Model and Analysis of the Geometric Characteristics of Primary Carpet Backing

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Model and Analysis of the Geometric Characteristics of Primary Carpet Backing

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Defect formation in carpets is poorly understood. It is postulated that a particular defect type, called the Moiré effect, is caused by the interaction between patterns of the color, pile height, and tuft arrangement. In order to study such phenomena, models of the carpet backing fabric are needed to understand the location of the tufts in relation to the backing yarns. To construct these models, data collected from primary carpet backing was analyzed. The validity of this method was then tested through comparison back to the original data. The method was designed to preserve certain statistical qualities among three parameters: yarn width, gap width, and centerline deviation. The distributions of these parameters and correlation relationships among them are reproduced through use of the Fourier transform, original distributions, and regression relationships. For Backing B, the backing followed most closely throughout this thesis, the generated parameters are from populations with means and standard deviations of the original data with 95% confidence.

It is proposed that this defect is caused by regions of irregularities in needle-yarn interaction produced during tufting. These irregularities were quantified in three ways using virtual backings and represented as images. Since the size of the irregular region needed to produce Moiré effect is not known, a suggestion was made for analyzing the images on different scales through use of Gaussian filters. Suggestions were also made for improvement of the method.
CHAPTER I

INTRODUCTION

1.1 Background

Primary carpet backing is a plain-weave woven fabric produced through a standard weaving process. The backing we will study is woven from polypropylene tape yarns. A woven fabric is made of two sets of yarns that are perpendicular to each other. The yarns in the machine direction are called warp yarns. To make a plain weave pattern, the warp yarns are fixed at one end and held alternately above and below a fixed middle height. Another yarn, called the weft, or filling yarn, is passed across them at the middle height. A large comb, called the reed, beats the weft yarn back against the previous weft yarns. The yarns’ positions are then traded so that those above the middle height are below and the ones that were below are above, and then another weft yarn is inserted, beat up and the sequence continues. The fabric is identified by the weave pattern or weave, the number of warp yarns or ends per inch, and the number of filling yarns or picks per inch. In the backings we will study, the weft yarns are significantly wider than the warp yarns, and are situated in the weave less compactly - with fewer yarns per inch.

To make carpet, the primary backing is fed through a tufting machine. The machine’s needles, each threaded with low yarns and arranged on bars oriented parallel to the weft yarns, puncture the backing and a looper underneath the apparatus grabs the yarn before the needle leaves, creating tufts. The resulting product is further processed to become a carpet; it is treated with chemicals and affixed to additional backings that provide weight and stability.

1.2 Motivation and Overview

The tufts are the visible portion of the finished carpet, and they are where our concern ultimately lies in this research. When a needle enters the backing, it may strike a weft yarn
or land between two weft yarns. If the needle strikes a yarn, it may push the yarn out of the way, split it, or possibly even break it. As in the case of yarn 3 in Figure 1, one needle in a row may strike on one side of a yarn, and the needle next to it may strike either on the other side or on the yarn itself. These transitions may have a profound impact on the quality of the finished product. In particular, in multicolored carpets, a phenomenon known as a Moiré effect may be observed, that is, a pattern of tubs that looks like a watermark and is considered to be an undesirable occurrence by the consumer. To study this effect and its causes, the properties of the backing itself must be studied. It is in this context that a method for generating virtual prinary carpet backing will be developed.

Once a virtual backing has been generated, tests can be performed to find the number of yarns skipped from one needle puncture to another, the transitions needle to needle from below a yarn to above and vice-versa, and other factors such as the amount of overlap between the needle tip and the yarn that may determine whether a given yarn breaks, splits, or moves. Once a model has been developed that takes all these factors into account, the action of tensing itself may be studied to determine the causes of defects such as the Moiré effect.

Arrays containing quantitative results from the tests listed above may be transformed to grayscale images, which can then be analyzed for patterns or deviant behavior that may create a Moiré effect. Since we do not know the scale at which such an effect may appear,
we need to analyze the images at several different scales. To do this, we transform the images using Gaussian filters of varying standard deviations.

1.3 Variation

The most straightforward way to produce a virtual backing is to use the mean values for yarn widths and the size of the space between yarns (gap widths), and make the yarns straight. This will produce a "vanilla" backing that represents only the most basic geometric characteristics of the original backing. We may then perform analysis of this backing and perhaps deduce the behavior of the real backing. This method relies on the assumption that the variation of the real backing from the vanilla backing is small enough to be unimportant with respect to needle strike behavior.

However, as we will see when analyzing collected data, there can be relatively large amounts of variation in the real backing parameters. Variation occurs in three ways - the yarn widths, gap widths, and "waviness" of the yarns. The waviness can be characterized as a single value by following the behavior of the yarn centerline along its length. We hypothesize that these variations are significant enough to require inclusion in the model.

To test this hypothesis, we first propose a model that includes variation and then compare results of its analysis with results of analysis of the vanilla backing.

1.4 Warp vs. Weft

In Figure 1 only weft yarns are displayed. In the course of this thesis, we will only consider placement and modeling of weft yarns, as these seem to be the more important contributors to the Moiré effect. The modeling of warp yarns may be done in a similar way and can be considered independent of the modeling of weft yarns. This independence assumption is based on the idea that correlation effects between the two sets of yarns have been accounted for in taking data of yarns already lying in the weave. Any effect the warp yarns may have on the way weft yarns lie in the fabric will be reflected in the measurements taken of the weft yarns.
CHAPTER II

SURVEY OF LITERATURE

Previous work on primary carpet backing has often been concerned with traits such as dimensional stability (2, 3) and tensile properties (17). [4] provides a summary of tests for many mechanical properties of carpet backing including coated weight, tuft anchorage, backing adhesion, and flamemobility. For a treatment of backing maneuverability as well as background on carpet manufacturing, see [1].

Models of various properties of woven fabrics such as axial stiffness (19) and deformation under impact (18) have previously been developed. However, these models do not include specifications for yarn size and placement.

For descriptions of Moiré effect and its cause, see [5]. This paper states that the cause of Moiré effect lies in the fact that "when woven primary backings are being tufted, two grids overlap, i.e., the material with its warp and weft and the tuft lom with its row of needles in the transverse direction and its stitches in the longitudinal direction." Moreover, when the two grids overlap, an interference pattern is produced through the grid interactions. This interaction is proposed as the cause of Moiré effect.
CHAPTER III

DATA COLLECTION

3.1 Overview of Collection Methods

To develop a realistic model, we need some sort of input data from the real backing. We have already identified values we want: yarn width, gap width, and centerline measurements for each yarn. We must take these measurements periodically along the lengths of the yarns with a reasonable interval between points. The initial data collection parameters were determined primarily by machine and software capabilities. The number of yarns studied was determined by the number of yarns that comfortably fit into the image size appropriate for the software. The interval was determined by the data collecting software’s capabilities. As will be seen during the data analysis, parameter variation occurred primarily on a scale much larger than interval size and so the interval was determined to be appropriate.

Images were taken of several yarns across the length of the backing. A sample image is shown in Figure 2. The backing was constructed of high contrast yarns (black and tan) to facilitate the detection of the yarn edges. The images were then amended - some dark spots not associated with a yarn were erased, and the images of the warp yarns were removed. Figure 3 shows the sample from Figure 2 after being amended. Next, a series of vertical lines were drawn across the yarns at regular intervals. These lines were measured to provide the yarn width value. The measurement was first given in pixels and then converted to mm. For a sample image with the lines drawn, see Figure 4. The number of yarns studied was increased in the second collection, at the expense of image resolution and therefore measurement accuracy. Parameter values in the second collection will be seen to clump around certain members. This is due to the increase in ratio of bit size to yarn image size, as the software measures from bit to bit on an image.

The backings studied included 24x15 tape (Backing A), 28x15 fibrillated (Backing B), 28x16 fibrillated (Backing C), and 24x15 stristed (Backing D). The numerals indicate the
Figure 2: A sample image.

Figure 3: A sample ameaded image.
Figure 4: A sample image with measurement lines included.

number of warp yarns per inch (or pick) and the number of weft yarns per inch, respectively. Tape yarn is a plain flat polypropylene tape yarn with rectangular cross-section. Fibrillated yarn is tape yarn that has been subjected to many short slices of various sizes along its length, a process called fibrillation. The fibrillation is believed to ease the insertion of a needle into the yarn, thereby decreasing breakage. It also provides an increase in the uniformity of the yarn statistics as it causes the yarn to constrict widthwise. This increase in uniformity helps in constructing a more accurate model. The striated yarn is tape yarn that has a non-uniform thickness across the cross-section. These variations in thickness are also used to help reduce breakage.

The data was collected by taking images which were then analyzed using software that provided measurements of yarn width and bottom edge y-value at data points every 0.7178 mm across the length of the image. Adding half yarn width to bottom edge y-values gives centerline y-values,

$$\text{centerline y-value} = \frac{\text{yarn width}}{2} + \text{bottom edge y-value.}$$  (1)

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Adding the whole yarn width to bottom edge y-values gives top edge y-values,

\[ \text{top edge y-value} = \text{yarn width} + \text{bottom edge y-value.} \] (2)

The gap values are then calculated by subtracting previous yarn top edge y-values from yarn bottom edge y-values.

\[ \text{gap value} = \text{bottom edge y-value} - \text{previous top edge y-value}. \] (3)

For each image, \( x=0 \), \( y=0 \) mm represents the lower left-hand corner of the image, and \( x=25.11 \) mm, \( y=20.74 \) mm represents the upper right-hand corner of the image. Although the same yarns can be caught in every image, the exact placement of the camera with respect to the yarns changes for each image. However, we can extract meaningful information by comparing y-values in one image, but not across images. We must find a way to relate centerlines in one image to those in another image. To do this, we find a mean y-value for the centerline across the whole image for each yarn. We then use as our characterization of the centerline the centerline deviation, the value obtained when the mean centerline y-value is subtracted from the centerline y-value at a particular data point.

\[ \text{centerline deviation} = \text{centerline y-value} - \text{mean centerline y-value}. \] (4)

We may reasonably assume that the mean centerline y-values are equivalent from image to image, and therefore model the centerline as a series of deviation values. Figure 5 represents portions of two yarns with the included gap. The solid horizontal lines are edges of yarns, with yarns and gaps as indicated. The dashed lines are yarn centerlines, and the dotted lines indicate the position of the centerline mean across the yarn. The yarn widths at the data point represented by the solid vertical line are the lengths of the segments AD and WH, the gap is the length of the segment DE, and the distances from the centerlines to the mean centerlines are segments BC and FG.

Figure 5 is deceptive in that the yarns are depicted as continuous. In fact, although the real yarns are continuous, the data we collect provides discrete values. Therefore, although y-values are continuous, they are collected at a finite set of discrete \( x \)-values, the collection points. In the future, when referring to yarn number, we call the yarn closest
to the machine yarn 1, that is, the first yarn encountered when moving in the increasing γ-direction. Subsequent yarns are numbered in order. The previous yarn is considered to be that whose number is one less, that is, the closest yarn encountered when moving in the decreasing γ-direction.

The images taken were within 3-3 mm of each other along the lengths of the yarns and so a linear estimate was included of 2 data points for each measured quantity between each pair of images. These were two separate instances of data collection on each of the four backings. In the first collection, seven images were taken of 5-6 yarns. 258 sets of measurements were obtained, including estimates between images. The last two were dropped in the interest of program speed to provide exactly 256 data points or 7.23 inches. Backings A and D provided data along 5 yarns and therefore 4 gaps. Each yarn's data was stored as three arrays - one 256x4 array for gap values and two 256x5 arrays for width and centerline deviation values. Backings B and C provided data along 6 yarns and therefore 5 gaps. Each yarn's data was stored as three arrays - one 256x5 array for gap values and two 256x6 arrays for width and centerline deviation values. In the second collection, twelve images were taken of 10-12 yarns. Eight yarns appeared in all images and therefore provided
778 sets of data, including estimates between images. All data was used since a significant amount - 276 sets - would have to be dropped to improve program speed.

