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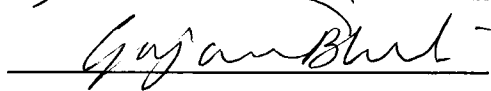
I am submitting herewith a dissertation written by Chang-Huei Hsi entitled "Image Analysis of Fabric Pills and Fuzz". I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Human Ecology.



Randall R. Bresee, Major Professor

We have read this dissertation
and recommend its acceptance:





m. A. Aert

Accepted for the Council:



Associate Vice Chancellor and
Dean of The Graduate School

***IMAGE ANALYSIS
OF
FABRIC PILLS AND FUZZ***

A Dissertation

Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Chang-Huei Hsi

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ABSTRACT

Image analysis was used to characterize pills and fuzz on fabric surfaces in order to extend measurements beyond the limit of human visual ability. Pill features were described in terms of number, size, contrast, dispersion, shape and orientation. Fuzz was described in terms of quantity, arrangement of dense-transition-sparse regions, and height.

To verify validity of the software developed for this project, pill features derived from machine vision were correlated to conventional pill ratings using human vision. Fuzz features derived from machine vision were measured for various fabric structures familiar to humans to validate machine-based measurements since no conventional human-based fuzz analysis method existed for comparison.

Factors influencing pills and fuzz growth under different abrasion conditions were examined to provide systematic information for those phenomena previously taken for granted. Relationships between pills and fuzz also were investigated with machine vision.

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PART 1

INTRODUCTION

Fabric structure and uniformity of fabric surface have always been a concern of both end-users and textile producers. Pills and fuzz are specific structural features affected by end-use and textile processing.

Pills have a negative influence on human visual perception of fabrics. Fuzz may hinder people from observing the intended luster of fabrics. During fabric processing, new fuzz development means fibers are plowed up from yarns whose structure are damaged. This problem may result in a significant change in fabric structure. For instance, fabrics may experience up to a 10% weight loss during some treatments.

People have attempted to measure pills and fuzz. Unfortunately assessment of structural features can only be done subjectively and tediously. In order to extend measurements beyond the limit of human visual ability, digital image analysis was utilized in this project to develop tools to systematically describe both pill and fuzz features objectively.

PART 2

LITERATURE REVIEW

2.1 Pills

More than 20 different test methods have been developed to evaluate pilling [1] but no method in widespread use detects pills conveniently and objectively or describes them comprehensively. Objective and detailed descriptions of pills would be expected to yield important information for understanding the effect of both textile structure and abrasion-related variables on pill formation.

Pills are usually evaluated by one of several methods. Photographic rating standards, series of photographs of pillared fabrics, have been used for subjective comparisons to assign pill ratings on an arbitrary scale which usually ranges from 5 (no pilling) to 1 (very severe pilling); alternately, series of actual pillared fabrics have been used to assign arbitrary ratings. The within laboratory precision for these techniques is said to be good (ratings fall within ± 1 scale unit) sometimes, but inter-laboratory agreement is not good. The lack of good inter-laboratory agreement among pill ratings may be associated with the fact that many pill features are integrated into a single rating, but the method of integration is unspecified so it is performed differently in different laboratories. For example, the effect of pill size or pill contrast may be more important to some evaluators than others.

A less subjective procedure used to evaluate pills involves counting the number of pills per unit fabric area; alternately, pills have been removed and weighed. Nevertheless, pill counting and weighing remain largely subjective processes because no unambiguous definition of pills is used for pill identification.

According to the American Society for Testing and Materials (ASTM), pills are “bunches or balls of entangled fibers that are held to the surface of a fabric by one or

more fibers.” Since the unaided eye possesses poor spatial resolution, one would expect to experience difficulty distinguishing low-density pills from fuzz. The definition of pills found in the Textile Institute’s Textile Terms and Definitions addresses this problem, since it adds the requirement that the density of pills must be great enough that light will not pass through them and they cast shadows. This shadow requirement is useful from a practical standpoint and has great appeal for automated image analysis since shadows normally can be readily detected if surrounded by non-shadowed image regions.

Although several instrumental methods of pill analysis have been reported, most are not based on the shadow requirement specified by the Textile Institute. One computer-based study measured laser light scattering from fibers on fabric surfaces to obtain a surface profile of the test fabric [1]. A height threshold was applied to the profile to identify fibers (pills) elevated above the base fabric. Once pills were detected, the number, projected area, and height of pills were computed. However, one would expect this technique to have difficulty distinguishing low-density pills from fuzz.

Video cameras and computer software have been used to acquire images and measure pill structure. In one study [2], a circular fluorescent tube was used to illuminate fabrics from all sides so objects evaluated above the base fabric surface such as fuzz and pills appeared bright and were differentiated from the base fabric by simple gray level thresholding. Pill measurements obtained from the thresholded image included the number of pills detected, percentage of the fabric area covered with pills, pill shape, pill perimeter, pill hairiness, and pill optical density. Again, the requirement of pill shadows is absent from this procedure.

As these studies illustrate, illumination used for pill detection has ranged from highly collimated laser light directed from a single direction to highly diffuse fluorescent light surrounding samples. It is well known that the appearance of objects and thus their detectability are affected markedly by the nature of illumination. ASTM has described a viewing chamber for pill evaluation, which consists of illumination by a single linearly shaped fluorescent tube positioned above and on one side of fabrics. This inexpensive configuration illuminates pills brightly on one side with diffused light but produces shadows within the remainder of the pill mass, so good contrast between pills and base fabric is usually observed. This lighting method presents pills to the viewer in a way that is amenable to identification using the Textile Institute's requirement of a pill shadow.

One study [3] used a somewhat similar approach to pill analysis. A single light source was located above and on one side of the fabric specimen and image analysis techniques were used to detect and describe the number and area of pills. However, a collimated rather than diffuse light source was used. This apparently precluded the necessity of image leveling, but collimated light would be expected to increase complications caused by highly textured fabrics. In addition, collimated light produces images which are less similar to the familiar images obtained with diffused light specified by ASTM. One would expect this to increase difficulty in correlating results from automated pill measurements with human-based pill grading following the familiar ASTM rating procedure.

2.2 Fuzz

Many technique have been developed to measure fuzz on yarns [4-15] but no technique has been developed to conveniently detect and describe fuzz on fabrics.

Objective and detailed descriptions of fabric fuzz would be expected to yield important information for understanding the effect of both textile structure and abrasion-related variables on fuzz formation. In addition, information about fabric fuzz would be expected to lead to increased understanding of pill formation since pills are formed from fuzz. Fuzz has not been described in geometrical terms. Several researchers observed fuzz appearance. The aim of most workers has been to relate some mechanical procedures (tenacity, bending rigidity, fatigue, etc) to pill formation. Cooke [16, 17] presented scanning electron microscopy (SEM) pictures of fiber damage and explained it in terms of fuzz fatigue.

Unfortunately, these efforts suffer from three major limitations. First, analytical techniques such as SEM severely limit the measurement area. Since abrasion is generally known to produce fuzz non-uniformly and it is not convenient to sample large fabric areas with SEM, experimental results may not be representative of the fabric being examined. The second limitation of most fuzz studies is that they ignore the influence of original fuzz and new fuzz formed during abrasion. That is, some processes such as pilling are expected to consume fuzz during pill formation and release fuzz during pill destruction. Consequently, fuzz measurements should be quantified to allow dynamic processes to be observed. The third limitation of most fuzz studies is that relatively no detailed description of fuzz is provided. This is important since fabric properties may depend on specific fuzz attributes. For example, it is possible that a minimum fuzz height is necessary to form pills. Without a tool to describe fuzz in detail, such hypotheses can not be investigated.

To extend fuzz measurements beyond these limitations, image analysis was applied in this project to obtain detailed measurement information. Hardware was developed to scan large fabric areas to generate global data to account for non-uniform fuzzing.

PART 3

DEVELOPMENT OF PILL ANALYSIS

3.1 Imaging

The basic structure of fabrics is complicated. Consequently, it is very difficult to extract a foreground feature such as pills from fabric images. To help extract pills from fabric images, a single illumination source was positioned on one side of a fabric at 30 degrees to the normal line to the fabric surface. The geometrical layout of this hardware configuration is shown in **Figure 3.1**. This configuration was selected in an attempt to imitate the pill observation chamber prescribed by ASTM Standard D3512 (Random Tumble Pilling Test Method) [18] shown in **Figure 3.2**. Since the illumination source was placed on only one side of fabrics, one side of each image was brighter than the other side. This is shown in **Figure 3.3** for a 512 pixel x 480 pixel image representing a 5.69 cm x 5.33 cm fabric area. Each pixel is equivalent to 0.11 cm x 0.11 cm. In this figure, the right side of the image can be seen to be brighter than its left side.

For any image analysis application, illumination is a major factor to be considered and several things have to be carefully calibrated. Before beginning imaging sample the first time, a photographic gray board was imaged to standardize illumination brightness. The gray board image was compared with a standard gray board image that was carefully acquired previously. Both mean brightness and brightness CV% of each quadrant region of the images were compared during calibration. Illumination can also be adjusted by comparing a pill image and a standard pill image also determined previously. Contrast, sharpness and brightness can be evaluated easily in these images. In practice, these calibrations can be easily done with the software package 'FabricPro' developed for this project.

In our laboratory, two different electronic cameras were evaluated: a DAGE-

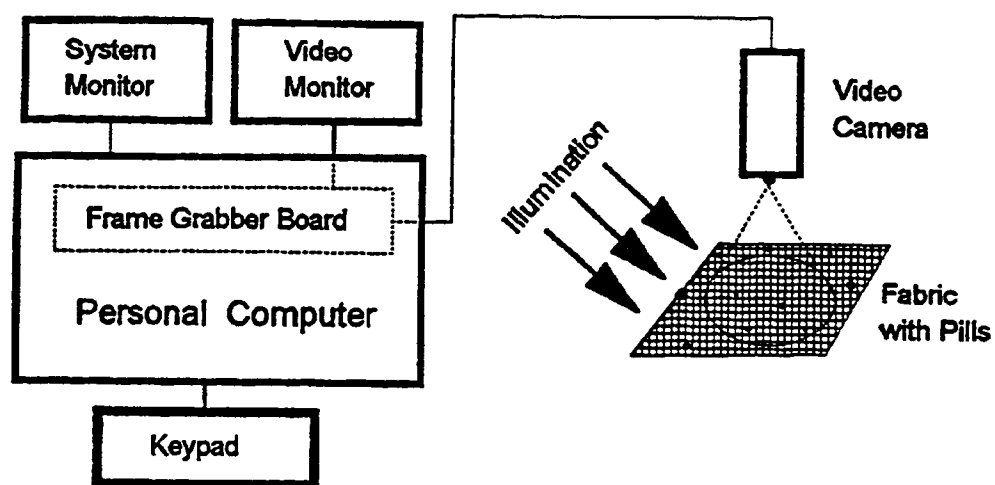


Figure 3.1 Hardware configuration for pill measurement.

