 of grade 1 is classified to grade 2, and sample 10 of grade 3 to grade 4. As shown in Figure 10, the pilling propensity differences between non-woven sample 15 and the grade 3 sample, the knitted sample 4 and the grade 2 sample, as well as sample 10 and the grade 4 sample could hardly be discerned by the human eye, and the influence of the different background illuminations makes it worse. We suggest that, as our method helps to remove the disturbances, it may give a more accurate classification.

Bayes' Rule 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. It has been shown [23] that the accuracy of the Bayes' Rule classification increases with training set size, which is in accordance with our results above. The results also indicate that, once the classification rules have been established, they can be saved and used as objective references for assigning similarly constructed real samples to one of the five pilling grades.

Table 1 Discriminant classification results (samples 1–4: grade 1, samples 5–8: grade 2, etc.).

WoolMark test image set	Training set (No. of samples)	Observation (No. of samples)	Training misclassification error ratio	Observation misclassification
SM50 non-woven	20	0	0	
	19	1	0	Sample 15 of grade 4 to grade 3
SM54 knitted	20	0	0	
	19	1	0	Sample 4 of grade 1 to grade 2 Sample 10 of grade 3 to grade 4
SM50 woven	20	0	0	
	19	1	0	No misclassification

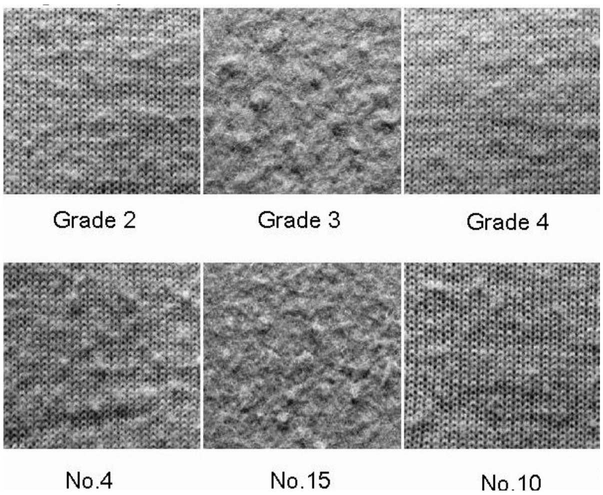


Figure 10 Misclassified samples: non-woven sample 15, knitted sample 4 and sample 10.

Conclusion

We have provided an effective way to identify the fuzz and pills from the high-frequency noise, fabric texture, surface unevenness, and background illuminative variation of a pilled fabric image by using a 2DDTCWT. Fuzz and pills of different size are captured by the reconstructed detail sub-images with six orientations at different scales. The energy of the sub-image is coherent with the given size and directional pill density and height that describe the pilling intensity, and is used as the element of the pilling feature vector. By using PCE and the linear discriminant function of Bayes' Rule, classification rules among the five grades can be established for each of the woven, knitted, and non-woven pilling test image sets. Those rules can be saved for use as objective references for objectively assigning the pilling propensity of a similarly constructed real fabric sample into one of the five pilling grades. This forms the next stage of our research work.

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