3.2 Data Analysis

Through data analysis, we wish to get an idea of what kind of characteristics are important in describing the backing. These characteristics will need to be considered in the model. We will analyze each parameter to find the amount and order of variation as well as a mean. We will also look at the distribution of each parameter's values. We would like for the distributions to be normal. Normal distributions are often easier to work with than other distributions, and can be modeled by tools currently available in mathematical software packages. However, we need to realize that we aren't simply dealing with data distributions. Instead, our collected data is ordered by collection point and yarn. We need to analyze relationships that may exist among parameters and even across yarns.

We want to make sure that this analysis pertains to both data collections. We will compare statistics from each collection, looking for similar means, standard deviations, and distribution shapes for each parameter. We also want to assure that any relationship existing between parameters in the first collection is repeated in the second collection.

3.2.1 Descriptive Statistics

We first find basic descriptive statistics of the data - mean and standard deviation - and plot a histogram to find the distribution. We suspect that the increased uniformity of the fibrillated yarns will provide a better model due to normally distributed data and so we first assess Backing B width values, which appear to be normally distributed, although weighted toward the mean, with mean 1.1925 mm and standard deviation 0.0119 mm, according to Figure 6. To check this, we look at the normal plot in Figure 7. Although the distribution is not perfect, we assume a normal distribution on the width data from the first collection of Backing B. The lower incidence of larger width values can be attributed to folding. Wherever a yarn is wider, it is more likely to fold over on itself due to a physical event such as the beating during weaving. Once a yarn has folded over on itself, it has decreased its width according to the image processing software. This folding behavior could be studied
Figure 6: Histogram of Collection 1 yarn width values: 1536 total measurements taken every 0.7175 mm along 7.53 inches of six adjacent yarns; bin size=0.025 mm; sample mean=1.1925 mm, standard deviation=0.0119 mm.

Figure 7: Normal probability plot for Collection 1 yarn width values: 1536 total measurements taken every 0.7175 mm along 7.23 inches of six adjacent yarns, sample mean=1.1925 mm, standard deviation=0.0119 mm. The dashed line represents the plot of a normal distribution with appropriate mean and standard deviation.
Figure 8: Normal probability plot for Collection 1 gap width values: 1280 total measurements taken every 0.7175 mm along 7.23 inches of five adjacent gaps, sample mean=0.5405 mm, standard deviation=0.0347 mm. The dashed line represents the plot of a normal distribution with appropriate mean and standard deviation.

...to develop a more accurate model, an idea that will be discussed in more depth in a later chapter.

Graphing normal plots for gap and centerline deviation values in Figures 8 and 9 respectively, we see that we may assume normal distributions for all of our data sets. The centerline deviations appear to follow a normal distribution with mean $-1.1391 \times 10^{-5}$ mm, which is very close to zero, as would be expected, and standard deviation 0.0006 mm. The gaps appear to follow a normal distribution with mean 0.5405 mm and standard deviation 0.0347 mm. To assure data integrity, we look at the normal plots for the second data collection as well and compare their distributions to the distributions of the first data collection. We see in Figure 10 that the width distribution for the second collection is close to normal. We find a sample mean of 1.1633 mm, which is close to the previous sample mean of 1.3925 mm and sample standard deviation 0.0125 mm, which is close to the previous sample standard deviation of 0.0119 mm. We see in Figure 11 that the gap distribution for the second collection is also close to normal. We find a sample mean of 0.5299 mm, which is close to the previous sample mean of 0.5405 mm, and sample standard deviation 0.0306
Figure 9: Normal probability plot for Collection 1 centerline deviation values: 1590 total measurements taken every 0.7175 mm along 7.23 inches of six adjacent yarns, sample mean = 1.1521 x 10^-5 mm, standard deviation = 0.0096 mm. The dashed line represents the plot of a normal distribution with appropriate mean and standard deviation.

Figure 10: Normal probability plot for Collection 2 yarn width values: 6224 total measurements taken every 0.4300 mm along 12.43 inches of eight consecutive yarns, sample mean = 1.1633 mm, standard deviation = 0.0125 mm. The dashed line represents the plot of a normal distribution with appropriate mean and standard deviation.
Figure 11: Normal probability plot for Collection 2 gap width values (mm): 5446 total measurements taken every 0.4650 mm along 12.41 inches of seven adjacent gaps, sample mean=0.5239 mm, standard deviation=0.0286 mm. The dashed line represents the plot of a normal distribution with appropriate mean and standard deviation.

mm, which is close to the previous sample standard deviation of 0.0347 mm. We see in Figure 11 that the centerline deviation distribution for the second collection is, again, close to normal. We find a sample mean of 0.0021 mm, which is larger than the previous sample mean of -1.592 x 10^{-5} mm, but still tolerably close to zero, and standard deviation 0.0166 mm, which is close to the previous sample standard deviation of 0.0096 mm.

In Figures 7 to 12, note that the normal plots appear to be a bit choppy - the values are clustered around certain points. This is more evident in the plots of collection 2 data than collection 1 data. As stated previously, the reason for this data 'clumping' is that the image resolution is limited. In the second collection, when the camera is pulled back so more yarns can be squeezed into the image size, the effect is even more noticeable.

Although the normal plots above are strong evidence for normality of distribution, we perform goodness-of-fit tests, comparing each sample to the appropriate normal distribution. We find that we can state, with 90% confidence, that each of these samples is pulled from a normal distribution.

Each of our collections has been from an isolated portion of the backing, so we must
Figure 12: Normal probability plot for Collection 2 centerline deviation values: 6224 total measurements taken every 0.406 mm along 12.41 inches of eight consecutive yarns; sample mean=0.0021 mm, standard deviation=0.0166 mm. The dashed line represents the plot of a normal distribution with appropriate mean and standard deviation.

assure that they accurately reflect the statistics of the whole. The close match between the two collections' distributions helps support this. A collection was also performed before data was taken from the four backings on two representative tape and filerated backings. Images were taken from several different locations around each backing. As seen in Figure 13, the histogram of width data from these collections also appears to follow a normal distribution. We may feel reasonably certain that we have appropriately captured the overall distribution of values.

3.2.2 Lengthwise Correlation

A reasonable question to ask about this data is whether it is correlated lengthwise across the yarn. We would not expect the width of a yarn to jump from 1.4 mm at one data point to 0.8 mm at the very next point, just 0.7175 mm away. To illustrate this, we plot the width, centerline deviation, and gap values across the first yarn in each collection in Figures 14 to 19. There is significant correlation in yarn width values across a yarn. This backs up our previous statement that parameter values are ordered. They cannot be modeled as values
Figure 13: Histogram of width values taken from around the backing sample.

Figure 14: Plot of width values across Collection 1 first yarn, 256 total measurements taken every 0.7175 mm along 7.23 inches.

Figure 15: Plot of width values across Collection 2 first yarn, 778 total measurements taken 0.4050 mm apart along 12.41 inches.
Figure 16: Plot of gap values across Collection 1 first yarn, 256 total measurements taken 0.7175 mm apart along 7.23 inches.

Figure 17: Plot of gap values across Collection 2 first yarn, 778 total measurements taken 0.4096 mm apart along 12.41 inches.

pulled randomly from a certain distribution. Instead, we must reproduce the appropriate overall distribution while ensuring the values are properly correlated across a yarn. Either of these tasks alone could be accomplished quite easily, but together they may require a model with more subtlety. After seeing the yarn width correlations, we expect that the gap width and centerline deviation cross-yarn plots will exhibit similar behavior. This is checked in Figures 16 to 19.

There is significant correlation in all three parameters across the length of a yarn. These values take the form of a data set that could be well described through Fourier analysis. In Chapter 4, we will attempt to reproduce this type of behavior through use of the Fourier transform.

3.2.3 Centerline-to-Centerline Correlations

If the physical constraints on the yarns produce a correlated effect across a yarn, other physical constraints could produce other types of correlations as well. Specifically, when the backing is woven, after a weft yarn is drawn across the warp it is beaten up by the reed in a process which assures compactness of weave, but which also may cause the yarn to deform around the previous yarn. This potential centerline-to-centerline correlation must be investigated.

Figure 20, shows scatter plots of the first collection’s centerline deviations. The scat-
Figure 18: Plot of centerline deviation values across Collection 1 first yarn, 256 total measurements taken, 0.7175 mm apart along 7.23 inches.

Figure 19: Plot of centerline deviation values across Collection 2 first yarn, 778 total measurements taken, 0.7175 mm apart along 12.41 inches.

Figure 20: Scatter plot of centerline deviation values for Collection 1 yarns: 1536 total measurements taken every 0.7175 mm along 7.23 inches.
**Figure 21:** Regression plot of centerline deviation values vs following centerline deviation values for Collection 1 yarns: 1280 total measurements taken every 0.7175 mm along 7.23 inches. Plot gives best fit line (graphed) of $y = 0.3018x - 0.0005$.

The plot matrix displays all possible centerline deviation vs centerline deviation plots. Each row or column represents one yarn. The plot in the intersection of a row and column is the plot of the row yarn’s centerline deviations against the column yarn’s centerline deviations. The diagonal plots are on the y=x line because they are plots of a set of centerline deviations against itself. A spherical “cloud” of points would represent no correlation. We notice that plots on the diagonals above and below the main diagonal display directed clouds. That is, although the plots certainly are not lines, they appear to have a shape that suggests not spheres so much as clouds oriented along a line with positive slope. These plots show a correlation between adjoining yarns’ centerline deviations, although it is a diluted association.

We look in Figure 21 at the regression plots of centerline vs previous centerline on the same plot. This set is best described by the relationship

\[
\text{centerline deviation} = 0.3018 \times \text{previous centerline deviation} - 0.0005 \tag{5}
\]

Let's look at the regression error:

\[
\text{error} = 0.3018 \times \text{previous centerline deviation} - 0.0005 - \text{centerline deviation} \tag{6}
\]

In Figure 25, we see that the error appears to oscillate and therefore could be modeled
Figure 22: Regression error plot for Collection 1 centerline deviation values vs previous centerline deviation values. 1280 total measurements taken every 0.7175 mm along 7.23 inches, using regression line $y = 0.3018x - 0.9005$. Each plotted line represents the error on one yarn.

using a Fourier transform. We want to find the similarities between these error plots. Each line represents one yarn and we notice that the lines seem to fall within the envelope of a larger frequency sine plot. We use the $\texttt{fft}$ command in MATLAB to transform the error plots to the frequency domain. Our result for each yarn is a set of complex numbers which are Fourier coefficients associated with particular frequencies. The absolute value of the coefficient for a particular frequency represents the power of that frequency. The larger the absolute value of a frequency’s coefficient, the larger the role that frequency plays in the behavior of the original plot. Plotting the coefficient power of each yarn together on the same plot in Figure 23, we see that the same frequencies play large roles in each error plot. To produce similar error, we would have to ensure that the lower frequencies play the largest roles.
Figure 23: Regression error power plot for Collection 1 centerline deviation values vs previous centerline deviation values: 1200 total measurements taken every 0.7175 mm along 7.23 inches, using regression line $y = 0.2018x - 0.0005$. Each plotted line represents the error on one yarn.

3.2.4 Width-to-Gap Correlation

The combing process described above as a cause of centerline-to-centerline correlations could also cause the wider part of a yarn to be compensated by a narrower gap and vice versa. This may cause a width-to-gap correlation as well. We look in Figure 24 at scatterplots of width and gap data from the first collection. These plots show a definite correlation between yarn width and the size of the adjoining gaps, as hypothesized. A positive correlation exists between a yarn's width and the width of the following gap. However, a much stronger negative correlation exists between a yarn's width and the width of the previous gap. We choose to investigate the stronger correlation. We plot in Figure 25 the width vs following gap values on the same graph to find a regression relationship for the entire sample. The best fit line for this data is

\[ \text{gap width} = -1.4843 \times \text{previous yarn width} + 2.2980 \]  

(7)
Figure 24: Scatter plot of gap width vs previous yarn width values for Collection 1 yarns. 1280 measurements taken every 0.7175 mm along 7.23 inches.