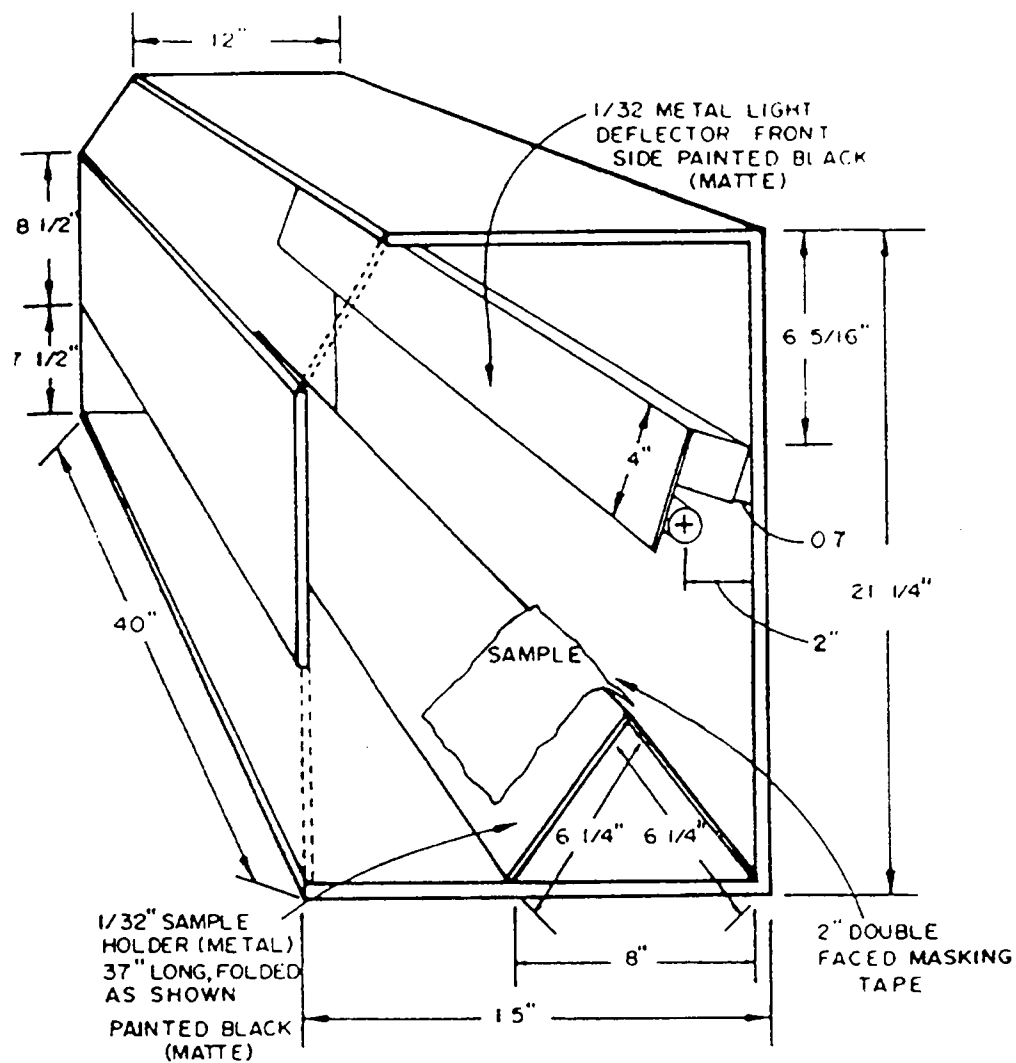


Figure 3.2 Observation chamber for ASTM Standard D3512 (Random Tumble Pilling Test Method).

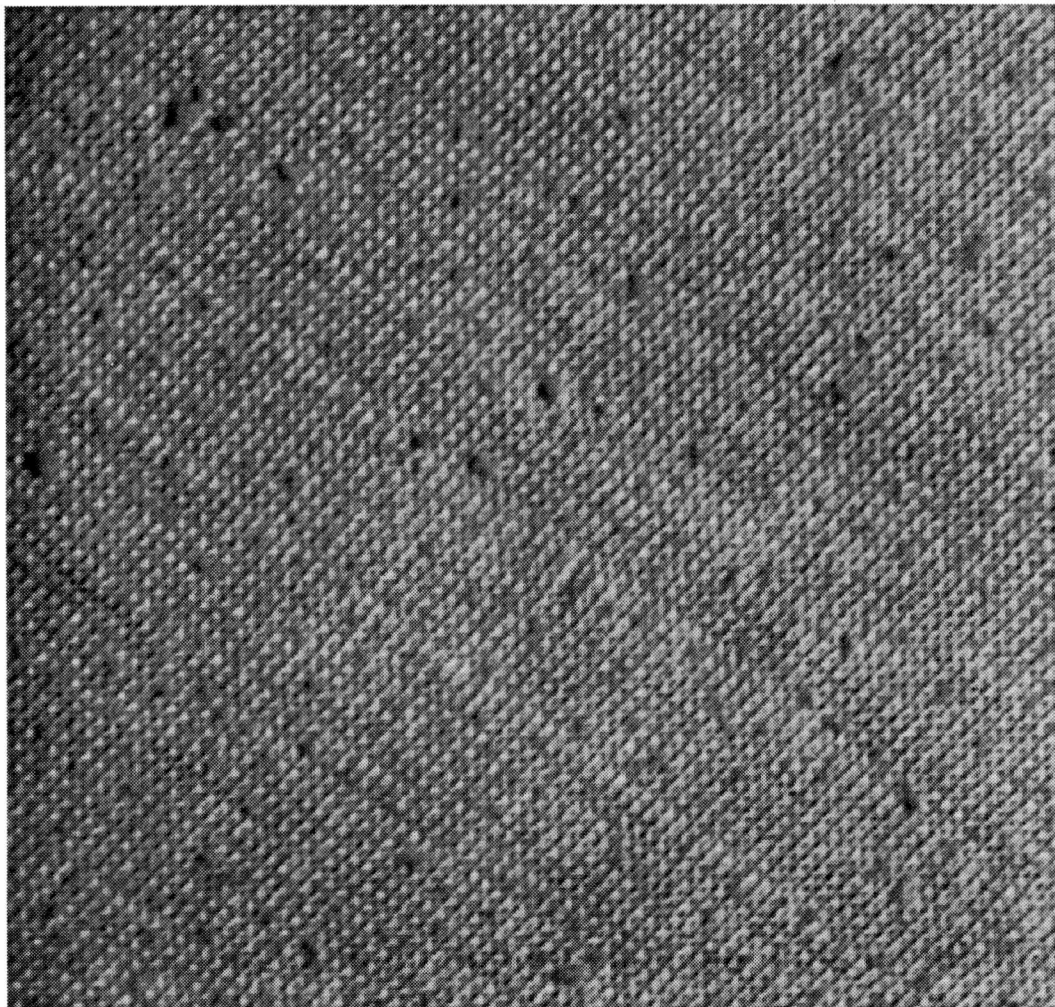


Figure 3.3 Original acquired image with pills.

MTI Series 68 vidicon camera and a PULNIX-TM\9700 CCD camera. The vidicon camera provided more satisfactory image contrast than the CCD camera as shown in **Figure 3.4**. This figure shows that the upper gray level histogram (vidicon camera) is broader than the lower histogram (CCD camera) for the same fabric and illumination conditions. The vidicon camera was selected to be the sensor for pill analysis rather than the CCD camera. Both default gain and offset settings on the camera were used to achieve more consistent contrast among different images. Deliberately enhanced contrast achieved by manual gain or offset adjustments strengthened some features from the base fabric structure which increased difficulty of pill detection.

3.2 Algorithms

An attempt was made to extract pills in the frequency domain since fabric textural background structure could be expected to be composed of low frequency signals, whereas pills could be viewed as a disturbance or high frequency addition to the base fabric signals. This approach was abandoned because of the time-consuming computation of the Fourier transform and also because numerous structural disturbances or imperfections were present on most base fabric structures. Therefore, an algorithm was developed to operate in the spatial domain.

3.2.1. Pill Detection

First, preprocessing was conducted to correct for uneven illumination. Image brightness was leveled by obtaining the local mean gray level of individual partitioned image regions and the global mean gray level of the entire image. Each local mean gray level was treated as a node of the corresponding region. Through a technique of bilinear interpolation [19], a threshold value of each pixel was calculated in relation to its four

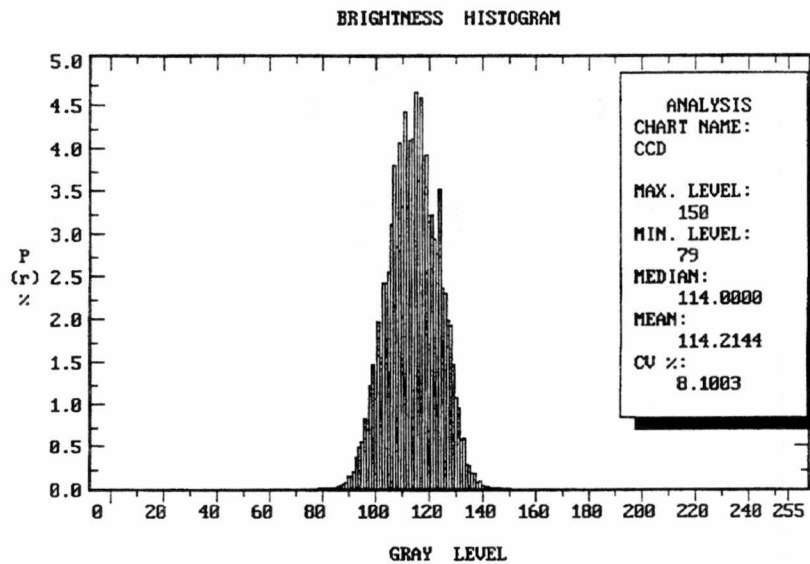
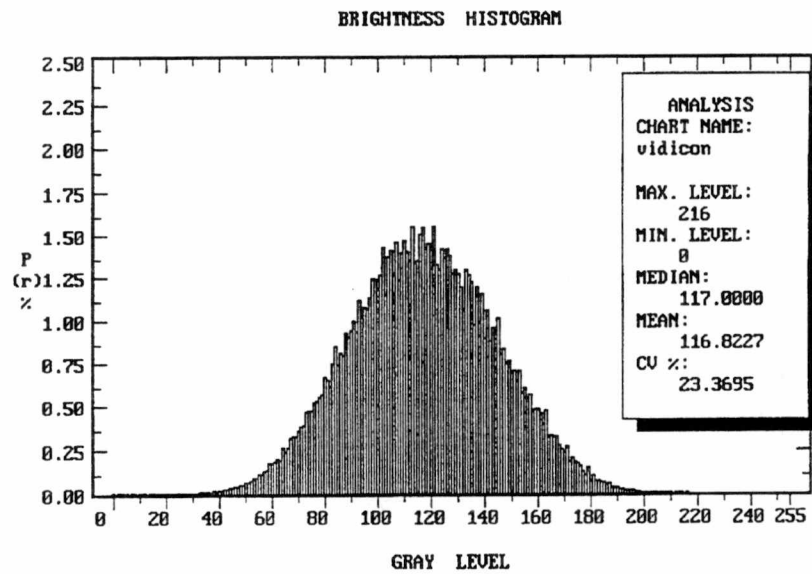


Figure 3.4 Comparison of vidicon camera (upper histogram) and CCD camera (lower histogram).

corners. The difference between this threshold and global mean was used to adjust the brightness of each pixel in the original image. Electronic noise was then reduced by filtering. To accomplish this, smoothing was performed using an averaged 3x3 kernel.

Next, image processing was implemented to extract pills from the leveled and smoothed image. A 3x3 kernel was used for high-pass filtering to enhance the blurred image resulting from smoothing. A binary image was obtained using a technique similar to that used for leveling. The only difference was that each pixel was set to black if its original pixel value was less than or equal to its corresponding threshold and was set to white if greater than its threshold. The black parts of an image were assumed to contain the features of interest (pills). However, black image parts contained too much unwanted base fabric structure.

To remove unwanted fabric background structure by the GBB algorithm developed by Huang and Bresee [20], prerequisites images were shrunk and then extended in order to reduce spatial resolution. Then images were input into the GBB algorithm, gradient-based brightness thresholding, which involves thresholding an image using both local brightness and gray level gradients. Roberts gradient of each pixel for image regions were first obtained. Local gray level means of each region were calculated by the average of the sum of maximum and minimum gradient values in their corresponding region. The interpolation mesh and threshold values were obtained as before. Pixels were set to black if original pixel values derived by extending were less than or equal to the corresponding threshold and set to white if greater than threshold. A size threshold was used to further remove small unwanted objects. Pills remained as black objects on a white background as shown in **Figure 3.5**.

