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Novel Measurement for Multidirectional Fabric Wrinkling Using Wavelet Analysis

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Abstract: Measuring and characterizing fabric wrinkling objectively and accurately is of vital importance because wrinkling behavior is one of the most important factors to determine visual aesthetic of fabrics and clothes. In this paper, a novel method for multidirectional fabric wrinkling measurement is presented. 12 fabrics with different fiber contents and weave structures are prepared and wrinkled by the new method. GLCM variables and standard deviation of wavelet decomposition coefficients are used to characterize fabric wrinkling. Results show that WRA (wrinkle recovery angle) does not have significant linear correlation with the GLCM variables (energy, entropy, contrast and correlation). The wavelet coefficient standard deviation at level 6 has the highest correlation with average WRA. The equations between average WRA and standard deviations can be used to predicate average WRA of a fabric conveniently, avoiding the time-consuming and tedious testing of WRA in each direction.

Keywords: Multidirectional fabric wrinkling, WRA, Measurement, GLCM, Wavelet analysis

Introduction

Wrinkling is vitally important for the textile and apparel industry because it determines and influences the visual appearance and quality of fabric or clothes. Consequently, it is extremely important to measure and characterize fabric wrinkling behavior objectively. Conventionally, the American Association of Textile Chemists and Colorists (AATCC) 66-2008 and AATCC 128-2004 are the most widely used methods. In the AATCC 66-2008 method, fabric specimen is folded in half and compressed to generate a wrinkle that takes the shape of straight line, and WRA (wrinkle recovery angle) of warp and weft is used to characterize the wrinkling behavior of fabric. In the AATCC 128-2004 method, the fabric specimen is rotated and compressed to produce wrinkles that are very similar to those caused by twisting after washing, and then expert subjective assessment is performed to assign the specimen with the grade score of a replica with maximum similarity. It is time-consuming and easily affected by human factors.

As there are many deficiencies in the subjective evaluation method, such as inconsistent results, difficult discrimination between the adjacent grades and low efficiency, etc, many efforts have been made to replace visual assessment with more objective and reliable methods using image processing and computer vision technology since 1969 [1,2]. In 1990s, Na [3], Xu [4], Kang [5], Amirbayat [6] applied various analysis techniques, laser line triangulation method, stereo vision algorithm, to evaluate fabric wrinkling or smoothness. Over the past decade, more digital image processing methods [7,8] and systems [9,10], such as photometric Stereo 3D reconstruction method [11], projected profile light line technique [12], wavelet analysis and SVM [13], GLCM [14], rank ordering [15], etc, have been developed and applied to more automated and efficient fabric wrinkling measurement and evaluation.

Summarizing the above methods, we know that there are still some problems in fabric wrinkling measurement. Creasing is not sufficiently realistically described [16] in the AATCC 66-2008 method and it is not sufficient or scientific to characterize the comprehensive wrinkling behavior of a fabric only by its wrinkling behavior in warp and weft directions because there is anisotropy in the wrinkle properties of fabrics [17]. It is time-consuming and tedious to obtain the multidirectional wrinkling behavior because quite a long time is needed to finish measuring WRA in each direction of a fabric. The AATCC 128-2004 method generates wrinkles similar to those caused by twisting after washing, most of which are nearly parallel and in the diagonal direction. Therefore, it is possibly not appropriate to characterize multidirectional wrinkling behavior by this method.

On the other hand, methods on fabric wrinkling using computer vision technology previously cited are mainly based on wrinkles generated by the AATCC 128-2004 method. As has been analyzed above, AATCC 128-2004 method can not be used to measure multidirectional fabric wrinkling. In this study, we will explore a new fabric wrinkling measurement and use image processing technology to extract wrinkling variables for characterization. Finally, the wrinkling parameters will be compared with results of AATCC 66-2008 method to validate the new method presented in this paper.

Experimental

Materials

12 fabrics with different fiber contents and weave structures were chosen for the experiment. All the fabrics were of solid color. The fabric parameters are shown in Table 1. Three

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Table 1. Parameters of fabrics

Fabric	Color	Weave	Fiber content	Density (/10 cm)(warp×weft)		Mass per unit area (g/m^2)	Thickness (mm)
F1	green	plain	55 L/45C	48	38	201	0.42
F2	yellow	plain	100 % C	83	84	76	0.21
F3	red	twill	100 % P	85	45	150	0.32
F4	cream	plain	100 % S	65	71	81	0.19
F5	khaki	twill	100 % C	112	40	257	0.56
F6	orange	twill	100 % W	60	49	177	0.38
F7	brown	plain	100 % S	129	72	71	0.35
F8	blue	plain	100 % C	60	54	63	0.23
F9	gray	twill	100 % W	75	49	226	0.52
F10	pink	plain	100 % C	136	70	237	0.49
F11	yellow	satin	100 % S	119	31	60	0.21
F12	gray	plain	70 L/30C	51	39	70	0.37

C: cotton, L: linen, S: silk, W: wool, P: polyester.

swatches of 12×12 cm were ironed and cut for each fabric.