Figure 25: Regression plot of gap values vs previous yarn width values for Collection 1 yarns. 1280 total measurements taken every 0.7175 mm along 7.23 inches of six yarns. Plot gives best fit line (graphed) of \( y = -1.446x + 2.396 \).
Figure 25: Regression error plot for Collection 1 gap values vs previous width values: 1280 total measurements taken every 0.7175 mm along 7.25 inches of six yarns, using regression line $y = -1.4843x + 2.2980$. Each line represents the error on one yarn.

Looking at the error function,

$$\text{error} = -1.4843 \times \text{previous yarn width} + 2.2980 - \text{gap width}$$  \hspace{1cm} (8)

We plot the Fourier coefficient power plot in Figure 27. Notice that, as in the centelline case, lower frequencies play a much larger role in the error than higher frequencies. When validating the generation model, we will check to see that similar relationships exist between the generated values.
Figure 27: Regression error power plot for Collection 1 pop values vs previous width values: 1280 total measurements taken every 0.7175 m at 7.28 inches of six yarns, using regression line $y = -1.4843x + 2.2880$. Each line represents the error on one yarn.
CHAPTER IV

METHOD OF BACKING GENERATION

The goal of this chapter is to present the methodology for generating the weft yarns as they appear in the backing fabric. The objective is to match yarn width, gap width, and centerline deviation sample means, standard deviations, and distribution shapes. The centerline-to-centerline and width-to-gap correlations must also be replicated. When generating the new parameter values, all of these requirements must be met simultaneously. The number of conditions imposed on the desired results makes this task difficult. Not all of these requirements will be met exactly, but we must try to achieve the closest match for each one as well as the best compromise between errors in one versus another. A further difficulty lies in the interdependence of the three parameters. The first set of statistics and lengthwise correlations can be reproduced on a yarn-to-yarn basis, therefore we will first concentrate on producing a yarn that is similar to those in the original fabric. Afterward, we will focus more specifically on relating yarns to each other to reproduce the correlation relationships present in the original data. The cross-yarn plots (Figures 14 to 19) have already suggested a Fourier approach, and that is where we begin.

4.1 Distribution Replication

Focusing on the first set of data collected, the one 256x5 and two 256x6 arrays can be transformed using the `fft` command in MATLAB. This command computes the discrete Fourier transform of a set of data using the formula

\[ X(k) = \sum_{n=1}^{N} x(n) e^{-j2\pi (k-1)(n-1)/N}, \quad 1 \leq k \leq N. \]

where \( N \) is the number of data points, in our case 256. The resulting \( X(k)'s, k = 1, ..., N, \) are the Fourier coefficients. \( W \) represents the Fourier coefficients of the width data, \( G \) represents the Fourier coefficients of the gap data, and \( C \) is used for the Fourier coefficients of the centerline deviation data. Recall that for Backing B, six sets of data were obtained.
The widths and centerlines and five sets were measured for the gaps. The mean and standard deviation of the Fourier coefficients \( W(k) \) and \( C(k) \) are found for each \( k \) across the six sets of width and centerline data and of the Fourier coefficients \( G(k) \) are determined for each \( k \) across the five sets of gap data.

Then, three new sets of Fourier coefficients are generated using the `normrnd` command in MATLAB, which generates numbers according to the normal distribution with input mean and standard deviation. Here, we input the mean and standard deviations of the original sets of coefficients calculated above. This data is transformed back to the space domain through the use of the formula

\[
z(n) = \frac{X(1)}{N} + \sum_{k=1}^{K} \left[ \frac{2\text{Re}(X(k+1))}{N} \cos\left(\frac{2\pi k n}{N}\right) + \frac{-2\text{Im}(X(k+1))}{N} \sin\left(\frac{2\pi k n}{N}\right) \right].
\]

(10)

where \( n \) is interpreted as discrete space and \( dt \) as the distance between data points. Generally, the original data domain is known as the time domain and the variable \( t \) denotes time. However, here we have used discrete spatial data and will instead use the term "space domain" for the original data domain.

Formula (6) provides equations in terms of trigonometric functions that generate width and gap values at approximation points 0.7175 mm apart for any length yarn. However, this equation repeats itself with a period equal to the length of the original data array. Yarns in real backing are not periodic, therefore, to keep the generated yarns from demonstrating false characteristics, we need to re-generate the data every so often. In this case, we chose a random number between 142 and 249, the number of data points it takes to produce 4 and 7 inches of yarn, respectively. Then we produce that amount of yarn before choosing another number and regenerating again. We also choose a random number between 1 and 256 at each regeneration point at which to start the next generation to avoid repeating the initial four inch yarn section throughout the generated yarn.
4.2 Correlation Replication

Once a yarn has been generated, more yarns are produced. In this way, a viable virtual backing is generated. The centerline deviation, width, and gap values for each data point across the fabric have been generated. However, these values are interdependent, and therefore all three generated cannot be used. The first approach is to make the centerline value the dependent variable. The placement of the centerline of a yarn is half the width of the previous yarn added to its centerline, plus the gap value and half the diameter of the new yarn.

\[
\text{centerline } n = \frac{\text{width } (n-1)}{2} + \text{centerline } (n-1) + \text{gap } (n-1) + \frac{\text{width } n}{2}. \quad (11)
\]

However, this approach causes a falsely large dependence on the first centerline. Consider the case of two fabrics with identical, uniform yarn widths equal to 0.3 mm, gap widths equal to 0.7 mm, and initial centerline a straight line. Figure 29 shows this fabric with initial yarn centerline the x-axis. In Figure 30, the initial yarn centerline is a sine wave.
The two fabrics are very different, yet the only differentiating parameter is the first yarn's centerline. This dependence can cause a "stacking" effect as large numbers of yarns are generated. See Figure 31 for an example of the propagation of this stacking across a 40 in wide fabric encountered with the use of this model. The error is evidenced by the fabric width being greater on the right side (x=40 in) of the generated fabric.

Therefore, a mean centerline for the next yarn should be chosen in such a way that the resulting gap behavior matches the gap behavior in the original data. We choose, for the first yarn's mean centerline, the x-axis. We have already transformed and regenerared the gap data in the same way as the width and centerline data. One data point across the length of the yarn is chosen at random and the gap is generated for that point. We already have information on the first yarn, and so for the second we take the p-value for the top yarn edge of the first yarn at our chosen data point (the centerline value plus half the yarn width at that point) and add to it the generated gap, half the width of the second yarn at that point, and the distance off the mean of the centerline of the second yarn at that point. We now have a value for the mean centerline across the length of the second yarn and can use generated values for the centerline deviation and yarn width at each point to
Figure 30: Backing with yarn width 0.3 mm, gap width 0.7 mm, and initial yarn center-line as a sine wave. Dotted lines are yarn bottom edges and solid lines are yarn top edges.

Figure 31: Backing generated using data from Collection 1 and the dependence model in equation 11. Backing is stowed 1.5 inches over 40 inches due to stacking.
characterize the second yarn completely.

We can produce sets of centerline deviation values that are generated from the Fourier coefficients of the original data that have been randomized. But we want these values to be correlated to the first yarn as in the original data. Instead of generating new centerline deviation values for each new yarn, we use our initial regression statistics to relate deviation values of a yarn to deviation values of the previous yarn. The polyfit command in MATLAB is used to find the regression line for our original data in Figure 21. Examining the error in Figure 23, we see that it has a definite Fourier-style structure. We can then model the error values the same way that we model the diameter and gap values. To calculate the centerline deviation values of the nth yarn, we take the centerline deviation values of the (n - 1)st yarn and transform them using our regression coefficients and then add our generated error term.

\[
generated \text{ centerline deviation} = 0.3018 (\text{previous centerline deviation}) - 0.0005 + \text{generated error term.} \tag{12}
\]

This procedure is repeated for as many weft yarns as are needed.
CHAPTER V

TESTING OF GENERATED DATA

5.1 A Sample Generation

Now we must investigate the model we have developed to see how well it matches the input data. For purposes of illustration, look at a small sample, comparable to the size of the original data. Figure 32 is a plot of the original five Backing B yarn used for input data. Figure 33 is a plot of five yarns generated using our method. In both figures, the dotted lines represent yarn bottom edges and the solid lines represent yarn top edges. Figures 34 and 35 are histograms of the width sizes of the original and generated Backing B samples. Although the means and standard deviations agree well, the distribution of the generated sample matches a normal distribution more closely. The original distribution is more heavily weighted toward the mean. Figures 36 and 37 are histograms of the gap sizes of the original and generated Backing B samples. Again, the generated distribution appears to match the normal distribution more closely than the original, which is weighted toward the mean. Figures 38 and 39 are histograms of the original and generated centerline deviation values for Backing B. Here we see a better match. For all of the data, the descriptive statistics have been reproduced well.

Figures 40 and 41 show the centerline regression plots of the original and generated fabrics, respectively. A good match between original and generated values is observed. This would be expected, as the best-fit line and error terms from the original sample were used directly to produce the generated piece. The regression error Fourier coefficient power obtained by using the line fitted to the original values is given in Figure 43. As before, we see a good fit for error. Lower frequencies are much more dominant in the generated error as well as the original error. This is expected because the original error was used to produce the generated error. Analysis of Figure 45, the regression plot of gaps against widths for the generated data, shows that the width-to-gap correlation relationship has

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Figure 32: Backing B original yarns: 6 yarns, 7.23 inches. Values graphed every 0.7175 mm along each yarn/gap.

Figure 33: Backing B type generated yarn: 6 yarns, 7.22 inches, values generated every 0.7175 mm along each yarn/gap.

Figure 34: Histogram of width values for Collection 1 yarns: 1536 total measurements, taken every 0.7175 mm along six consecutive yarns.

Figure 35: Histogram of width values for generated Collection 1-type yarns: 1536 total data points generated every 0.7175 mm along six consecutive yarns.
Figure 36: Histogram of gap values for Collection 1 yarns: 1280 total measurements, taken every 0.7175 mm along five consecutive gaps.

Figure 37: Histogram of gap values for generated Collection 1-type: 1280 total data points generated every 0.7175 mm along five consecutive gaps.

Figure 38: Histogram of centerline deviation values for Collection 1 yarns: 1536 total measurements, taken every 0.7175 mm along six consecutive yarns.

Figure 39: Histogram of centerline deviation values for generated Collection 1-type yarns: 1536 total data points generated every 0.7175 mm along six consecutive yarns.
Figure 40: Regression plot of centerline deviation values vs following centerline deviation values for collection 1 years: 1280 total measurements taken every 0.7175 mm along 7.23 inches. Plot gives best fit line (graphed) of $y = 0.3018x - 0.0005$.

Figure 41: Regression plot of centerline deviation values vs previous centerline deviation values for collection 1-type generated yam: 1280 total data points, taken every 0.7175 mm along 7.23 inches of five consecutive yams. Plot graphs best fit line of $y = 0.3018x - 0.0005$.

Figure 42: Regression error power plot of centerline deviation values vs following centerline deviation values for Collection 1 backing: 1280 total data points generated every 0.7175 mm along 7.23 inches of five consecutive yams, with respect to original data best-fit regression line $y = 0.3018x - 0.0005$.

Figure 43: Regression error power plot of centerline deviation values vs following centerline deviation values for Collection 1-type generated backing: 1280 total data points generated every 0.7175 mm along 7.23 inches of five consecutive yams, with respect to original data best-fit regression line $y = 0.3018x - 0.0005$. 

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Figure 44: Regression plot of gap values vs previous yarn width values for collection 1 yarns. 1260 total measurements taken every 0.7175 mm along 7.23 inches of six yarns. Plot gives best fit line (graphed) of $y = -1.4843x + 2.2980$.

Figure 45: Regression plot of gap values vs previous width values for collection 1-type generated backing: 1260 total data points, generated every 0.7175 mm along 7.23 inches of five consecutive yarns/gaps. Plot generated with original best fit line of $y = -1.4843x + 2.2980$.

not been as well preserved as the centerline regression relationship. However, the gap was the dependent variable, which means that this relationship was produced indirectly, relying on yarn width and centerline deviation distributions as well as the one generated gap and centerline correlation. The errors in these variables has combined to make the width-to-gap regression less well-described than other variables. However, we see that the fits are still reasonable.