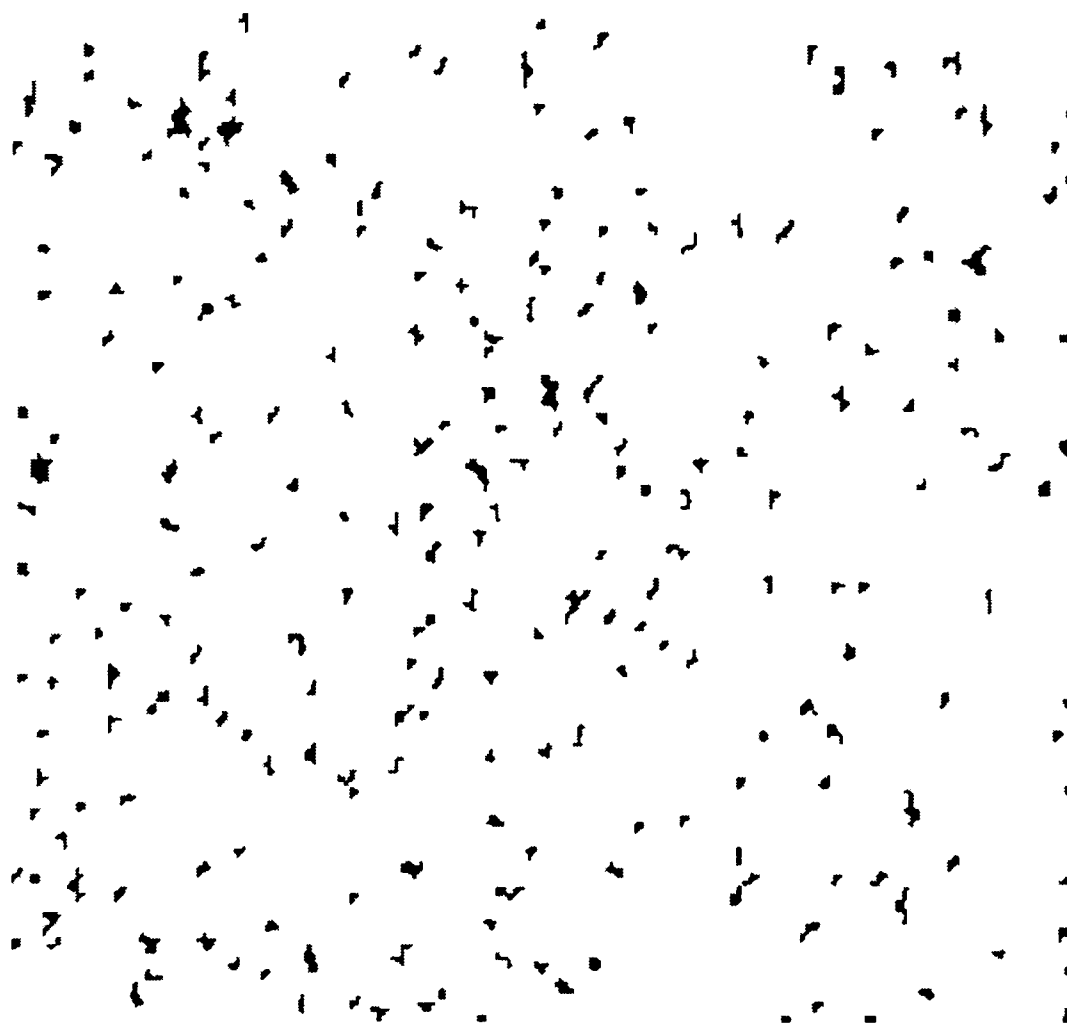


Figure 3.5 Binary image obtained with pills identified by black areas (input image was Fig. 3.3).

To allow the user to evaluate the accuracy of pill extraction, each pill was marked by an inner edge on the original image. This task was implemented by edging and negating the resultant image derived from main-processing and combining the output image with the original image. The result of this process is shown in **Figure 3.6** for the original image shown in **Figure 3.3**.

3.2.2 Pill Description

One other task was accomplished after GBB thresholding during main-processing. The location of each pill was recorded by run length encoding. This procedure is an area-based method rather than a perimeter-based method such as chain coding. Several analyses were then conducted for each pill to describe pilling in images.

First, pill number, pill size, pill contrast and pill dispersion pattern were computed. Pill size has the units of pixel. Pill contrast represents the optical height of pills and was computed from the difference between the mean gray level of a pill and its surrounding area. The units of pill contrast are gray level. Dispersion index [21] was determined by

$$Dispersion = \frac{\text{variance of pill number among all areas}}{\text{mean pill number among all areas}} \quad (1)$$

where areas are various sized partitioned regions of an image. A dispersion value of 0 (or 1) corresponds to a regular (or random) pattern of pill dispersion whereas a value $\gg 1$ corresponds to an aggregated pattern. Pill total area was computed by the product of pill number and mean pill size. Total pill volume was computed by the product of pill total area and pill contrast.

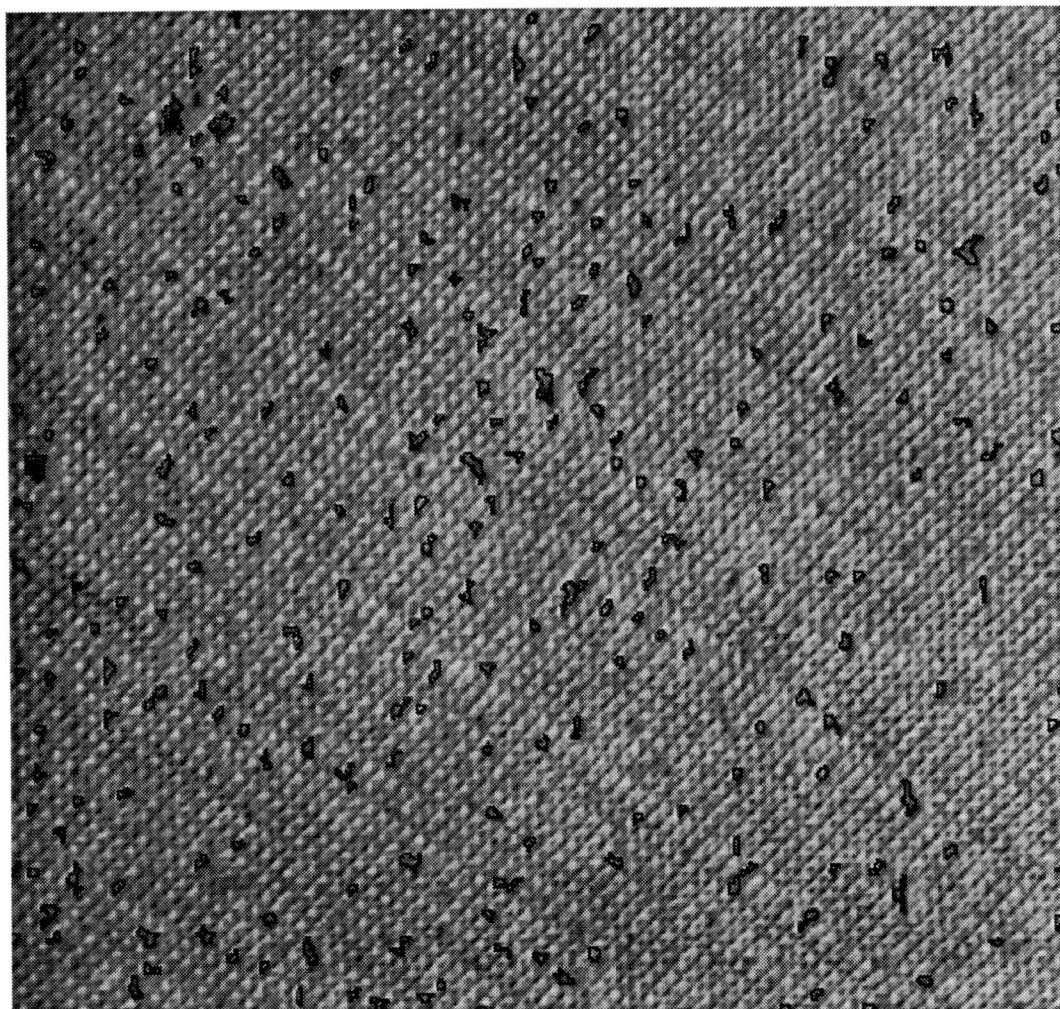


Figure 3.6 Processed image with pills identified by black edges for accuracy reference.

Shape index [22] was determined by

$$Shape = \frac{4 \text{ area}}{\pi \text{ length}^2} \quad (2)$$

where area denotes the area of a pill and length is the maximum straight distance connecting any two points on the pill perimeter. A shape value of near 0 (or 1) corresponds to linear (or round) pills.

Finally orientation index [22] was determined by

$$Orientation = \arctan \frac{(M_{xx} - M_{yy}) + R}{2 M_{xy}} \quad (3)$$

$$R = ((M_{xx} - M_{yy})^2 + 4 \cdot M_{xy}^2)^{1/2} \quad (4)$$

where M is a rotational moment computed using pill locations, and R is a quantity based on the moment. Any well-balanced object such as a round or square object does not have meaning in terms of orientation. Zero, 90 and 180 degree pill orientation angles correspond to the right, top and left side of each image, respectively.

3.3 Evaluation of Algorithm

The results of pill algorithms were evaluated two ways. First, an image of a fabric containing both abraded and unabraded regions was processed with the software to subjectively evaluate errors associated with pill detection. Second, the results of pill detection and pill description obtained from machine vision were compared with pill analysis results from conventional human vision-based pill rating.

3.3.1 Half-abraded Image

Figure 3.7 shows a fabric which was abraded only on the upper half of the image and unabraded on the lower half of the image. The edge of the sample appears at the left-

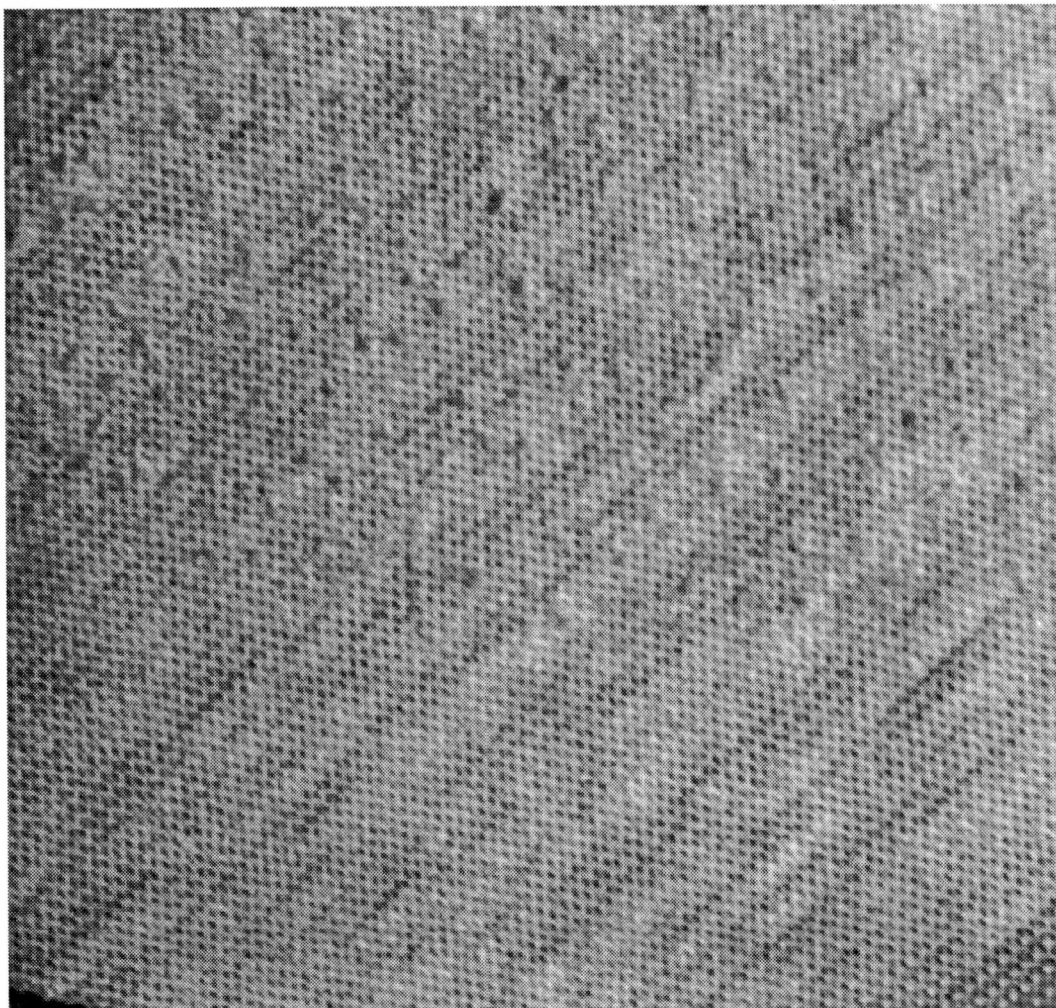


Figure 3.7 Image of fabric containing pills on the upper half and unabraded area containing no pills on the bottom half.

bottom corner of the figure. The results of processing the image of **Figure 3.7** is shown in **Figure 3.8**. This figure shows that most pills were extracted from the upper half of the image. However, a few pills were extracted from the bottom portion of the image which was unabraded and did not contain pills. This shows that some algorithm error associated with falsely detecting pills exists. However, this level of error was considered to be satisfactory.