Figure 47 is plot of error power with respect to the best fit line of the original data. Once more the error takes the expected form. We believe that, in this case, the correlation statistics have been well reproduced.

We see that a small piece of fabric can be generated successfully, but what about a large piece? A 14.5 inch by 34.5 inch swatch is generated. In Figure 69, we look at a plot of the new fabric. This plot shows the first ten inches, to get an idea of the kind of result that can be produced. We look in Figures 49 and 50 at the width-to-gap correlation and best-fit error power. We see that the correlation fit is actually better than the first swatch. This correlation can produce a reliable approximation over time. Again the error behavior is dominated by low-frequency changes. Now that we have an idea of what can
be generated using this method, we will look at the overall picture.

5.2 General Backings

Our goal is to generate large pieces of backing fabrics that are statistically similar to the original fabric. An interesting question is: over a large amount of time and generations, will these similarities persist?

To investigate this, we set up a program to generate 50 swatches the same size as our original piece - 7.23 inches wide and about 4.4 inches long. Instead of comparing every statistic and correlation relationship of all 50 swatches, which would be very time-consuming. We determine the most important conditions and check these. We use the original lengthwise correlation and yarn width distribution to generate new yarn width values directly, so we may be reasonably certain that the yarn width distribution will be appropriate. We use the original lengthwise correlation and distribution of centerline deviation to generate the original centerlines, and original centerline-to-centerline correlation to generate more centerlines.

This makes us reasonably certain that we've appropriately reproduced centerline deviation distributions and correlations. The one dependent parameter is the gap width. Each time a
Figure 48: Backing B type generated yarns, 14.5 inches by 34.5 inches (365 yarns), values generated every 3.7175 mm along each yarn/gap.

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Figure 49: Regression plot of gap values vs previous width values for collection 1-type generated backing; generated every 0.7175mm along 14.5 inches of 505 consecutive yarns/gaps. Plotted with original best-fit line $y = -1.483x + 2.969$.

Figure 50: Regression error power plot of gap values vs previous width values for collection 1-type generated backing; generated every 0.7175mm along 14.5 inches of 505 consecutive yarns/gaps, with respect to original data best-fit regression line $y = -1.483x + 2.969$. 
swatch is generated, the program calculates the mean, standard deviation, and skewness of the resulting centerline deviation distribution, as well as the best-fit width-to-gap regression line. This is done to check that we’ve managed to generate an appropriate gap distribution from the centerline deviation and yarn width distribution and the centerline-to-centerline correlations. We also need to check the width-to-gap correlations of the generated yarn width and gap width distributions. We expect that these values will form distributions centered around the original values, without too much variation. Figures 51 to 53 show that our gap statistics are appropriate. The best-fit regression lines are plotted in Figure 54. Here, the width-to-gap correlations are well matched.
Figure 54: Best-fit regression lines for 50 swatches of generated Backing E-type backing, 7.23 in.-cm by 0.4 inches (6 yarns).
CHAPTER VI

FLEXIBILITY OF MODEL

6.1 Other Backing Types

So far we have focused solely on Backing B. However, we have collected data on three other backing types. We want to know if the model can be applied more generally. We expect that any backing with geometric characteristics similar to those of Backing B will be well described by our model. However, not all of the backings are as uniform as the fibrillated backing. We’ve already discussed the higher incidence of unfolding present in the tape (Backing A) and striated (Backing D) backings. The level of incidence of folding may skew the parameter distributions beyond what can be approximated by a normal distribution. In Figure 55, we see that the yarn width distribution of the tape backing does not fit a normal distribution as well as the yarn width distribution of Backing B (Figure 7). This leads to less appropriate fits of gap distribution and width-to-width correlation. The normal probability plots for Backing D also are not well approximated by a normal distribution. For complete analysis and results of the remaining three backings, see Appendix A. Tables 1 and 2 provide a summary of generation and analysis results for descriptive statistics.

<table>
<thead>
<tr>
<th>Backing</th>
<th>Original Yarn Width</th>
<th>Original Gap Width</th>
<th>Original Centerline Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.578</td>
<td>0.1913</td>
<td>-0.0006192</td>
</tr>
<tr>
<td></td>
<td>generated</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>1.583</td>
<td>0.2432</td>
<td>-0.00013077</td>
</tr>
<tr>
<td></td>
<td>original</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>generated</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>1.570</td>
<td>0.489</td>
<td>-0.00064175</td>
</tr>
<tr>
<td></td>
<td>generated</td>
<td></td>
<td></td>
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<tr>
<td>D</td>
<td>1.600</td>
<td>0.2045</td>
<td>-0.034</td>
</tr>
<tr>
<td></td>
<td>generated</td>
<td></td>
<td></td>
</tr>
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</table>

Table 1: Original and generated backing means
Figure 55: Normal probability plot for Collection 1 Backing A yarn width values: 1280 total measurements taken every 0.7177 mm along 7.23 inches of five adjacent yarns, sample mean=1.5780 mm, standard deviation=0.3380 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.

<table>
<thead>
<tr>
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<th>Standard Deviation</th>
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<tr>
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<td>original</td>
<td>0.238</td>
</tr>
<tr>
<td>generated</td>
<td>0.1614</td>
</tr>
<tr>
<td>Backing B</td>
<td></td>
</tr>
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<td>original</td>
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</tr>
<tr>
<td>generated</td>
<td>0.1311</td>
</tr>
<tr>
<td>Backing C</td>
<td></td>
</tr>
<tr>
<td>original</td>
<td>0.1393</td>
</tr>
<tr>
<td>generated</td>
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</tr>
<tr>
<td>Backing D</td>
<td></td>
</tr>
<tr>
<td>original</td>
<td>0.1998</td>
</tr>
<tr>
<td>generated</td>
<td>0.2079</td>
</tr>
</tbody>
</table>

Table 2: Original and generated backing standard deviations.
6.2 Simulation of Common Flaws

We can also simulate common flaws occurring in carpet backing to determine how they impact the final product. Two flaws commonly encountered in carpet manufacturing are bowing and skewing of the primary backing fabric. Bowing occurs when the backing stretches out from the horizontal towards the middle of the machine, and skewing occurs when the backing goes in diagonally. Figures 56 to 59 show examples of bowing and skewing compared to the original straight fabric. Industry standards allow for 1 inch of bowing or skewing in the machine direction across 12 feet of backing. We can simulate these phenomena by adding a function to the generated values to analyze strike patterns on flawed backings.
7.1 Methods of Strike Pattern Analysis

Now that we can generate a virtual backing, we will investigate strike patterns. To do this, we first must have an idea of what phenomena we would like to quantify. The hypothesis is that Moiré effect is caused by adjacent needles striking on different sides of the same yarn. One way to quantify this idea is to count the number of yarns skipped between strikes on each needle. Another is to identify when a transition is made from one side to the other of a yarn from needle to needle along the needle bar.

A program was developed that tracks the center of each needle strike based on the geometry of the needles and needle bar. The needle bar setup used in this paper is a common two-bar system. Input values are number of needle bars, offset amount between bars, distance between bars, distance between needles on each bar, distance between first needle and side of the backing, and stitch length (distance between strikes). These measures are shown in Figure 60. Our input values for this analysis are listed in Table 3. The x (cross-machine direction) and y (machine direction) coordinates of each strike are calculated and stored in an array whose rows represent individual needles and whose columns represent strikes. Other variables that can be associated with each needle and strike are stitch color.

<table>
<thead>
<tr>
<th>Input Type</th>
<th>Input Value</th>
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<tbody>
<tr>
<td>Number of Needle Bars</td>
<td>2</td>
</tr>
<tr>
<td>Offset Amount Between Bars</td>
<td>0.0125 in</td>
</tr>
<tr>
<td>Distance Between Bars</td>
<td>0.25 in</td>
</tr>
<tr>
<td>Distance Between Needles on a Bar</td>
<td>0.0025 in</td>
</tr>
<tr>
<td>Initial Needle Registration, X-Direction</td>
<td>0 in</td>
</tr>
<tr>
<td>Initial Needle Registration, Y-Direction</td>
<td>0.03 in</td>
</tr>
<tr>
<td>Stitch Length</td>
<td>0.1111 in</td>
</tr>
<tr>
<td>Needle Strike Area Length</td>
<td>0.0774 in</td>
</tr>
<tr>
<td>Needle Strike Area Width</td>
<td>0.0233 in</td>
</tr>
</tbody>
</table>

Table 3: Needle bar input values.
Figure 60: Diagram of needle bar input values.
and pile height, which may entered as an \( m \times n \) matrix with \( m \) the number of needles and \( n \) the number of strikes. All these indicators are stored within our array. For each entry, the \( x \)-coordinate is used to find the closest generation point and the \( y \)-coordinate is used to find the closest yarn as well as the last yarn encountered before the strike. The algorithm for finding these values is displayed in Figure 62. To find the number of yarns skipped between strikes on a single needle, we subtract the closest yarn before the \( k \)th strike from the closest yarn before the \( (k+1) \)st strike.

\[
\# \text{yarns skipped}(j,k) = \# \text{of last yarn before } k\text{th strike} - \# \text{of last yarn before } (k-1)\text{st strike.}
\] (13)

To find transitions across yarns from needle to needle, we record whether a needle strikes before or beyond its closest yarn and the closest yarn to its neighbor on the left. We assign a '1' when a needle strikes after the yarn and a '0' when the needle strikes before the yarn. To find the transition value for the \( k \)th needle, we subtract the value for the \( (k-1) \)st needle (the needle located to the left when looking out from the machine) with respect to the \( n \)th needle’s closest yarn (Figure 61). The algorithm is given in Figure 62. When calculating transitions across two needle bars, the values for the needle located closest to the concerned needle in the \( x \)-direction are used, even though they are on different needle bars. In the final product, we are concerned with tufts that lie next to each other in the carpet. Therefore, even though needles on different bars strike the same part of the backing at different times, we are interested in their ‘tufts’ ultimate position and therefore compare across the bars. Possible results are 1, which indicates a transition from beyond to before a yarn, 0, which indicates no transition, and 1, which indicates a transition from before to beyond the yarn.

\[
\text{transition value}(j,k) = \text{position value}(j,k)-1-\text{position value}(j,k).
\] (14)

We produce two \( m \times n \) arrays, where \( m \) represents the number of needles and \( n \) the number of needle strikes. The first array catalogs the number of yarns skipped between the current and previous strikes. The second array catalogs the transition occurring from needle to needle across the needle bar.

Following through with this idea of needle strike/weft yarn interaction, another...
Figure 61: Sample yarn with needle strikes.
For each needle strike:

i. Find closest generation point along yarn using x-position:

```
if (y > y1) {
  x1 = x1 + step;
  x2 = x2 + step;
} else if (y < y2) {
  x1 = x1 - step;
  x2 = x2 - step;
}
```

ii. Find closest yarn using y-position:

```
if (x > x1) {
  y1 = y1 + step;
  y2 = y2 + step;
} else if (x < x2) {
  y1 = y1 - step;
  y2 = y2 - step;
}
```

Figure 62: Flow chart of skip and transition calculation.
indicator of Moiré effect could be the amount of overlap between the needle and the yarn. Certainly incidences of splitting and breakage would be dependent on such a factor. We already have the closest yarn and generation point calculated for each needle and strike. We calculate whether the needle strikes on a yarn and then find the overlap. The algorithm for this calculation is described in Figure 63. We now have an $m \times n$ array where $m$ is the number of needles and $n$ is the number of needle strikes which stores the amount of linear overlap between the needle strike area and the closest yarn.

We have arrays quantifying cross yarn transitions, yarn skips, and linear overlaps.
Figure 64: Needle strike pattern overlaid on generated Backing B-type backing. Dark ovals represent the needle strike areas of needles on the second bar, white ovals represent the needle strike areas of needles on the first bar, dotted lines represent yarn cotton edges, and solid lines represent yarn top edges.