3.3.2 Comparison with Visual Ratings

A set of 122 fabrics was accumulated to test the general reasonableness of analysis results from machine vision for fabrics that varied widely in fabric structure, fiber content and color. One image was acquired from each of the 122 fabrics and all these images were processed with the algorithm developed for this dissertation. The same 122 samples were independently graded visually by 10 different people using ASTM D3512. When the data from machine vision and human-based rating were examined, several errors could be seen. Many fabrics exhibited unreliable human-based visual ratings. This problem was associated with fabrics having loosely entangled fuzz which was considered to be pills by some people but not others. Some fabrics exhibited many errors associated with falsely detecting pills by machine vision. This problem was associated with fabrics having extensive three-dimensional texture which created shadows falsely detected to be pills. Finally, some fabrics exhibited errors associated with not detecting pills by machine vision. This problem was associated with dark colored fabrics. Of course, the use of a color rather than a monochrome imaging system would be expected to eliminate these errors. At any rate, the set of 122 fabrics were reduced to 28 by discarding samples having unreliable visual ratings (std. dev. > 0.5), high texture or

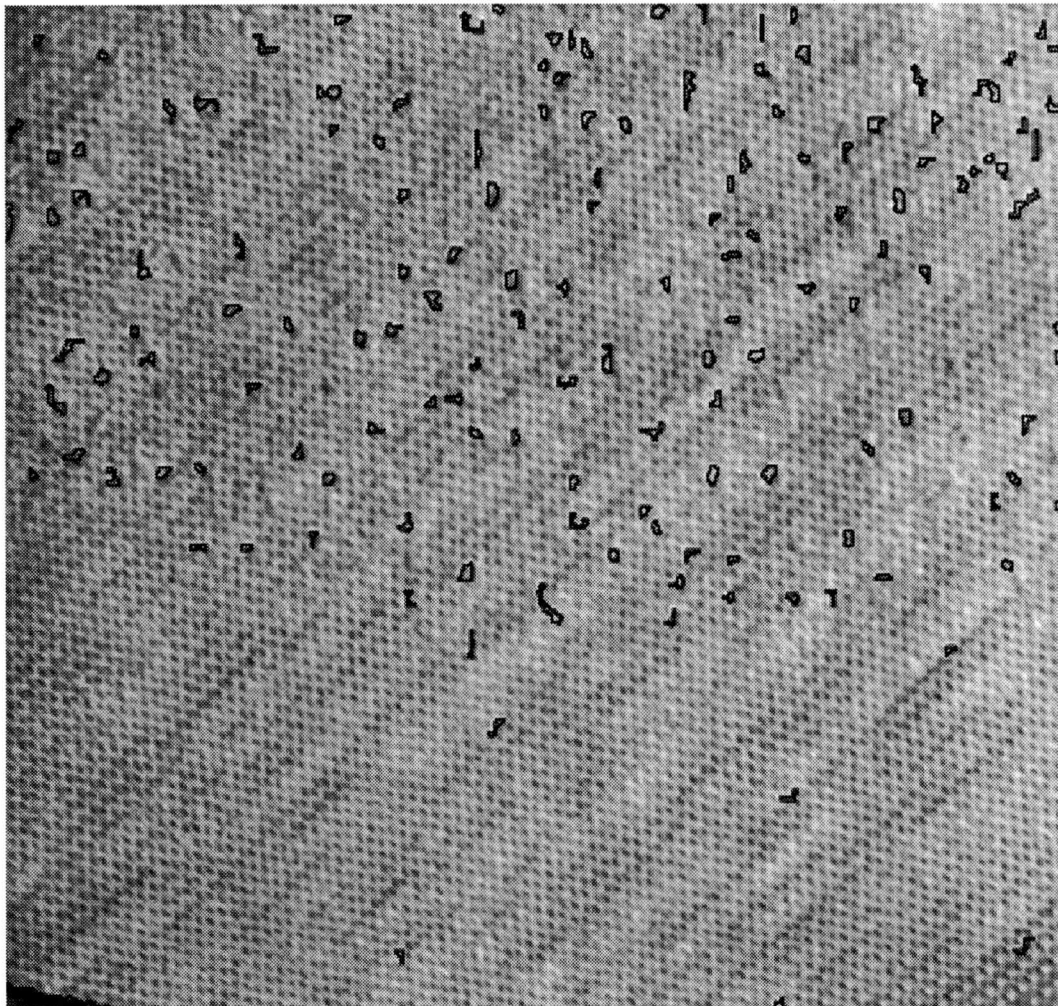


Figure 3.8 Processed image (Fig. 3.7) with pills identified by black edges.

dark color.

Correlation between individual pill features and visual ratings were evaluated for the 28 fabrics considered to possess both reliable human-based and reliable machine-based data. Multiple regression analysis was used for this task. Results of regression analysis showed that pill number, total area and total volume were best correlated to visual ratings with values of $r^2 = 0.75$, 0.74 and 0.69 , respectively. Pill size and contrast were weakly correlated with $r^2 = 0.49$ and 0.48 , respectively. Other pill features exhibited no correlation.

Among the three best-correlated features, pill number is most fundamental since it is also included in total pill area (pill number $\times$ mean pill size) and total pill volume (total pill area $\times$ pill contrast). This was no surprise since ASTM standard photographs used for human-based grading systematically vary only in pill number. Unfortunately, close examination of the ASTM photographs reveal that inconsistent illumination was used when acquiring the five grading photographs. In view of the limitations of the standard ASTM photographs, the correlations we observed between machine and human vision were considered to be satisfactory. Overall, pill detection and pill description by machine vision were considered to be reasonable within the limits of fabric texture and color discussed previously.

PART 4

DEVELOPMENT OF FUZZ ANALYSIS

4.1 Imaging

Fuzz is difficult to measure since both in- and out-of-focus regions are present in images. This problem results from the fact that the depth of field of lenses required to image individual fuzz fibers is smaller than the thickness of fabrics. Fabric samples were wrapped around metal rod connected to a motorized XY table in such a way that the fabric could be moved along X and Y axes by computer control. The general hardware configuration used for fuzz analysis is shown in **Figure 4.1**. Unlike pill measurement, a CCD camera rather than vidicon camera was used for fuzz analysis since image contrast was not as critical for fuzz analysis and the lightweight CCD camera required less hardware support structure than the substantially heavier vidicon camera. Camera selection differences resulted largely because transmitted light was used for fuzz measurement whereas reflected light was used for pill measurement.

Before mounting a fabric sample on the rod, the background illumination was compared with a standard image previously acquired. Of course, image quality also was subjectively evaluated after a fabric sample was mounted on the rod by comparing it with another standard fabric image.

Once illumination was adjusted, the camera position was adjusted to position the surface of a fabric sample at the very top of each image. Consequently, fuzz exists in the lower portion of images when longer (or higher) fuzz is present on a fabric. Different lenses can be used to acquire image with different magnification. **Figure 4.2** shows a typical image which is composed of 512 pixels x 480 pixels and represents a 1.932 mm x 1.825 mm sample area. Each pixel is equivalent to $3.77\text{E-}3$ mm x $3.80\text{E-}3$ mm.

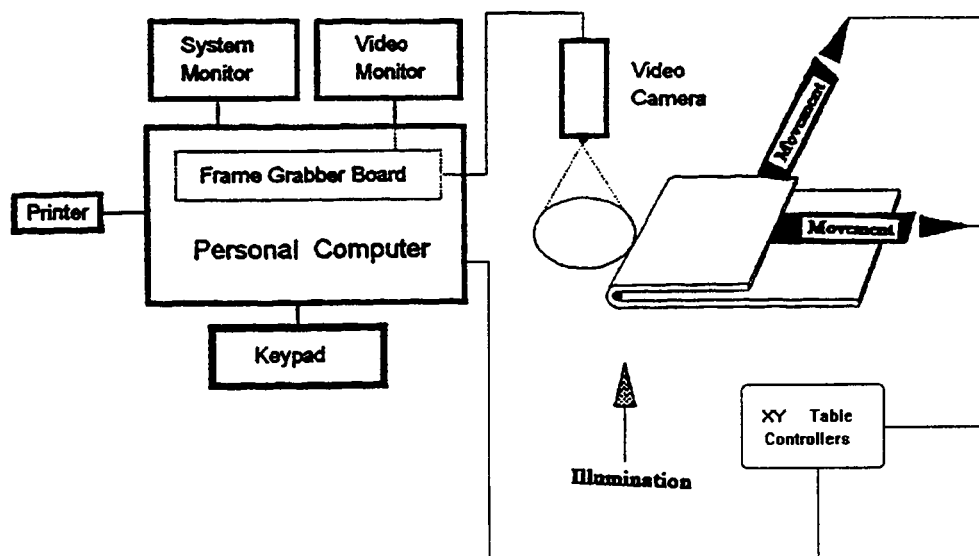


Figure 4.1 Hardware configuration for fuzz measurement.

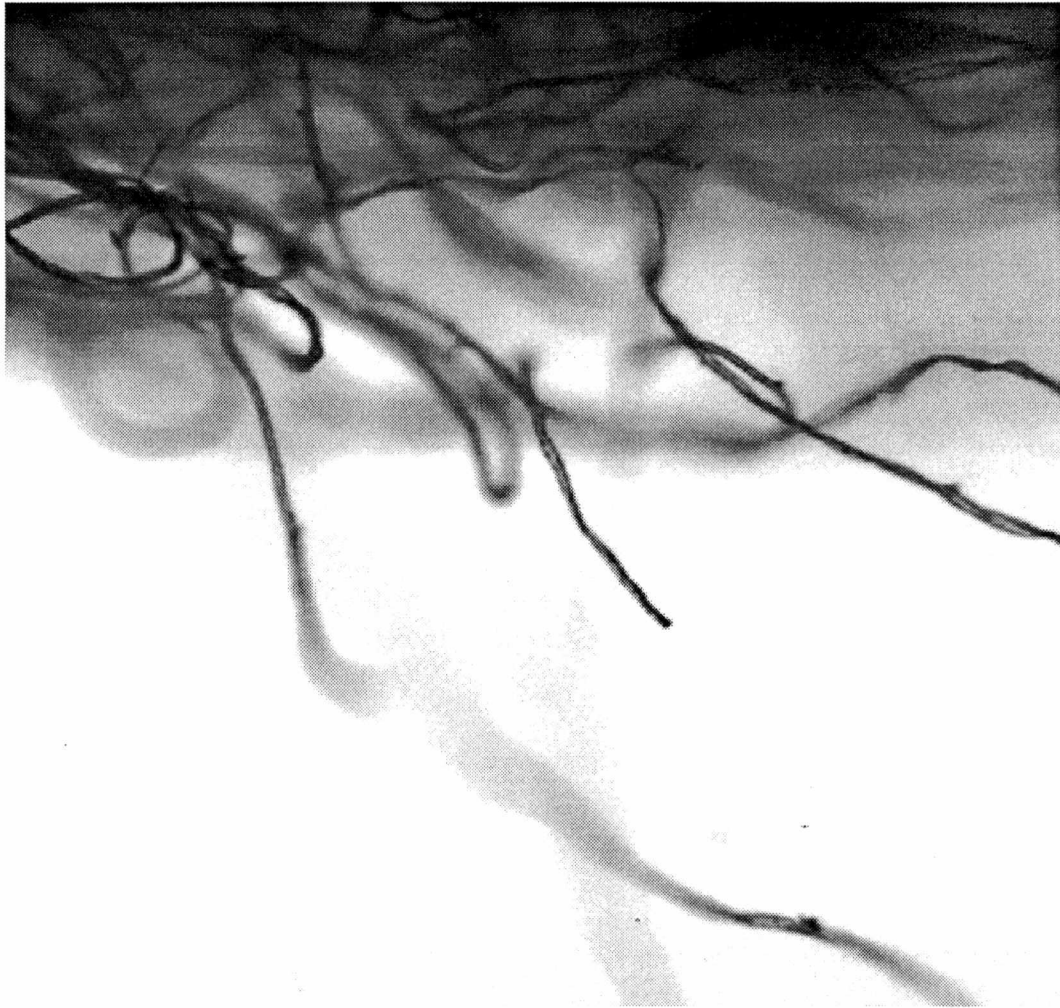


Figure 4.2 Original image with in- and out-of-focus fuzz.