The task of interpretation remains. The *imshow* command in MATLAB is used to convert the arrays to a grayscale image. The image can then be altered using gaussian filters of successively larger standard deviations to find patterns caused on a larger scale.

As an example of what we have, we look at the needle strike pattern on a swatch of generated Backing B-type backing. Figure 64 displays the result. Results for the transition, skip, and linear overlap arrays can be found in Appendix B. It is easier to look at image than a set of numbers, and so we use the *mat2gray* command in MATLAB to convert each array to an image (Figures 65 to 67). We want to look for areas where the needles move forward or backward for some persisted distance. Again, we note that “forward” indicates a movement in the increasing y-direction and away from the needle bar, and “backward” indicates a move in the decreasing y-direction and towards the needle bar.

In the transition image, black represents -1, a change from striking after to before the yarn from needle-to-needle moving right across the needle bar. Gray represents 0 - that is, no change. Both the current needle and the needle to its left strike on the same side
Figure 65: Transition array for generated Backing B-type generated backing displayed as a grayscale image. Each column represents the needle bar on a particular spike, and each row represents the set of strikes for one needle. Gray=0 and means that the needle stayed on the same side of the yarn as the previous needle. White=1 and means that the needle skipped forward across the yarn from the previous needle. Black=-1 and means that the needle skipped backward across the yarn from the previous needle.
Figure 66. Yarn skip array for generated Backing B-type generated backing displayed as a grayscale image. Each column represents the needle bar on a particular strike, and each row represents the set of strikes for one needle. Black=0, gray=1, white=2. The number indicates the number of yarns skipped from the previous strike of that needle.
Figure 67: Linear overlap array for generated Backing B-type generated backing displayed as a grayscale image. Each column represents a yarn, and each row represents a needle. Black=0, white=maximum overlap, and shades of gray are lower numbers when darker and lighter numbers are higher numbers.
of the current needle's closest yarn. White represents a 1 - a change from striking before
to after the yarn from needle-to-needle moving right across the needle bar. In the skips
image, black represents a 0 - or no yarn skipped between the current and previous needle
strikes. Gray represents 1 yarn skipped between the current previous needle strike, and
white means that 2 yarns were skipped. Notice that the first column is black, meaning that
no yarn was skipped - because there was no previous strike. In every other case, at least
one yarn was skipped between strikes, as would be expected based on a stitch length of 1/9
inch or approximately 2.8 mm and average yarn width of 1.1925 mm. A large area of white
in either the transition or skip images would represent a portion of the needles moving
forward across the yarns, and black would represent a portion of the needles moving back
across the yarns. For the linear overlap array, a large area of white would represent an area
of yarn splits and breakage, whereas a large area of black would represent a large area of
unharmed yarns. We can now use these techniques to investigate the results for much larger
backings.

7.2 Strike Pattern Analysis of Generated Backings

We stated originally that the model of generated backing would not only have to be
validated with the original fabric data, but also be able to be used for strike pattern analysis.
To verify the necessity of modeling variation, we compare strike pattern analysis results for
the generated backing as described in Chapter 4 with results from a generated uniform,
straight backing. For purposes of illustration, a small portion of the uniform backing is
plotted in Figure 68 and a same-size portion of the generated backing is plotted in Figure
69. The entire backings analyzed are 14.5 inches wide by 34.5 inches long. These dimensions
were chosen to provide a page appropriate sized image discus approximately 512 bits square.
Each row of bits represents a needle and each column of bits represents one strike of the
double needle bar. The image of skips for the uniform generated backing is displayed in
Figure 70 and the image of skips for the model generated backing is displayed in Figure 71.
The image of transitions for the uniform generated backing is displayed in Figure 72 and
the image of transitions for the model generated backing is displayed in Figure 73. The
Figure 68: Uniform generated backing.

Figure 69: Model generated backing.

Figure 70: Uniform generated backing skips.

Figure 71: Model generated backing skips.

Figure 72: Uniform generated backing transitions.

Figure 73: Model generated backing transitions.
image of linear overlap for the uniform generated backing is displayed in Figure 74 and the image of linear overlap for the model generated backing is shown in Figure 75. As expected, needle-yarn interactions in the uniform generated backing set up regular patterns of skips and transitions. Either this is not the sort of pattern that would cause a Moiré effect, or the real backing is different enough to disturb the patterns. Looking at the images of the model generated backing results, we see that the images are clearly different from the uniform generated backing images. This suggests that the method proposed was necessary — there is enough variation to cause differences between needle-yarn interactions in uniform and real backings. This difference does not suggest that the model was inadequate because we have seen in our analysis that the model's failure was in not capturing enough variation. The model made distributions more normal and decreased the slope in the width-to-gap regression relationship. These changes would decrease variation. Also, the images of the model generated backing results do not confirm or reject the possibility that regular patterns such as those seen in the images of uniform backing results cause a Moiré effect. If regular patterns did emerge consistently on the model generated backing, then we could reject this idea, as Moiré defects do not consistently appear on real backing.

We have, through needle stripe pattern analysis, illustrated the need for a method to produce realistic backing. However, this analysis neglects the fact that the first needle bar hits the fabric before the second needle bar. This changes the fabric geometry so that the second needle bar sees fabric with different statistics. Will these changes be enough to change needle-yarn interactions significantly? We will investigate this idea in the next chapter.
7.3 Color and Pile Height

Before moving on to the dynamic model, consider the causes of Moiré effect. Needle-yarn interactions are only part of the picture. How these interactions overlap with changes in color and pile height must be recorded and investigated as a cause of the defect. As mentioned in Section 7.1, values for the color and pile height of the inserted tufts are also stored in the program that calculates skips, transitions, and linear overlap.

Figure 76 shows sample color and pile height patterns - here we have chosen two-color, two-height checkerboard patterns. The plot represents the surface of the tufts. The heights chosen are 1/2 and 1 unit. The two colors are represented by black and dark grey ink. One hundred tufts are plotted, a ten by ten square. Here we see how the tuft color and pile height interact to form a wedge-shaped pattern. These images can be overlayed onto skip, transition, and linear overlap images in order to look for interaction patterns.
CHAPTER VIII

DYNAMIC MODEL

The previous chapter focused on various methods of characterizing the generated backing with respect to the needle strike patterns. However, we have not yet taken into account changes in the backing caused by the needle strikes. When the needle enters the fabric, it changes the fabric geometry. These changes should not disappear completely after the needle leaves; at the very least the deformation will be the size of the yarn tuft inserted into the backing. Moreover, if the tufting machine uses more than one needle bar, the bars will not hit the same part of the backing at the same time. Instead, the second needle bar will encounter the backing after it has already been changed by the first needle bar.

In addition, the two needle bars hit the fabric at the same time. When the first needle bar moves some yarns forward and the second needle bar moves some yarns backward, there may be bunching of the yarns caught between the two bars. This effect may also be a factor in the appearance of defects such as the Moiré effect.

We hypothesize that such changes in fabric geometry will alter strike pattern analysis results and therefore must be included in the model used to study Moiré effect. We will look at a worst case scenario of yarn movement and then determine whether such effects must be accounted for in the dynamic model.

8.1 Yarn Movement Simulation

We simulate the a large amount of yarn movement by assuming that no material is lost in the strike. Instead, wherever a needle strikes a yarn, we will calculate the linear overlap and move the yarn that amount in the appropriate direction. If the strike center lies on a yarn, we will move both the yarn top and bottom to account for the needle's entry. If the strike center lies below a yarn, we will move the entire yarn the appropriate amount in the increasing y-direction. If the strike center lies after a yarn, we will move the entire yarn
the appropriate amount in the decreasing y-direction. We then calculate the yarn top and bottom edge averages of the two points to the left and right of each point and use these averages for our new values. This captures yarn movement across the entire yarn, not just at the generation points affected by the first needle bar. The algorithm used is displayed in Figure 77.

8.2 Strike Pattern Analysis of Generated and Moved Backing

As an illustration, we plot one model generated backing from Chapter 4 in Figure 78 and the move backing after applying the moved yarns algorithm in Figure 79. We also apply the moved yarns algorithm to the longer model generated backing from Chapter 6. Figures 80 and 81 display the slips images for the original generated and moved generated backings,
Figure 78: Generated Backing B-type Backing

Figure 79: Moved Generated Backing B-type Backing

Figure 80: Generated Backing Slips

Figure 81: Generated moved Backing Slips

respectively. Since there does not appear to be much difference between these two images to the unassisted eye, we calculate the difference in the two arrays and display that new array as an image in Figure 82. Here we see that there are some changes. The proportion of transition change is just under 4%. 2708 out of 71610 pixels in the image are white indicating a change in transition type at that point.

Figures 83 and 84 display the transitions images for the original generated and moved generated backings, respectively. Since we cannot determine the amount of change with the unassisted eye, we again calculate the difference in the two arrays and display that new array as an image in Figure 85. Here, we see a significant amount of change from the unmoved transitions array. The average change is just under 10%. 6988 out of 71610 pixels
Figure 82: Absolute value of difference between yarn skip arrays on generated and generated moved Backing B-type backing. Black represents 0 - a place where no change occurred. Gray indicates a change of 1 - either an additional yarn was skipped or one fewer was skipped.

Figure 83: Generated Backing Transitions

Figure 84: Generated Moved Backing Transition
Figure 85: Absolute value of difference between needle transition arrays on generated and generated moved Backing B-type backing. Black represents 0 - a place where no change occurred. White indicates a change in transition type.

In the image, the values are white - indicating a change in transition type at that point. We would expect that yarn placement would change more on a micro- than macro scale. This idea is confirmed by the larger amount of difference in the transition array, which will be affected by movement on a smaller scale than in the skips array.

We assumed as much change as possible for the shifts caused by the first needle bar. We saw that with that amount of shift, needle-yarn interaction was affected. We postulate that with the amount of shift caused in a real situation, which we assume to be less than the amount simulated here, the changes in needle-yarn interaction could be significant. It would be worthwhile to model this shift in order to verify its necessity.
CHAPTER IX

SUGGESTIONS FOR FURTHER RESEARCH

9.1 Scale-Space Imaging

We have examined Moiré effect using stripe pattern analysis of skips, transitions and linear overlap. We postulate that patches where needles skip forward over a series of yarns may indicate Moiré effect. However, we don’t know the scale at which these effects may appear. It may require a large number of needles skipping over a small amount of yarns, a small number of needles skipping over a large amount of yarns, or a large number of needles skipping over a large amount of yarns. In any case, the images that we have now provide information only on the scale of the needle size. To look at effects on a larger scale, we can try using a Gaussian filter, as suggested in [4]. Ultimately, we would like to stack images of the original filtered through Gaussian filters with different standard deviation for visualization purposes. We would develop an algorithm that characterizes blob size and placement. However, for now we can look at images filtered with different standard deviations for purposes of comparison and illustration. Figure 66 is the transitions image for our 14.5°x34.5° generated Backing B-type backing filtered with a Gaussian filter of standard deviation 1. We choose to analyze transitions rather than skips or linear overlap because the three shades provide the most visually dramatic images. Figure 87 is the transitions image for our 14.5°x34.5° generated Backing B-type backing filtered with a Gaussian filter of standard deviation 2. We notice that as we increase the standard deviation in Figures 26 and 89, we see patterns on slightly different scales.

In Figure 89, we see blurs that we would be hard-pressed to find in Figure 73. The filters make associations that our eyes can’t. We can produce many images at very close standard deviations. If we could ‘stack’ these images as suggested in [4], we could perform the same kind of blob analysis. This kind of analysis could give us an idea on what scale changes such as shearing or bowing would cause. We could also try finding changes between
Figure 86: Filtered generated backing transition image, std=1

Figure 87: Filtered generated backing transition image, std=2
Figure 88: Filtered generated backing transition image, std=3

Figure 89: Filtered generated backing transition image, std=4
uniform and generated or generated and generated moved on some scales.