4.2 Algorithms

Image restoration procedure was considered as a means to recover out-of-focus fuzz fibers. This idea was abandoned since our fuzz images contained both in-focus and out-of-focus fibers together rather than overall image blur. In addition, the point spread function of an optical system which characterizes the transformation of an input object to an output image is not easy to determine [23]. We adopted the approach of identifying out-of-focus fuzz fibers on the basis of their brighter gray levels and blurred boundaries. Fiber boundaries were difficult to define in image areas where heavy fuzz exists as seen in **Figure 4.2**. Consequently, the brighter gray levels associated with out-of-focus fibers became the image feature that we used to identify and remove out-of-focus fuzz fibers.

4.2.1. Fuzz Detection

During preprocessing, images were smoothed using an averaged 3x3 kernel to reduce electronic noise. Next, main processing was implemented to locate in-focus fuzz fibers. A dense fuzz region was located with a brightness threshold located near the darker position of the brightness histogram because a dense fuzz region was entirely covered by in-focus fuzz and was located next to the fabric surface. After thresholding, a binary image was obtained with the black image area representing the dense fuzz region and the white image area representing all other image areas. This binary image contained small isolated black (or white) spots completely surrounded by white (or black) image areas. These spots were removed or filled using a labeling algorithm [24] to simplify the contour of dense image areas.

A process we call “coarse focusing” was performed to remove unfocused image areas using a modified optimal thresholding [25] procedure applied to nondense image

areas that were identified by the labeled and original images. A transition fuzz region was identified based on the mean fuzz length in the initially trimmed nondense fuzz region. In the transition region, fuzz occupied a larger image area than the background illumination. Of course, the transition fuzz region existed next to the dense fuzz region. The remaining image areas were then defined as sparse regions. In these image areas, the background illumination occupied a larger image area than the fuzz region. The process of coarse focusing was performed a second time using modified optimal thresholding of the transition region to further remove unfocused image areas.

The previous steps removed most but not enough out-of-focus image areas. Therefore a process we call "fine focusing" was performed to further remove out-of-focus image areas. Fine focusing involved applying modified optimal thresholding to transition and then sparse fuzz regions. Thresholding during both coarse and fine focusing were the same except that the effective areas involved in thresholding were different. During coarse focusing, thresholding was performed on partial portions of the entire image. In other words, the effective thresholding area included both background illumination and fuzz image areas. During fine focusing, the effective thresholding area included only fuzz image areas. The three image regions resulting from both coarse and fine focusing the image shown in **Figure 4.2** are shown in **Figure 4.3**. In this figure, the dense fuzz region is identified by dark gray whereas the transition fuzz region is identified by light gray and the sparse fuzz region is identified by black.

To allow the user to evaluate the reasonableness of fuzz extraction, in-focus fibers were marked by an inner edge on the original image. This task was accomplished by edging and negating the resultant image derived from main processing and combining the

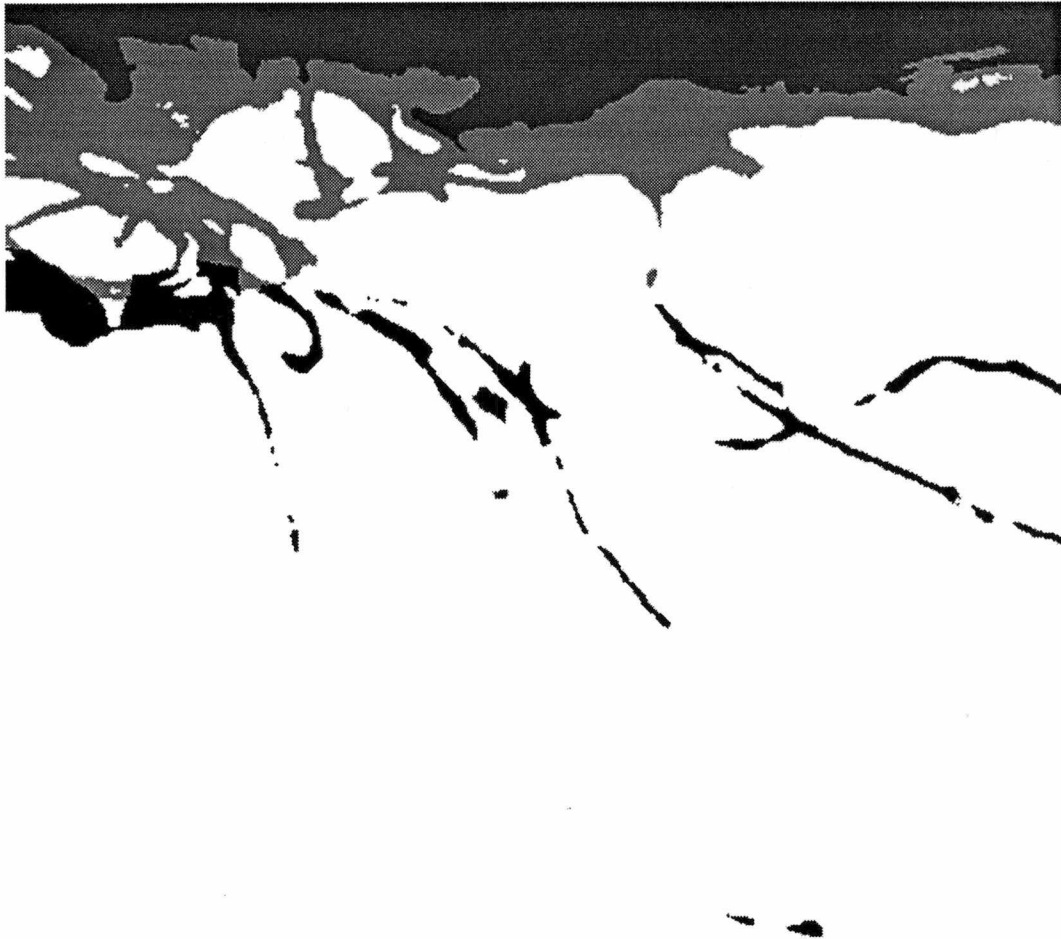


Figure 4.3 Image with three fuzz regions identified by different gray levels, dense (dark gray), transition (light gray) and sparse (black) regions are located from top-to-bottom in the image.

output image with the original image. The result of this process when applied to **Figure 4.2** is shown in **Figure 4.4**.

4.2.2 Fuzz Description

Fuzz was scanned row-by-row from top-to-bottom of images. Fuzz density was defined as the percentage of the entire image covered with in-focus fuzz. Three fuzz height averages were computed to characterize fuzz height. These were the number (H_n), height (H_h) and z- (H_z) average fuzz heights. They were computed as follows.

$$H_n = \frac{\sum H_i n_i}{\sum n_i} \quad (5)$$

$$H_h = \frac{\sum H_i^2 n_i}{\sum H_i n_i} \quad (6)$$

$$H_z = \frac{\sum H_i^3 n_i}{\sum H_i^2 n_i} \quad (7)$$

where H denotes fuzz height from the fabric surface (top edge of images), n denotes the fuzz percentage in each column and i denotes current location.

Next, fuzz was scanned column-by-column from left-to-right of images. Mean fuzz height from the fabric surface (top edge of image) and percentages of dense, transition and sparse regions were computed. In order to obtain height distributions from left-to-right of images, a modified H_z was computed by replacing n with 1 for each fuzz pixel.

4.3 Evaluation of Algorithm

The results of fuzz algorithms were evaluated two ways. First, individual images for a variety of fabrics were subjectively evaluated after in-focus fuzz was marked by

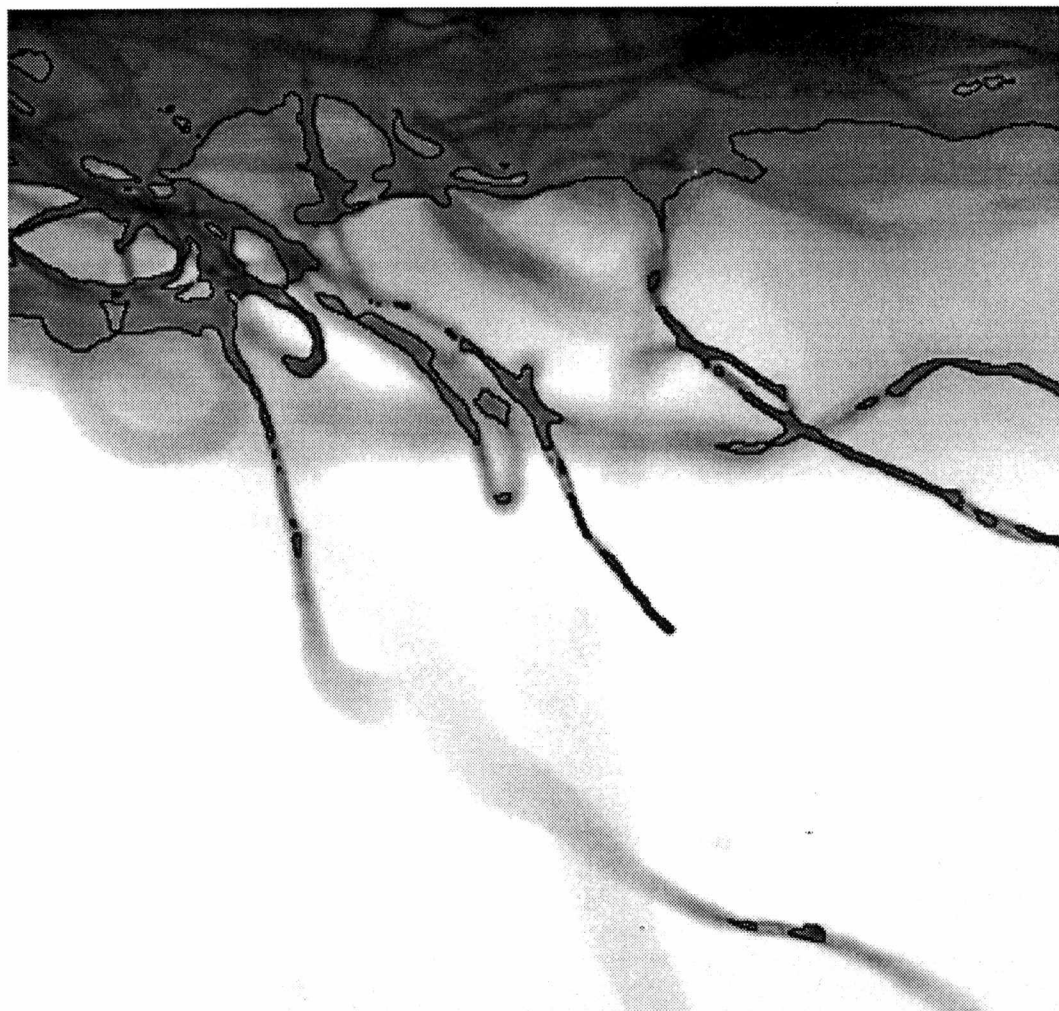


Figure 4.4 Processed image (Fig. 4.2) with fuzz identified by black edges.

edging. Second, results from machine vision were compared with results expected intuitively for a variety of fabrics.

4.3.1 Individual Images

Figure 4.5 shows an example of an image used to evaluate the reasonableness of fuzz detection. This image has a solid pill on its right side and normal fuzz fibers elsewhere. After the image was processed, **Figure 4.6** shows that most in-focus fuzz was labeled correctly. The fuzz detection accuracy demonstrated by **Figures 4.5-4.6** was typical and was considered to be satisfactory.