One weakness in these patterns is the vertical tendency of the patterns. As would be expected, the patterns depend much more on yarn than needle. However, if we could filter more horizontally than vertically to try and de-emphasize vertical patterns, we may gain more information about needle-yarn interactions. These analyses would be time-consuming and difficult, and therefore are beyond the scope of this thesis, but are certainly possible.

9.2 Dynamic Model Development

The moved yarn algorithm is another potential topic for future research. The algorithm we use in this thesis is just a simple model that moves yarns the distance of the needle overlap. However, real needle-yarn interactions are far more complicated. The yarn will not be moved perfectly in most instances, but will move, fold, and perhaps even lose some material when impacted by a needle. The yarn left in the fabric will have some additional effect on the yarn, as may the possible bucking between needle bars. All of these effects must be studied and their impact on yarn movement must be determined.

As determining exact physical consequences is not always easy, we could instead make measurements on a backing before and after it is tufted to determine the effect tufting has on the distribution and correlation properties of the three parameters. We can then adjust our moved yarns program until the first data set is carried to something similar to the second data set when put through the program.

9.3 Improvement of Generation Model

Two main problems with our data affect the accuracy of the proposed model. The first of these has already been discussed - the high incidence of folding in some backings. This problem can be addressed by analyzing incidence of folding through the same image software used to collect backing data. The place where a yarn is folded on itself appears somewhat darker than the rest of the yarn. The image processing software could be used to identify these areas and produce a fourth parameter - fold width. In a separate analysis, the total yarn width could also be taken at the same images at the same data points, along
with gap width and centerline deviation. Then, the fold width could be added to the yarn width to produce a distribution for unfolded yarn width. Two separate models could then be constructed using our method—one for unfolded yarns and one for folds. Then two could be combined to provide the final yarn width. We expect that unfolded yarn widths and fold widths would be more normally distributed than folded yarn. If this is the case, then each distribution would be more accurately reproduced separately and then when combined would provide a more accurate result for folded yarn widths.

The other main data problem is the lack of centerline continuity between images. To account for this, we found a mean centerline in each image and then equated these means across the yarn. Although this is a reasonable approximation, it is not entirely accurate. Some image means from images with a significant amount of distance between them could be quite different. By making this assumption, we have neglected some low frequency behavior of the data. By taking or merging images to provide a continuous centerline, we could increase the variability of the generated yarns to be closer to the variability of the original yarns. This could have an effect on the results in searching for causes of Moiré effect and other defects.
CHAPTER X

CONCLUSIONS

We have proposed a method for numerically simulating woven fabric that extends the original data and displays the same statistical properties. This model has been shown effective on a sample whose yarn widths, gap widths, and centilime deviations can be approximated as normal distributions. We believe that, in general, a woven fabric meeting these requirements would be well represented by this model. As suggested in Section 9.3, additional data collection capabilities could further expand this model to include many types of woven fabrics.

We have established the need for such a model in carpet manufacturing for use in examining needle strike patterns. We have also established the need for further study of the effects of needle-yarn interaction to examine needle strike patterns.
APPENDIX A

STATISTICS ON OTHER BACKING TYPES

We see in Figures 92 to 94 that the distributions of original values match a normal distribution well for Backing C - the 18 pick fibrillated backing. Since the model worked on the 15 pick fibrillated backing, it is expected that it works on the 18 pick fibrillated as well. Looking at the regression plots in Figures 95 and 96, we see that the correlation is well preserved. Figures 97 and 98 show the gap distributions for the original and generated backings. Looking at Backing A, the plain tape backing, note that this type of yarn lacks the slits that make the fibrillated so uniform. This data exhibits a wider mean width, and therefore narrower gap. The incidence of folding is also more likely to occur and to persist in the tape yarn. This phenomenon results in a skew of the distribution, as can be seen in Figures 101 to 103. Looking at the regression plots in Figures 104 and 105, we see that the original best fit line still looks like the best fit. However, the generated values do not exhibit as strong a correlation relationship as in the previous two fibrillated backing types. The gap width distributions shown in Figures 106 and 107 also exhibit a worse match than those in the fibrillated backings. The last backing to model is Backing D, composed of striated yams. Again, the folding occurs often enough and persists in such a way as to skew the distributions. Notice in Figures 110 to 112 that the distributions cannot be modeled as a normal distribution. Looking at the regression plots in Figures 113 and 114, we see again that although correlation is weakly preserved, it is not as a good a fit as in the previous backings. The gap histograms in Figures 115 and 116 clearly do not match.
Figure 90: Backing C original yarns: 6 yarns, 7.23 inches. Values graphed every 0.7175mm along each yarn/gap.

Figure 91: Backing C type generated yarns: 5 yarns, 7.23 inches. Values generated every 0.7175mm along each yarn/gap.
Figure 92: Normal probability plot for Collection 1 Backing C yarn width values: 1536 total measurements taken every 0.7175 mm along 7.23 inches of six adjacent yarns, sample mean=1.1598 mm, standard deviation=0.1393 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.

Figure 93: Normal probability plot for Collection 1 Backing C gap width values: 1280 total measurements taken every 0.7175 mm along 7.23 inches of five adjacent gaps, sample mean=0.2555 mm, standard deviation=0.2223 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.

Figure 94: Normal probability plot for Collection 1 Backing C centerline deviation values: 1536 total measurements taken every 0.7175 mm along 7.23 inches of six adjacent yarns, sample mean=8.0743 x 10^{-4} mm, standard deviation=0.1216 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.
Figure 95: Regression plot of gap values vs previous width values for Collection 1 Backing C-type generated backing. 1280 total data points, generated every 0.7175 mm, along 7.23 inches of five consecutive yarn/gaps. Best-fit line \( y = -1.0865 + 1.5136 \) is plotted.

Figure 96: Regression error plot of gap values vs previous width values for Collection 1 Backing C-type generated backing. 1280 total data points generated every 0.1775 mm along 7.23 inches of five consecutive yarn/gaps, with respect to original data. Best-fit regression line \( y = -1.0865x + 1 + 5136 \).

Figure 97: Regression plot of gap values vs previous width values for Collection 1 Backing C-type generated backing. 1280 total data points, generated every 0.7175 mm, along 7.23 inches of five consecutive yarn/gaps. Best-fit line \( y = -1.0865 + 1.5136 \) is plotted.

Figure 98: Regression error plot of gap values vs previous width values for Collection 1 Backing C-type generated backing. 1280 total data points generated every 0.1775 mm along 7.23 inches of five consecutive yarn/gaps, with respect to original data. Best-fit regression line \( y = -1.0865x + 1 + 5136 \).
Figure 99: Backing A original yarn: 8 yarns, 7.23 inches. Values graphed every 0.7175mm along each yarn/gap.

Figure 100: Backing A type generated yarns: 5 yarns, 7.23 inches, values generated every 0.7175mm along each yarn/gap.
Figure 101: Normal probability plot for Collection 1 Backing A yarn width values: 1280 total measurements taken every 0.7175 mm along 7.23 inches of five adjacent yarns, sample mean=1.5780 mm, standard deviation=0.0900 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.

Figure 102: Normal probability plot for Collection 1 Backing A gap width values: 1084 total measurements taken every 0.7175 mm along 7.23 inches of four adjacent gaps, sample mean=0.1913 mm, standard deviation=0.3052 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.

Figure 103: Normal probability plot for Collection 1 Backing A centerline deviation values: 1280 total measurements taken every 0.7175 mm along 7.23 inches of five adjacent yarns, sample mean=6.1922 x 10^{-4} mm, standard deviation=0.1424 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.
Figure 104: Regression plot of gap values vs previous width values for Collection 1 Backing A-type generated backing. 1034 total data points, generated every 0.7175 mm along 7.23 inches of four consecutive yarn/gaps. Best-fit line $y = 1.4532x + 2.4845$ is plotted.

Figure 105: Regression error plot of gap values vs previous width values for Collection 1 Backing A-type generated backing. 1034 total data points generated every 0.7175 mm along 7.23 inches of five consecutive yarn/gaps, with respect to original data best-fit regression line $y = 1.4532x + 2.4845$.

Figure 106: Regression plot of gap values vs previous width values for Collection 1 Backing A-type generated backing. 1034 total data points, generated every 0.7175 mm along 7.33 inches of four consecutive yarn/gaps. Best-fit line $y = 1.4532x + 2.4845$ is plotted.

Figure 107: Regression error plot of gap values vs previous width values for Collection 1 Backing A-type generated backing. 1034 total data points generated every 0.7175 mm along 7.33 inches of five consecutive yarn/gaps, with respect to original data best-fit regression line $y = 1.4532x + 2.4845$. 

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Figure 108: Backing D original yarns: 8 yarns, 7.23 inches, values graphed every 0.7175mm along each yarn/gap.

Figure 109: Backing D type generated yarns: 8 yarns, 7.23 inches, values generated every 0.7175mm along each yarn/gap.
Figure 110: Normal probability plot for Collection 1 Backing D yarn width values: 1280 total measurements taken every 0.7175 mm along 7.23 inches of five adjacent yarns, sample mean=1.6106 mm, standard deviation=0.1993 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.

Figure 111: Normal probability plot for Collection 1 Backing D gap width values: 1034 total measurements taken every 0.7175 mm along 7.23 inches of four adjacent gaps, sample mean=0.2045 mm, standard deviation=0.2578 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.

Figure 112: Normal probability plot for Collection 1 Backing D centerline deviation values: 1280 total measurements taken every 0.7175 mm along 7.23 inches of five adjacent yarns, sample mean=0.0340 mm, standard deviation=0.0665 mm. The dashed line represents the plot of a perfectly normal distribution with appropriate mean and standard deviation.
Figure 113: Regression plot of gap values vs. previous width values for Collection 1 Backing D. 1034 total data points, generated every 0.7175 mm along 7.23 inches of four consecutive yarns/gaps. Best-fit line \( y = -1.3376x + 2.3587 \) is plotted.

Figure 114: Regression error plot of gap values vs. previous width values for Collection 1 Backing D-type generated backing. 1034 total data points generated every 0.7175 mm along 7.23 inches of five consecutive yarns/gaps, with respect to original data best-fit regression line \( y = -1.3376x + 2.3587 \).

Figure 115: Regression plot of gap values vs. previous width values for Collection 1 Backing D-type generated backing: 1034 total data points, generated every 0.7175 mm along 7.23 inches of four consecutive yarns/gaps. Best-fit line \( y = -1.3376x + 2.3587 \) is plotted.