4.3.2 Intuitive Comparisons

Seven different fabrics (acetate satin, cotton sateen, wool worsted, wool flannel, cotton broadcloth, cotton flannel and interlock-knit) were selected for this test since these fabrics were known to exhibit a wide range of fuzzing. 30 images were acquired from each fabric using random sampling. **Table 4.1** summarizes the mean fuzz heights from fabric surfaces measured by machine vision for each of the seven fabrics. In addition, **Figures 4.7-4.8** show the three-region arrangement and height values (H_n and H_z) for the seven fabrics. These results generally satisfy intuitive expectations of fuzz. That is, cotton sateen has more fuzz than acetate satin, wool flannel has more fuzz than worsted wool, and cotton flannel has more fuzz than cotton broadcloth. Although satin was measured to have little fuzz, no fuzz would be expected to be observed on its surface. This problem was determined to result from inaccurate positioning of the fabric surface at the top of images prior to image acquisition. More accurate hardware control would be expected to substantially reduce this problem. Consequently, the overall conclusion from software evaluation was that reasonable results were obtained from machine vision.



Figure 4.5 Fuzz image including a solid pill on the right side.



Figure 4.6 Processed image (Fig. 4.5) with fuzz identified by black edges.

Table 4.1 Mean fuzz heights from fabric surfaces for seven different fabrics.

Fabrics	Mean Height (pixel*/mmE-2)
Acetate satin**	10.2/3.88
Cotton sateen	23.8/9.04
Wool worsted	15.4/5.85
Wool flannel	33.5/12.73
Cotton broadcloth	5.9/2.24
Cotton flannel	25.5/9.69
Interlock	17.7/6.73

* Each pixel is equivalent to 3.80E-3 mm.

** Invalid data for satin caused by relief of hairless surface.

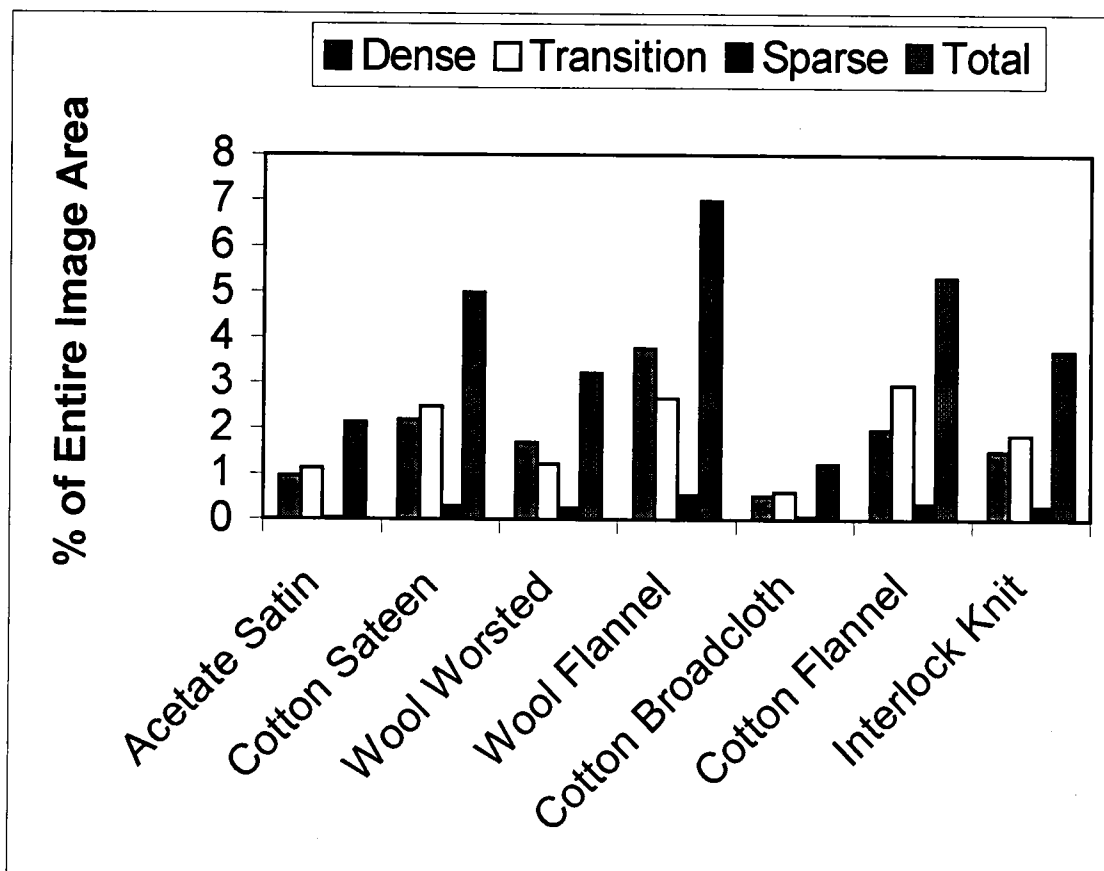


Figure 4.7 Three fuzz regions for seven different fabrics.

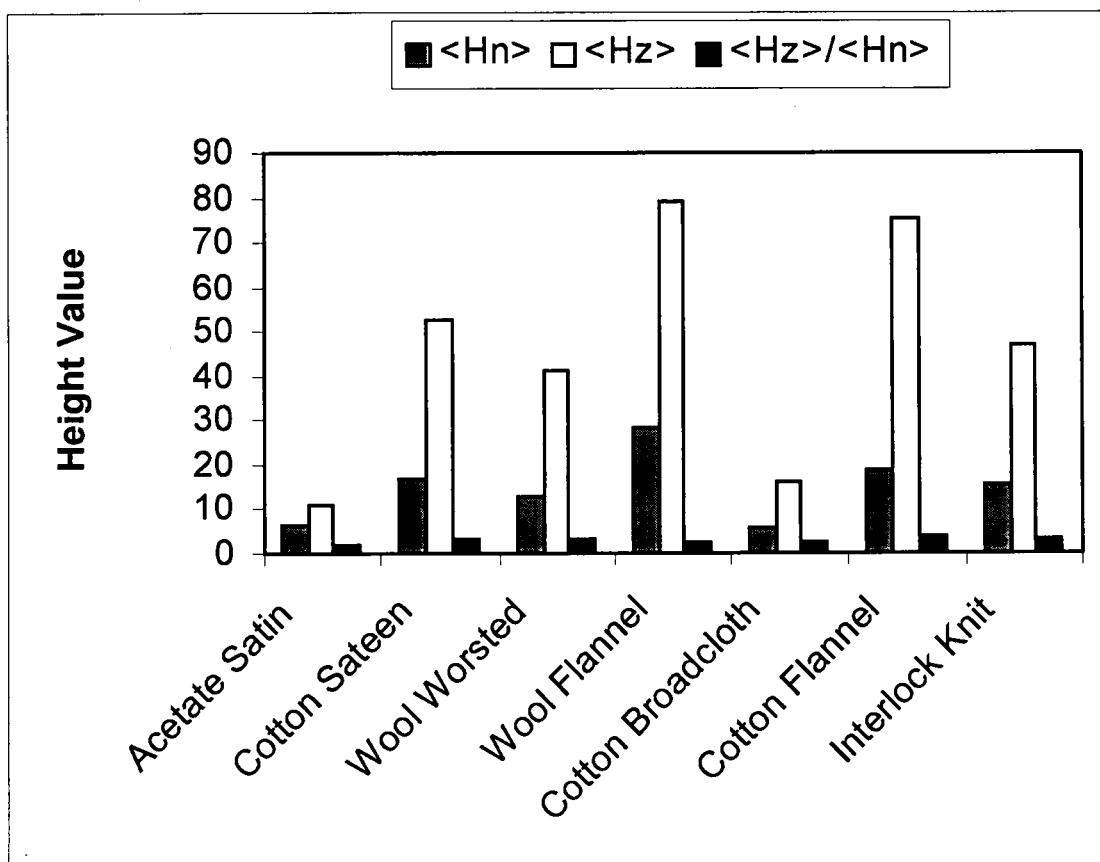


Figure 4.8 Number (H_n) and z (H_z) average fuzz height for seven different fabrics.

PART 5

APPLICATIONS OF IMAGE ANALYSIS TOOLS

5.1 Surface Structure vs. Fuzz

One use of the fuzz analysis tool developed for this project is to examine the influence of fabric structure on fuzz formation during abrasion. One fabric structural parameter that is thought to influence fuzzing is yarn interlacing pattern. To test that, plain, twill and basket weaves constructed from the same fibers and yarns were abraded, imaged and processed using the algorithms developed here. Each weave was abraded with 0, 10 and 25 cycles using the Fiber Transfer Abrasion Tester (FTAT). A total of 270 images were acquired from the 9 fabric samples with 30 images acquired for each fabric using adjacent sampling to completely cover an area of 1 cm^2 .

To examine the influence of yarn interlacing pattern on fuzzing , local fuzz density (height) was plotted in three dimensions for the whole 1 cm^2 sample area. Unfortunately, no clear meaningful periodic data was detected as shown in **Figure 5.1** for the twill weave. Since hardware was previously seen to be a problem (satin fuzz measurement), we suspected that positioning in accuracy associated with inadequate hardware resulted in random data noise which obscured the periodic data we expected to observe.

Consequently, a global measure of fuzz density was employed to examine the influence of yarn interlacing pattern on fuzzing. The mean fuzz height among all 30 images on each fabrics was computed. This data is summarized in **Figure 5.2**. In this figure, the twill fabric shows significantly more fuzz than the other two fabrics through 25 abrasion cycles. Since the interlacing pattern of twill is 3 over 1, plain is 1 over 1 and basket is 2 over 1, this data apparently indicates that the longer yarn floats of twill weaves resulted in more fuzz.

FUZZ DENSITY vs SPATIAL POSITION
TWILL WEAVE

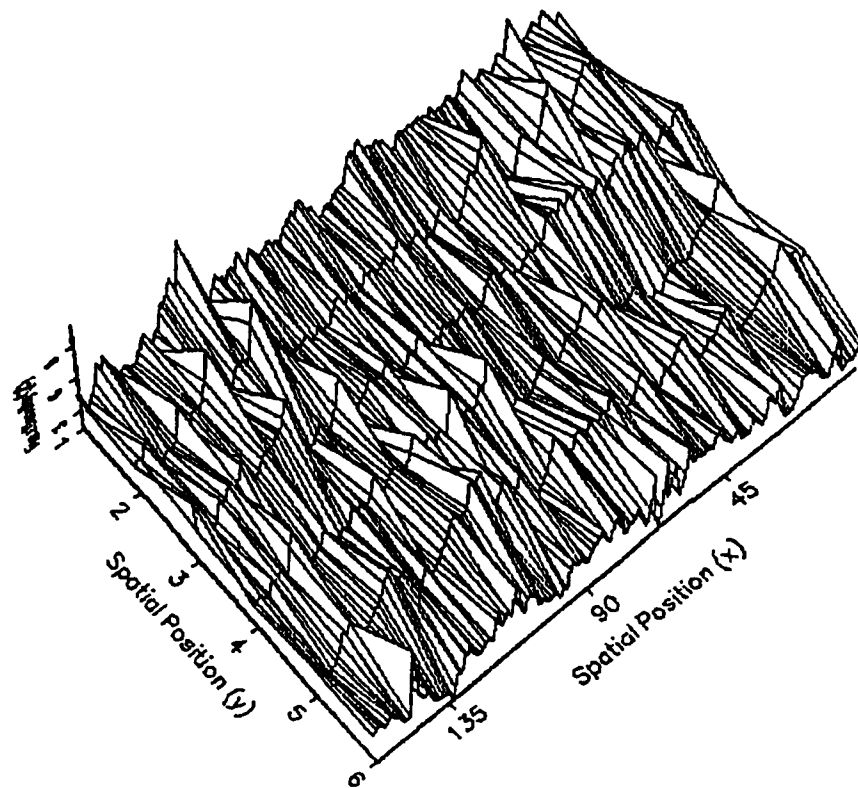
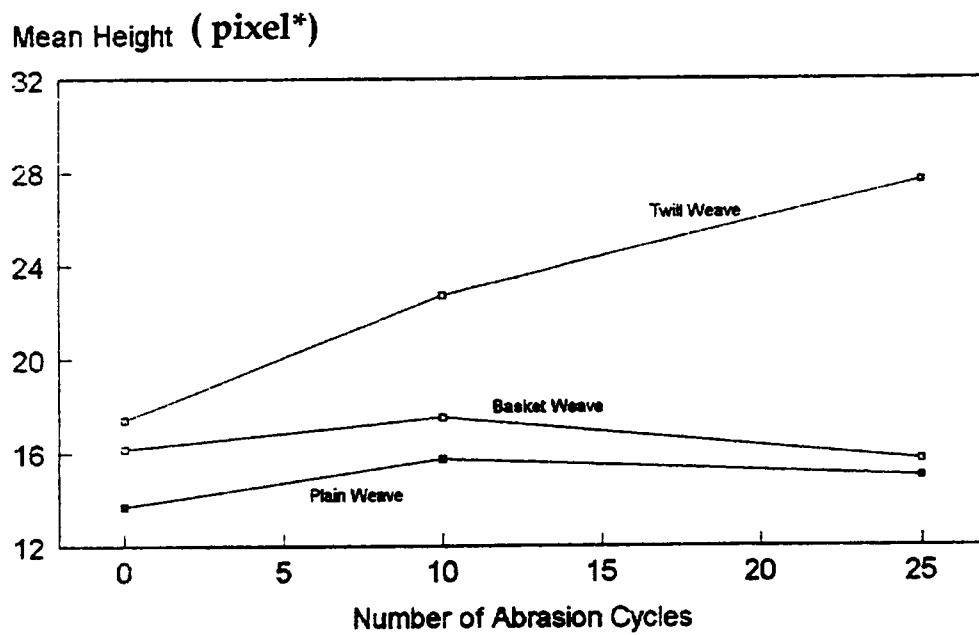