Figure 116: Regression error plot of gap values vs. previous width values for Collection 1 Backing D-type generated backing: 2034 total data points generated every 0.7175 mm along 7.23 inches of five consecutive yarns/gaps, with respect to original data best-fit regression line \( y = -1.3376x + 2.3587 \).
B.1 Backing Generation Code

function backinggenerator(width,machinelen,name)  
\% This function generates a swatch of primary carpet backing with inputs
\% (backing width, backing length, backing type), where backing width is the
\% required width in inches, backing length is the required length (machine    
\% direction) in inches, and backing type is one of the following:
\% 'mp26x15', 'pl26fib', 'pl12fib', or 'sl150tape'. Note that single 
\% quotes are necessary.

machinelen=machinelen;  \% length of backing to be generated, inches
width=width;  \% width of backing to be generated, inches
numpoints=floor(width*95.4/.7175);  \% number of generation points needed

fileorig=strcat(['/home/fordra/datafiles/diameterdata',name,'.dat']);
gapfileorig=strcat(['/home/fordra/datafiles/gapdata',name,'.dat']);
centfileorig=strcat(['/home/fordra/datafiles/centerlinedata',name,'.dat']);
diamfileorig=strcat(['/home/fordra/datafiles/diameterdata',name,'.dat']);
gapfileorig=strcat(['/home/fordra/datafiles/gapdata',name,'.dat']);
centfileorig=strcat(['/home/fordra/datafiles/centerlinedata',name,'.dat']);

dim=size(diamfileorig);
origdiam=mean(mean(diamfileorig));
origdiamstd=sum(sum((diamfileorig-origdiam)*ones(size(diamfileorig)))/
(length(diamfileorig(:,1)));2); 
origgapmean=mean(mean(gapfileorig));
\text{origgapstd}=\text{sum}((\text{gaporig}-\text{origgapmean})^2)*\text{ones(size(gaporig))})^{.5}/(\text{length(gaporig(:,1))})\); \\
\text{origcentmean}=\text{mean}((\text{mean}(\text{centorig}))); \\
\text{origcentstd}=\text{sum}((\text{centorig}-\text{origcentmean})^2)*\text{ones(size(centorig}))^{.5}/(\text{length(centorig(:,1))})\); \\
\text{numyarns}=(\text{machine length}+25.4)/((\text{origdiamean}-\text{origgapmean})); \text{ Number of yarns necessary for generation} \\
\% perform fast fourier transform of original diameter data \\
\text{X}=\text{fft}((\text{diamorig},256); \% perform fast fourier transform of departure from the mean of original diameter data \\
\text{XX}=\text{fft}((\text{diamorig-mean(}\text{diamorig})*\text{ones(size(diamorig)))})*\text{diag(}\text{mean(}\text{diamorig}))^{.5},256); \% perform fast fourier transform of original gap data \\
\text{Y}=\text{fft}((\text{gaporig},256); \% perform fast fourier transform of departure from the mean of original gap data \\
\text{YY}=\text{fft}((\text{gaporig-mean(}\text{gaporig})*\text{ones(size(gaporig)))})*\text{diag(}\text{mean(}\text{gaporig}))^{.5},256); \% perform fast fourier transform of original centerline data \\
\text{Z}=\text{fft}((\text{centorig},256); \% perform fast fourier transform of departure from the mean of original centerline data \\
\text{ZZ}=\text{fft}((\text{centorig-mean(}\text{centorig})*\text{ones(size(centorig)))})*\text{diag(}\text{mean(}\text{centorig}))^{.5},256); \% find mean and standard deviation of fourier coefficients at one position across all sets of data \% for \text{j}=1:256 \\
\% for diameter data
nudiamre(j)=mean(real(XX(j,:)));
nudiamre(j+26)=nudiamre(j);
signadiamre(j)=std(real(XX(j,:)));
signadiamre(j+26)=signadiamre(j);
muadiam(j)=mean(imag(XX(j,:)));
muadiam(j+26)=muadiam(j);
signadiam(j)=std(imag(XX(j,:)));
signadiam(j+26)=signadiam(j);
% for gap data
mugapre(j)=mean(real(YY(j,:)));
mugapre(j+26)=mugapre(j);
signgapre(j)=std(real(YY(j,:)));
signgapre(j+26)=signgapre(j);
mugapin(j)=mean(imag(YY(j,:)));
mugapin(j+26)=mugapin(j);
signgapin(j)=std(imag(YY(j,:)));
signgapin(j+26)=signgapin(j);
% for centerlize data
mucentre(j)=mean(real(Z(j,:)));
mucentre(j+26)=mucentre(j);
signcentre(j)=std(real(Z(j,:)));
signcentre(j+26)=signcentre(j);
uccentim(j)=mean(imag(Z(j,:)));
uccentim(j+26)=uccentim(j);
signcentim(j)=std(imag(Z(j,:)));
signcentim(j+26)=signcentim(j);
end

% apply yarn generating subfunction to generate first of a specified number
of grouped sets of departure from mean of width, gap, and centerline data
Yarns= yarngenerator;mediamd, sigmadiam, medgap, sigmagap, medcentre, sigmacentre, medcent, sigmacent, medgapcent, sigmagent, numpoints);  
% this subroutine is a three-dimensional 2xnumpointsx which stores diameter deviations in Yarns(1:1,1), centerline deviations in Yarns(2:1,1), and the randomly selected gap point number in Yarns(1,1,3) and value in Yarns(1,1,2).
  
% use mean and standard deviations of original data calculated above to
% produce a mean value that can be added to the generated departures
yarnmean=normrnd(origmean,origmeanstd);  
yarncent=normrnd(origcent,origcentstd);  
yarngap=normrnd(origgaps,origgapsstd);  

% add this produced value to generated departures to create new sets of
% width, gap and centerline data
for m=1:numpoints
  diameter(m,1)=(Yarns(1,m,1)+1)*yarnmean diam;  
  centerline(m,1)=(Yarns(2,m,1)+1)*yarnmean cent;  
  centerlinediff(n,1)=centerline(n,1);  
  ki(1)=Yarns(1,1,3);  
  Sgap(1)=(Yarns(1,1,2)+1)*yarnmean gap;  
end

% find least squares fit of centerline-to-centerline correlation of original
data for use calculating new centerline values
nbcc1=polylfit(centorig(:,1),centorig(:,2,1),1);  
nbcc2=polylfit(centorig(:,2),centorig(:,3,1),1);  

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mbcc3=polyfit(centorig(:,3),centorig(:,4),1);
mbcc4=polyfit(centorig(:,4),centorig(:,5),1);
mbcc5=polyfit(centorig(:,5),centorig(:,6),1);
N=[mbcc1(:,1),mbcc2(:,1),mbcc3(:,1),mbcc4(:,1),mbcc5(:,1)];
mbcc=mean(N);
mscc=std(N);
B=[mbcc(:,2),mbcc(:,3),mbcc(:,4)];
bbcc=mean(B);\nbscc=std(B);
for m=2:nurnyarns
    % apply yarn generating subfunction to generate specified number of
    % grouped sets of departure from mean of width, gap, and centerline data
    Yarndc=yarngenerator(shaftm,shaftm,shaftm,shaftm,shaftm,shaftm,shaftm,shaftm,shaftm,shaftm,shaftm,shaftm,shaftm);
    yarmean=normrnd(shaftm,shaftm);
    yarmean=normrnd(shaftm,shaftm);
    % track data point used to generate gap
    % track gap generated
    Sgap(:,1)=Yarndc(:,1,3);
    % choose whether next set of centerlines is correlated to previous set or
    % regenerated from original data (m will be regenerated above every n times
    % where n is an input value)
mn(n)=randint(1,1,[0,4]);
if mn(n)==0
    for n=1:numpoints
        centeredifff(n,n)=(Yarndc(2,n,1)+1)*yarn=ancient;
    end
else
    centeredifff(:,n)=normrnd(mmcc,mscc)*centerlinedifff(:,n-1)+
    normrnd(hbcc,bscc);
end

%n print n (number of yarn data set just completed) in order to track
progress
n
end

kl
% calculate centerline of yarn based on chosen generated gap from previous
yarn
for n=2:nnumyarns
    for n=1:numpoints
        centerline(n,n)=centerline(ki(n-1),n-1)+diameter(n,n-1)/2+gap(n-1)+
        diameter(n,n)/2-centerlinedifff(ki(n-1),n)+
        centerlinedifff(m,n),
    end
end

% set up array Y of lines representing yarn edges (odd columns "bottom"
edges, even columns "top" edges) for visual purposes
for n=1:nnumyarns
    for n=1:numpoints
        drawyarn(n,2*n-1)=[centerline(n,n)-diameter(n,n)/2]/25.4;
end
end
drawyarn(m,2*n)=[centerline(m,n)+diameter(m,n)/2]/25.4;
end

% set up array of data points for later graphing purposes with above Y array
for n=1:1:numpoints
xxx(n)=0.7175*n/25.4;
end

% calculate gap values based on generated widths and centerlines
for n=1:1:numpoints
for m=1:1:numpoints-1
gap(m,n)=centerline(m,n+1)-centerline(m,n)-diameter(m,n)/2-
diameter(n,n+1)/2;
end
end

plot(xxx,Y)

% save necessary information in files for later use
savefile=strcat(["/home/ford/ra/output/",name,'diamoutpt.mat'])
save(savefile,'diameter')

savefile=strcat(["/home/ford/ra/output/",name,'gapoutpt.mat'])
save(savefile,'gap')

savefile=strcat(["/home/ford/ra/output/",name,'centoutpt.mat'])
save(savefile,'centerline')

savefile=strcat(["/home/ford/ra/output/",name,'drawoutput.mat'])
save(savefile,'drawyarn')

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% yarn generating subfunction
function y=yrngenerator(medianre, sigmadiamre, numpre, sigmagapre, 
  mucentre, sigmacentre, medianspin, sigmaspin, numpspin, sigmagapspin, 
  mucentrin, sigmacentrin, numpoints)
% read in Fourier coefficient distribution statistics
k=1;
n0=1;
ni=1;
% each cycle of this loop produces one yarn segment
while ni<numpoints
  n=266;
  Ddiam=zeros(n,1);
  Sdiam=zeros(n,1);
  jjj=1;
  Cdiam(1)=0;
  Cgap(1)=0;
  % generate new coefficients based on statistics of old distributions
  for j=jjj+1:jjj+n-1
    Ddiam(j-jjj+1)=normrnd(medianre(j), sigmadiamre(j)) + 
      normrnd(medianre(j), sigmadiamre(j)) + 
    Cgap(j-jjj+1)=normrnd(magapre(j), sigmagapre(j)) + 
      normrnd(magapre(j), sigmagapre(j)) + 
    Cent(j-jjj+1)=normrnd(mucentre(j), sigmacentre(j)) + 
      normrnd(mucentre(j), sigmacentre(j)) + 
  end
% choose new starting point
jj=round(1,1,128);
% convert to space domain
for k=jj:jj+n-1
for k2=1:128
    \[ S_{\text{diam}}(k1-jj+1) = S_{\text{diam}}(k1-jj+1) + 2 \times \text{real}(\text{Diam}(k2+1))/256 \]
    \[ \cos(2\pi k2/k1 \times .7175/(256+.7175)) - 2 \times \text{imag}(
        \text{Diam}(k2+1))/256 \]
    \[ \sin(2\pi k2/k1 \times .7175/(256+.7175)) \]
    \[ S_{\text{cent}}(k1-jj+1) = S_{\text{cent}}(k1-jj+1) + 2 \times \text{real}(
        \text{Ccent}(k2+1))/256 \]
    \[ \cos(2\pi k2/k1 \times .7175/(256+.7175)) - 2 \times \text{imag}(
        \text{Ccent}(k2+1))/256 \]
    \[ \sin(2\pi k2/k1 \times .7175/(256+.7175)) \]
end

\[ S_{\text{diam}}(k1-jj+1) = S_{\text{diam}}(k1-jj+1) + \text{Diam}(1)/256 \]
\[ S_{\text{cent}}(k1-jj+1) = S_{\text{cent}}(k1-jj+1) + \text{Ccent}(1)/256 \]
end

n0=m1;
n1=m1+1;

for j=n0:m1
    if n0==1:
        \[ \text{NewDiam}(j) = \text{Diam}(j-n0+1) \]
        \[ \text{NewCcent}(j) = \text{Ccent}(j-n0+1) \]
    else
        \[ \text{NewDiam}(j) = \text{Diam}(j-n0+1) + \text{NewDiam}(n0-1) - \text{Diam}(1) \]
        \[ \text{NewCcent}(j) = \text{Ccent}(j-n0+1) + \text{NewCcent}(n0-1) - \text{Diam}(1) \]
    end
end
k=k+1;
end
gap=0;
%
choose point for gap generation
kkl=randint(1,1,[1,numpoints]);
for k2=1:128
    Sgap=Sgap+2*real(Cgap(k2+1))/256*cos(2*pi*k2+kkl+1)*7175/(256*.7175)
    -2*imag(Cgap(k2+1))/256*sin(2*pi*k2+kkl+1)*7175/(256*.7175));
end
Sgap=Sgap*Cgap(1)/256;
%
save result in matrix to output to backing generation function
Yarnc=2*rcos(2,length(NewDiam),3);
Yarnc(:,1)=NewDiam;
Yarnc(:,1)=NewCen;
Yarnc(1,1,2)=Sgap;
Yarnc(1,1,3)=kkl;