Figure 5.1 Local fuzz density (height) for a 1 cm² area of a twill fabric.



* Each pixel is equivalent to $3.80\text{E-}3$ mm.

Figure 5.2 Global fuzz density (height) for a 1 cm^2 fabric area in plain, basket and twill weaves.

This observation is supported by Annis et al. [26] who reported that 387, 177 and 167 polyester fibers were transferred from twill, basket and plain weaves, respectively, after abrasion. Transferred fibers can be viewed as aged fuzz although they are usually termed lint. Consequently, one would expect to observe similar trends for fuzz formation and lint formation.

5.2 Abrasion vs. Pilling

Another application of the image analysis tools developed for this project is to quantitatively describe the relationship between abrasion and pilling. In addition, the influence of finishing treatments on pill formation can be evaluated quantitatively. To study these things, a total of 120 images were acquired from 24 cotton interlock knit fabrics with 5 images from each fabric. Half of these fabrics were treated with enzyme whereas the other half were treated similarly but without enzyme. All fabrics were abraded for 0, 1, 3, 5, 7, 10, 25, 50, 100, 200, 500 and 1,000 abrasion cycles using the FTAT.

After image processing for pill analysis, pill number, size and contrast were examined because they provided one-dimensional, two-dimensional and three-dimensional information and because they are fundamental elements of pill structure. Results are shown in **Figures 5.3-5.5**. These figures show that treatment with enzyme reduced pill number, size and contrast. Enzyme treatment resulted in the largest reduction in pill number. In addition, enzyme treatment shifted the critical abrasion level where the number of pills remains approximately constant from 200 to 50 cycles as can be seen in **Figure 5.3**. **Figures 5.4-5.5** show that pill size and contrast are also reduced by enzyme treatment. These figures suggest that enzyme treatment affected pill size more than pill

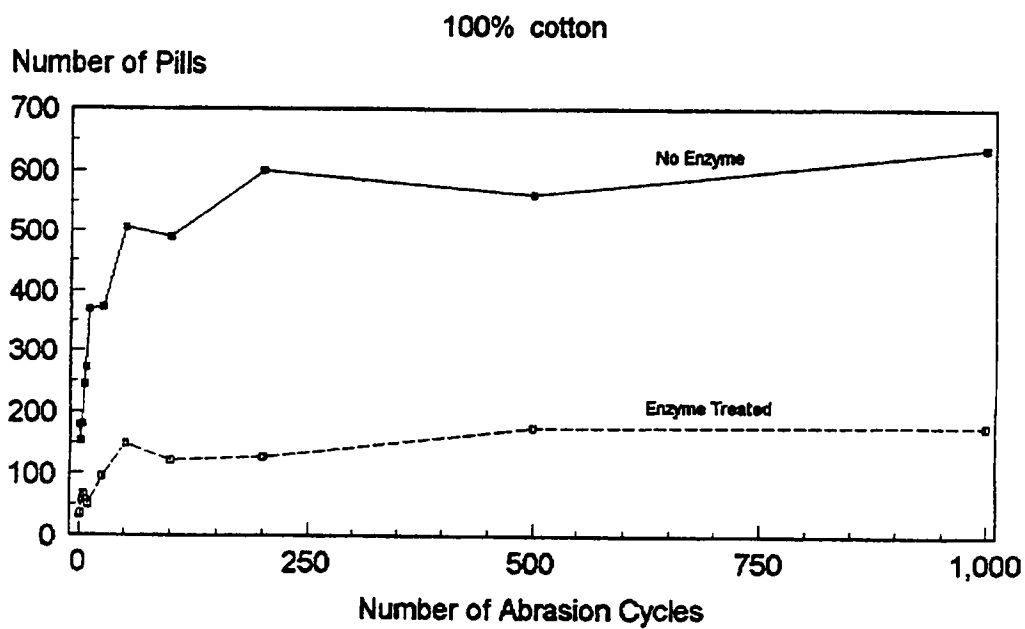
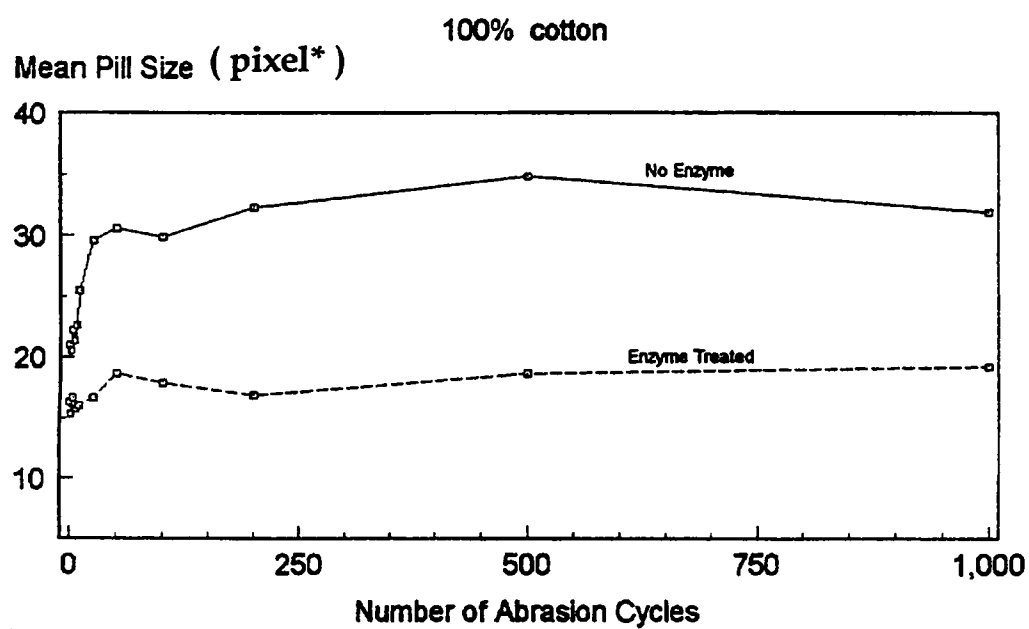
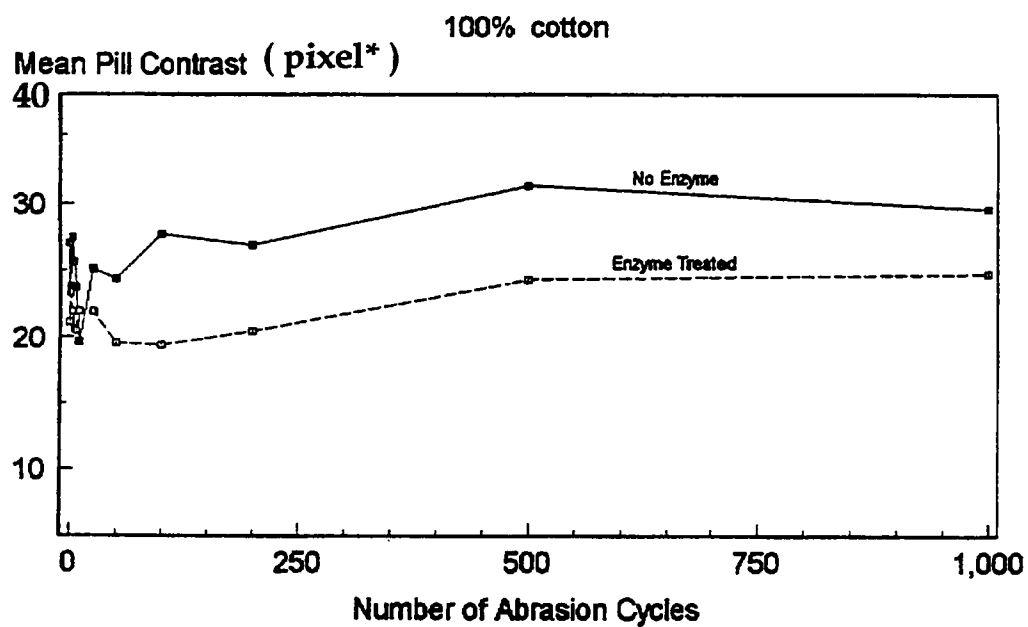


Figure 5.3 Pill number through 1,000 abrasion cycles.



* Each pixel is equivalent to 0.11 mm x 0.11 mm.

Figure 5.4 Pill size through 1,000 abrasion cycles.



* Each pixel is equivalent to 0.11 mm.

Figure 5.5 Pill contrast through 1,000 abrasion cycles.

contrast. Since pill contrast represents optical height, this may indicate that the growth of pills in the height direction was restricted by abrasion pressure. At any rate, these experimental data indicate that the pill analysis tool developed for this project provides reasonable data since enzyme treatment is known to reduce fabric pilling.

5.3 Abrasion vs. Fuzzing

The same set of cotton interlock knit fabrics was used to study the influence of abrasion and enzyme treatment on fuzzing. A total of 360 images were acquired from 18 interlock fabrics

with 20 images of each fabric. Half of these fabrics were treated with enzyme whereas the other half were treated similarly but without enzyme. All fabrics were abraded for 0, 3, 10, 25, 50, 100, 200, 500 and 1,000 abrasion cycles using the FTAT. Random sampling was conducted to image a total area of 1 cm^2 for each fabric. After image processing for fuzz analysis, fuzz height, three-region arrangement and height values (H_n , H_z) were examined. Results are shown in **Figures 5.6-5.8**.

Figures 5.6-5.7 show that enzyme treatment primarily reduced the quantity of fuzz rather than the pattern of fuzz growth. **Figure 5.7** shows that enzyme treatment primarily influences dense and transition regions rather than sparse regions. The data in **Figures 5.6-5.7** may provide a clue about how enzyme treatment decreases pill number, size and contrast. That is, enzyme treatment decreased fuzz height values (**Figure 5.8**) rather than sparse region size (**Figure 5.7**). Since longer fuzz would be expected to produce larger pills, fuzz height values might be a good way to explain the previously discussed pilling data. At any rate, the fuzz analysis tool developed in this project seems to provide data which is both reasonable and useful.

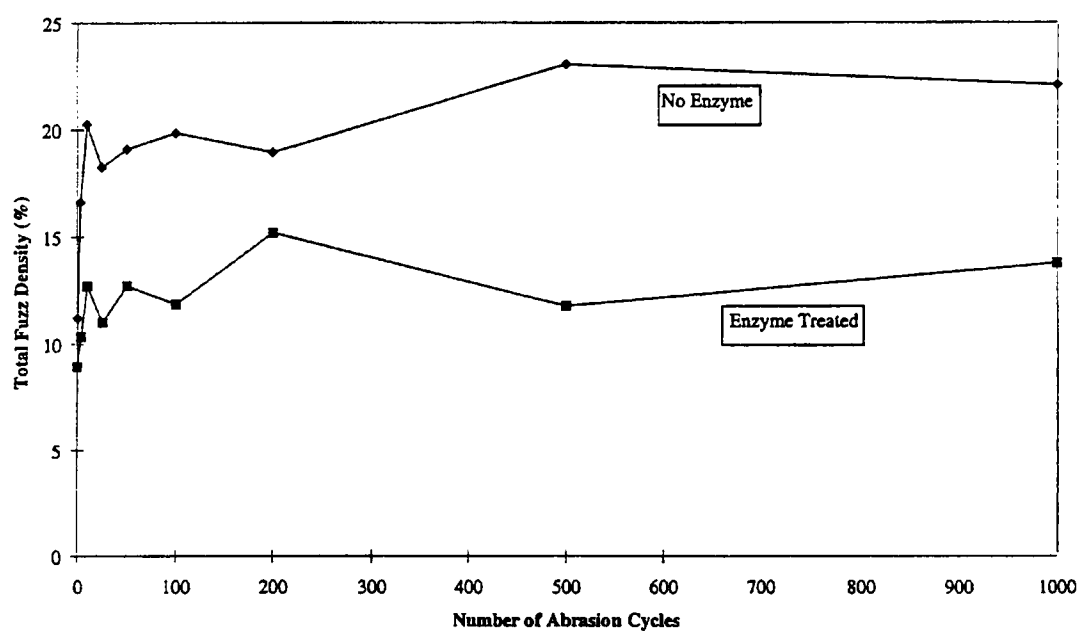


Figure 5.6 Fuzz density (height) through 1,000 abrasion cycles.

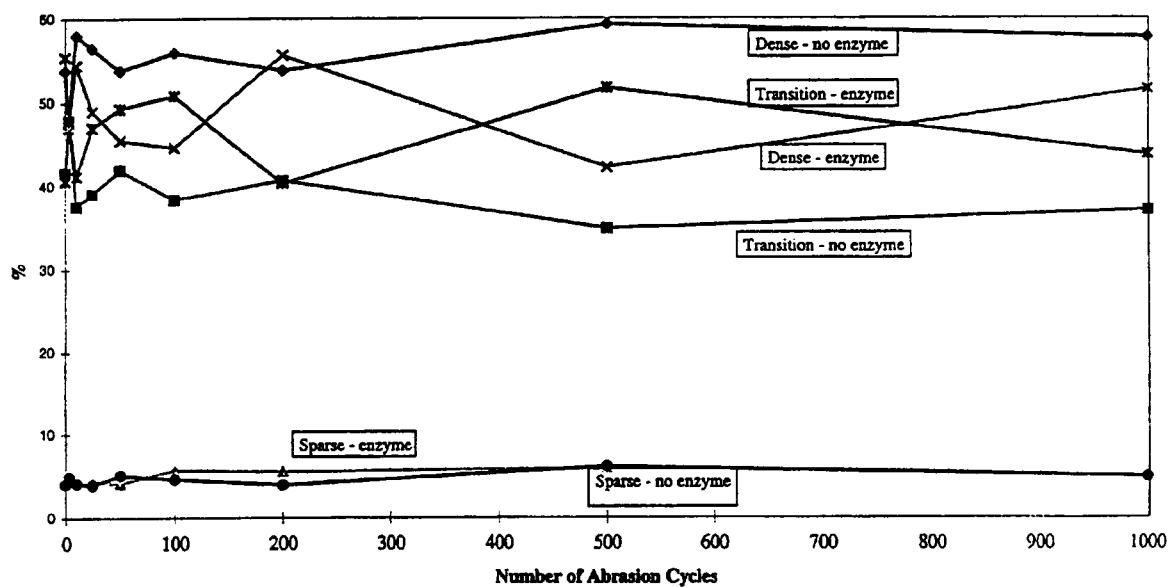


Figure 5.7 Fuzz three-region arrangement through 1,000 abrasion cycles.

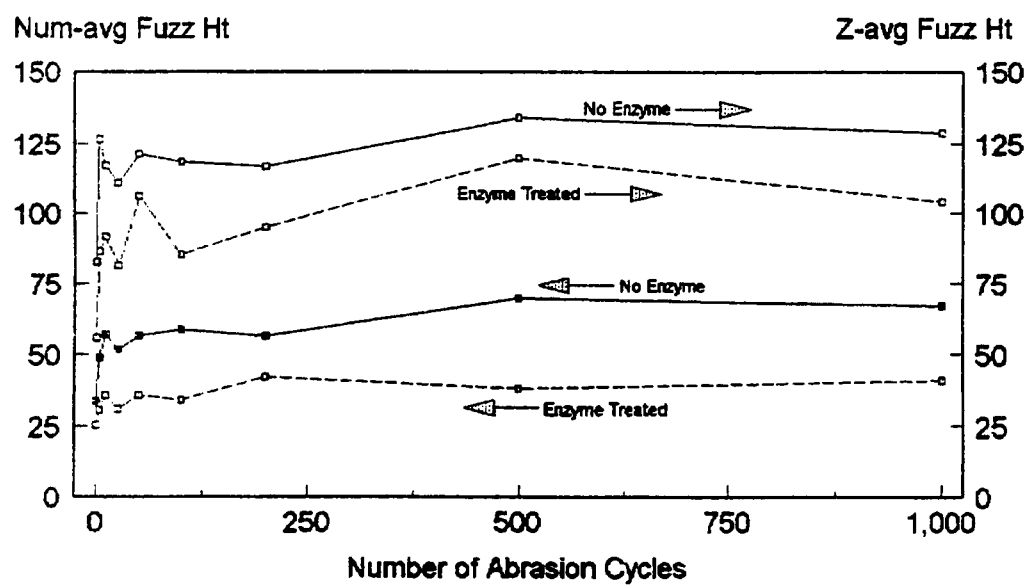


Figure 5.8 Fuzz height values (H_n , H_z) through 1,000 abrasion cycles.

5.4 Relation between Pills and Fuzz

One of the more interesting opportunities provided by the two image analysis tools developed for this project is the ability to obtain quantitative information about both pills and fuzz so their relationship can be investigated. To investigate this relationship, data from section 5.2 and 5.3 were regrouped and plotted in **Figure 5.9**. In this figure, adjusted fuzz density was used rather than fuzz density since fuzz images might include pills. This was computed as the difference of total fuzz density and pill area.

For the case of non-enzyme treatment, **Figure 5.9** shows that pilling varied inversely with fuzzing once a maximum level of fuzz density was achieved. This behavior can be seen after 50 abrasion cycles for the upper two curves of **Figure 5.9**. Another interesting observation was that enzyme treatment apparently decreased fuzz entanglement as well as the quantity of fuzz. This was concluded by observing the greater difference between adjusted fuzz density and pill area for enzyme treatment than for non-enzyme treatment. In other words, the ratio of pill area to the quantity of fuzz was greatly decreased by enzyme treatment.

One other interesting observation from **Figure 5.9** was the steep slope for the initial section of each fuzz curve but decreasing slope after increased abrasion. This indicates that the formation of fuzz influences the formation of additional fuzz. A possible explanation for this observation is that the greatest fabric surface area directly contacted by the abradant occurred at low abrasion levels where short and low density fuzz predominated. One would expect this fuzz to provide limited cover of the fabric surface. This situation would allow more friction to be developed and allow many fibers to be released from fabric surface. The observed affect would be the steep slope at initial

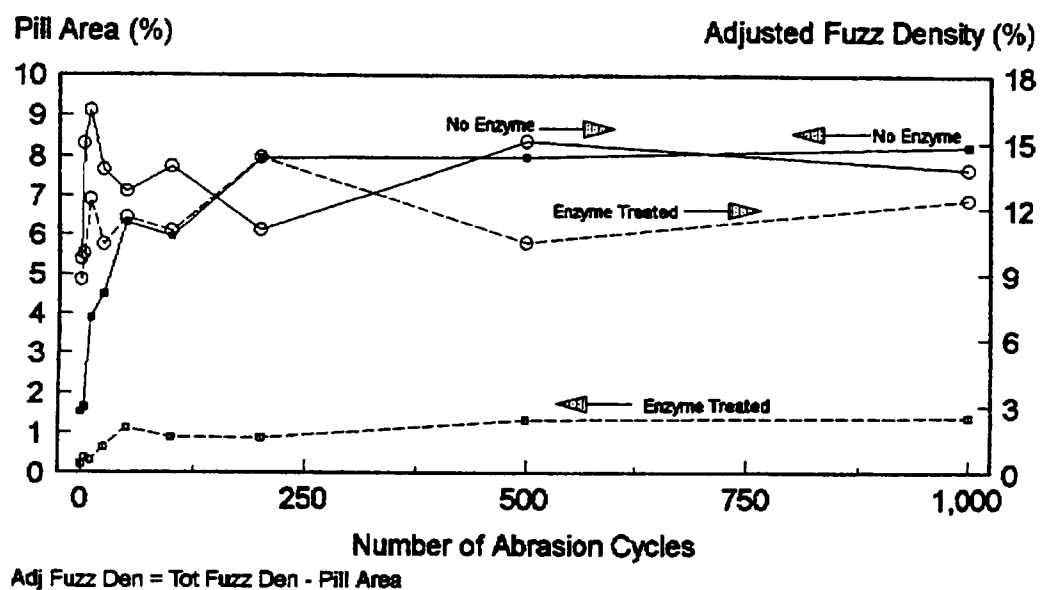


Figure 5.9 Pills and fuzz through 1,000 abrasion cycles.

abrasion levels. After prolonged abrasion, fuzz was observed to become longer and more dense so one would expect fuzz to cover the fabric surface more. This might allow more friction to exist between the abradant and fuzz fibers rather than between the abradant and the fabric/yarn surface. That is, the presence of fuzz reduces friction so the production rate of additional fuzz decreases. One might view fuzz as a “lubricant” between the abradant and fabric surface.

The slope for each pilling curve was similarly steep initially and then was reduced at increased abrasion levels. This might be explained in terms of a high probability of pill formation existing initially since no fabric surface area was occupied by pills before abrasion. This high rate of pill growth gives a steep slope during the initial period of abrasion. The probability of forming pills decreases during subsequent abrasion because less available fuzz is present and also because the previously formed pills create spaces between the abradant and fabric surface to decrease friction. This resulted in decreased slopes for pilling curves after initial pill formation occurred.

Although this dissertation included a considerable amount of speculation, it served to illustrate that the image analysis tools developed for this project provide many opportunities to learn more about the science of textile materials.

PART 6

CONCLUSIONS

The software tools developed for this project demonstrate that useful information can be obtained using relatively inexpensive personal computer-based hardware and image analysis techniques. Developing a fabric fuzz analysis tool was a particularly noteworthy task, since subjective observations using microscopy were the only analytical method available before this project.

Quantitative information derived from this project was used to describe geometrical features of both pills and fuzz. Work correlated machine vision with human vision of pills, evaluated the influence of fabric structure on fuzz, compared growing patterns of pills and fuzz with enzyme treatment and different abrasion levels, and explored relationships between pills and fuzz. Results indicated that more fabric surface questions become answerable with direct and quantitative results.

Limitations of the tools developed for this project are that it is difficult to measure pills on high textured fabric and dark colored fabrics (which is expected to be overcome by using a color imaging system). In addition, some parameters used in this project such as partition, zoom and minimum pill size are closely related to lighting geometry and image magnification so these must be carefully adjusted before image acquisition. Limitations of fuzz measurement are primarily related to hardware factors. Specifically, the accuracy of motion control was seen to reduce the usefulness of fuzz measurements for some applications.

A software package called "FabricPro" was developed in Visual C with 26,000 lines of code as part of this project. The friendly interface of this package allows pill and fuzz measurements to be easily implemented repeatedly which include tasks of calibration for imaging acquisition, detection and object description with chart

expression. Corresponding help information is also available. In addition, common image functions such as point, area, frame, geometric, frequency and recognition processes, are included. In general, tools developed here have commercial potential.

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