B.2 Skip and Transition Calculation Code

function skips(width, machinelen, backingtype, datafile, needletype, needlearytype, outputfile)
%
This function takes input data from user and machine files and computes
the number of yarn skips between each needle strike for each needle across
the specified backing, as well as the side-by-side needle transitions across
each yarn.
if width=0
    diamorig=load(strcat('/home/ford/ra/data files/diameterdata',
                           backingtype, '.dat'));
    gaporig=load(strcat('/home/ford/ra/data files/gapdata',
                           backingtype, '.dat'));
else
    strcat('/home/ford/ra/backing generators/
backinggenerator('','width','','machinellength','','backingtype','');
end
load(strcat('/home/ford/ra/output/','datafile'));
[numpoints,y]=size(drawyarn1);
numyarns=floor(y/2);
width=numpoints*.7175/25.4;
load(strcat('/home/ford/ra/data files/needleinfo','.needletype','.'mat'))
load(strcat('/home/ford/ra/data files/needlebarinfo','.needlebartype','.'mat'))
#ndllength=nulwidth*pi; #needle strike area
 nondistrikes=floor(max(drawyarn2(:,y))/stitchlength); % number of needle strikes
 nondl=floor(width/spacebunds);
 colorpattern=zeros(nondl,nondistrikes);
 heightpattern=zeros(nondl,nondistrikes);
 h=zeros(nondl,nondistrikes,4); % information stored - 4 parameters of x position, y position, color, and pile height stored for each strike of each needle on each needle bar
 m1=1;
 n2=1;
 m=1;
 nn=zeros(nondl,nondistrikes,2);

% find centerlines
 for  j=1:numpoints
 for  k=1:numyarns
  centerline1(j,k)=drawyarn1(j,2*k-1)+(drawyarn1(j,2*k)-
  drawyarn1(j,2*k-1))/2;
  centerline2(j,k)=drawyarn2(j,2*k-1)+(drawyarn2(j,2*k)-
  drawyarn2(j,2*k-1))/2;
end
end
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% track puncture information
for k=1:nondisks
    for i=1:nondistrict
        if gcd(k,shiftmo)<>1
            h(k,i,1)=h(k,i,1)+申thshift;
        end
        h(k,i,1)=xtvans*(k-1)*spacebundls;
        h(k,i,2)=yttrans*(k-1)*stitchlength;
        if gcd(2,k)<>1
            h(k,i,2)=h(k,i,2)+1/20;
        end
        h(k,i,3)=colorpattern(k,i);
        h(k,i,4)=heightpattern(k,i);
    end
end
dim=size(drawyarn1);
for j=1:dim(1)
    for k=1:dim(2)/2
        Ybottom1(j,k)=drawyarn1(j,2*k-1);
        Ytop1(j,k)=drawyarn1(j,2*k);
        Ybottom2(j,k)=drawyarn2(j,2*k-1);
        Ytop2(j,k)=drawyarn2(j,2*k);
    end
end

% plot visual of generated backing and needle strike areas
xxx=0.7175/25.4:(numpoints-1)*0.7175/25.4;
plot(xxx,Ybottom,'.‐')
hold
plot(xxx,Ytop)
hold
for k=1:nondidis
    for i=1:nondistrikes
        if gcd(k,2)==1
            rectangle('Position',[h(k,i,1)-ndlwidth/2, h(k,i,2)-
                          ndlwidth/2, ndlwidth, ndlwidth],'Curvature',[1,1],
                          'Facecolor','r')
        else
            rectangle('Position',[h(k,i,1)-ndlwidth/2, h(k,i,2)-
                          ndlwidth/2, ndlwidth, ndlwidth],'Curvature',[1,1]);
        end
    end
end
nondistrikes

% find closest generation point to test for an intersection
for k=1:nondidis
    n=1;
    for m=1:numpoints
        if .7175*m<=h(k,i,1)+25.4
            n1=m;
        end
    end
    if h(k,i,1)+25.4-.7175*n1<=.7175*(m1+1)-h(k,i,1)+25.4
        m2(m)=n1;
    else
        m2(m)=m1;
    end
end
\[ m(k) = n_1 + 1; \]
end
end

\% find closest yarn
\% puncture number
for \( i = 1:nondistrikes \)
\% needle number
for \( k = 1:nondis \)

\% find closest yarn
if \( \gcd(k, 2) = 1 \)
    \[ m(2*k-1, i, :) = h(k, i, 2) - \text{centerline}(m(k), 1); \]
else
    \[ m(2*k-1, i, :) = h(k, i, 2) - \text{centerline2}(m(k), 1); \]
end
for \( n = 2:numyarns \)
if \( \gcd(k, 2) = 1 \)
    if \( \text{abs}(h(k, i, 2) - \text{centerline}(m(k), n)) > \text{abs}(h(k, i, 2) - \text{centerline2}(m(k), n)) \)
        \[ m(2*k-1, i, :) = h(k, i, 2) - \text{centerline}(m(k), n); \]
    end
else
    if \( \text{abs}(h(k, i, 2) - \text{centerline2}(m(k), n)) > \text{abs}(h(k, i, 2) - \text{centerline2}(m(k), n)) \)
        \[ m(2*k-1, i, :) = h(k, i, 2) - \text{centerline2}(m(k), n); \]
    end
end
end
\[ R(k, i) = m(2*k-1, i, 1); \]
if \( k > 1 \)
if g=d(k,2)==1
    \( n(i+k,1,:) = [r(k-1,1), h(k,1,2) - centerline1(mm(k), r(k-1,1))] \);
else
    \( n(i+k,1,:) = [r(k-1,1), h(k,1,2) - centerline2(mm(k), r(k-1,1))] \);
end
end
end

% assign strike placement information for closest yarns for i=1:nondistrikes
    for k=1:2*nondists
        if \( mz(k,i,2) > 0 \)
            \( S(k,i) = 1 \);
        else
            \( S(k,i) = 0 \);
        end
    end
end

% calculate transitions for i=1:nondistrikes
    for k=2:nondists
        \( \text{transitions}(k,i) = S(2*k,i) - S(2*(k-1),i) \);
    end
end

% calculate skips for i=2:nondistrikes
    for k=1:nondists
        \( \text{skips}(k,i) = n(2*k-1,1,1) - n(2*k-1,1,1) + S(2*k-1,1) - S(2*k-1,1-1) \);
    end
end
B.3 Linear Overlap and Moved Yarns Code

function movedyarns(inputfile, outputfile, needletype, needlebarotype)
load(strcat(’/home/ford/ra/output’,outputfile))

% This function takes input data from user and machine files and computes
% the amount of linear overlap between each needle and yarn across the
% specified backing. This information is then used to move the yarns to
% reflect new yarn placement after the first needle bar strikes.
% each yarn.

Y = drawyarn;
dim = size(Y);
[numpoints,y]=size(Y);
numyarns = floor(y/2);
width = numpoints*.7175/25.4;
load(strcat(’/home/ford/ra/data files/needleinfo’,needletype,’.mat’))
load(strcat(’/home/ford/ra/data files/needlebarinfo’,needlebarotype,’.mat’))

A = nelength=ndlwidth=pi; % needle strike area
nondistrikes = floor(max(Y(:,dim(2)))/stitchlength); % number of needle strikes
ondils = floor(width/spacebetween);
colorpattern = zeros(ondils,nondistrikes);
heightpattern = zeros(ondils,nondistrikes);
b = zeros(ondils,nondistrikes,4); % information store - 4 parameters of x

position, y position, color, and pile height
% stored for each strike of each needle on each needle bar
nondlbars=1; % number of needle bars
m1=1;
m2=1;
mn=1;
linearoverlap=zeros(nondlbars,mnynarns);
% reshape input backing data
for j=1:dim(1)
    for k=1:dim(2)/2
        Ybottom(j,k)=Y(j,2*k-1);
        Ytop(j,k)=Y(j,2*k);
        drawyarn1(j,2*k-1)=Ybottom(j,k);
        drawyarn1(j,2*k)=Ytop(j,k);
    end
end
% track puncture information
for k=1:nondlbs
    for i=1:nondlstrikes
        h(k,i,1)=xtrans*(k-1)*spacebdls;
        h(k,i,2)=ytrans*(i-1)*stitchlength;
        h(k,i,3)=colorpattern(k,i);
        h(k,i,4)=heightpattern(k,i);
    end
end
% find closest generation point to test for an intersection
for k=1:nondlbs
    m=1;
    for n=1:npnpoints

if $0.7175*n <= h(k,i,1) + 25.4$
    $m1=m$;
end
end
if $h(k,1,1) + 25.4 - 0.7175*m1 < 0.7175*(m1+1) - h(k,1,1) + 25.4$
    $mm(k)=m1$;
else
    $mm(k)=m1+1$;
end
end
% calculate linear overlap
% puncture number
for k=1:nondis
    % needle number
    for i=1:nondistrikes
        % test for an intersection
        for n=1:numyarns
            if $h(k,i,2) > bottom(mm(k),n) - 0.5*ndlength$
                if $h(k,i,2) < top(mm(k),n) + 0.5*ndlength$
                    linearoverlap(k,n) = min(h(k,i,2) +
                        0.5*ndlength, top(mm(k),n)) - max(h(k,i,2) -
                        0.5*ndlength, bottom(mm(k),n));
                end
            end
        end
    end
end
k
end
% move yarns at closest generation point

for k=1:nondists
    for i=1:nondistrikes
        for m=1:nyarns
            if (h(k,i,2)>Ybottom(mm(k),n)) & (h(k,i,2)<Ybottom(mm(k),n) + 0.5*ndlendlength)
                Ybottom(mm(k),n) = Ybottom(mm(k),n) + linearoverlap(k,n); 
                Ytop(mm(k),n) = Ytop(mm(k),n) + linearoverlap(k,n); 
            end
            if (h(k,i,2)>Ybottom(mm(k),n)) & (h(k,i,2)<Ytop(mm(k),n))
                Ytop(mm(k),n) = Ytop(mm(k),n) + 0.5*linearoverlap(k,n); 
                Ybottom(mm(k),n) = Ybottom(mm(k),n) - 0.5*linearoverlap(k,n); 
            end
            if (h(k,i,2)>Ytop(mm(k),n)) & (h(k,i,2)<Ytop(mm(k),n) + 0.5*ndlendlength)
                Ytop(mm(k),n) = Ytop(mm(k),n) + linearoverlap(k,n); 
                Ybottom(mm(k),n) = Ybottom(mm(k),n) + linearoverlap(k,n); 
            end
        end
    end
end

% average after movement

for m=3:numpoints-2
    bottomaverage(mm,n) = (Ybottom(mm-1,n)+Ybottom(mm-2,n)+Ybottom(mm+1,n)+Ybottom(mm+2,n))/4;
    topaverage(mm,n) = (Ytop(mm-1,n)+Ytop(mm-2,n)+Ytop(mm+1,n)+Ytop(mm+2,n))/4;
end
end
end
% define moved backing
for n=1:numyarns
    for n=3:numpoints-2
        Ybottom(n,n)=bottomaverage(n,n);
        Ytop(n,n)=topaverage(n,n);
    end
    Ybottom(2,n)=(Ybottom(3,n)+Ybottom(4,n))/2;
    Ybottom(1,n)=(Ybottom(2,n)+Ybottom(3,n))/2;
    Ybottom(numpoints-1,n)=(Ybottom(numpoints-3,n)+Ybottom(numpoints-2,n))/2;
    Ybottom(numpoints,n)=(Ybottom(numpoints-2,n)+Ybottom(numpoints-1,n))/2;
    Ytop(2,n)=(Ytop(3,n)+Ytop(4,n))/2;
    Ytop(1,n)=(Ytop(2,n)+Ytop(3,n))/2;
    Ytop(numpoints-1,n)=(Ytop(numpoints-3,n)+Ytop(numpoints-2,n))/2;
    Ytop(numpoints,n)=(Ytop(numpoints-2,n)+Ytop(numpoints-1,n))/2;
end

for j=1:numyarns
    for k=1:numyarns
        drawyarn2(j,2*k-1)=Ybottom(j,k);
        drawyarn2(j,2*k)=Ytop(j,k);
    end
end
% output to file
savefile=strcat('~/home/mdn/ra/output/','outputfile')
save(savefile,'linearoverlap',drawyarn1,drawyarn2')
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REFERENCES