WRA (Wrinkle recovery angle)

As it is not sufficient to test measure wrinkling behavior in AATCC 66-2008 method only by WRA in two directions (warp and weft), to characterize the wrinkling behavior of fabrics more comprehensively and completely, WRA in every other 15^{o} direction from 0^{o} (warp) - 360^{o} were tested. The WRA in each direction was tested three times and averaged for the final value of that direction.

Fabric Multidirectional Wrinkling Method

Materials needed for the new measurement of multi-directional fabric wrinkling consists of a ball with the diameter of 1.5 cm, a pair of scissors and some elastics. To generate multidirectional wrinkles on fabric, the ball was put on the center of the fabric swatch. The ball was wrapped with the swatch evenly, avoiding different amount of gathering in different directions. The elastic was then used to bundle the ball with the fabric swatch with the same operating force possibly. 1 minute later, the elastic was cut with scissors and the ball was removed. Finally, the fabric was spread gently (see Figure 1). Figure 1 shows that diverging wrinkles in different directions are generated on the fabrics.

Figure 1. Wrinkled fabric.

Image Capture

After recovering from the wrinkling for 1 min, the wrinkled fabric was scanned with a LiDE210 CanoScan scanner to capture the image with a resolution of 300 dpi. After capture, the image was cut into 800×800 pixel segments for further processing and analysis.

Wrinkle Characterization

Gray-level Co-occurrence Matrix Variables (GLCM)

GLCM is a widely used texture description method to characterize the spatial distributions of gray levels in the image. It is defined as the probability of a pixel of gray-level i occurred in the specified spatial relationship of $\delta=(d, \theta)$ with a gray-level j, in which d and j are the distance and positional angle between the two gray-level pairs (i, j) [14]. Conventionally, the positional angle consists of 0^{o}, 45^{o}, 90^{o} and 135^{o}. In this work, the images were monochromatic with 16 gray levels, d was 1 and the variables were as follows:

Energy or angular second moment measures the textural homogeneity, which is calculated by equation (1):

$$Energy = \sum_i \sum_j \{p(i,j)\}^2 \quad (1)$$

Entropy indicates the disorder of the texture, which is calculated by equation (2):

$$Entropy = -\sum_i \sum_j p(i,j)\log\{p(i,j)\} \quad (2)$$

Correlation represents the linear dependency between gray levels in the texture, which is calculated by equation (3):

$$Correlation = \frac{\sum_i \sum_j (ij)p(i,j) - \mu_x \mu_y}{\delta_x \delta_y} \tag{3}$$

Contrast reflects the local variations of texture, which is calculated by equation (4):

$$Contrast = \sum_i \sum_j (i-j)^2 p(i,j) \tag{4}$$

Wavelet Analysis

Wavelet analysis is a signal processing method by transforming domain, which is widely used in computer vision and image processing recently. It has such advantages as multi-resolution decompositions and the ability to characterize the signals both in time domain and frequency domain. Its principle is to break up the image into low-frequency and high-frequency parts, in which the former reflects the major characteristics and the latter shows the details of the image (see Figure 2). Figure 2(b) shows after wavelet decomposition at level 1, the image is broken up into 4 sub-images, in which CA is the approximate coefficient that represents the low-frequency component both in horizontal and vertical directions. The other three sub-images are detail coefficients, in which CH_1 is the horizontal detail coefficient representing the high-frequency component in horizontal direction and low-frequency component in vertical direction. CV_1 is the vertical detail coefficient representing the high-frequency component in vertical direction and low-frequency component in horizontal direction while CD_1 is the diagonal detail coefficient representing the high-frequency component in both vertical and horizontal direction. The approximate coefficient CA can be further decomposed at level 2 (see Figure 2(c)), level 3, etc. Figure 2(d) is the wavelet decomposition of wrinkled fabric at level 2.

Fabric wrinkling has the local sharpening features, that is, fabric has the local mutation caused by wrinkling. By using wavelet analysis, the image signal can be accurately segmented and useful feature information can be extracted to measure the wrinkling objectively and precisely.

In this study, to investigate the effect of wavelet decomposition level on fabric wrinkling characterization, wavelet decomposition was performed at level 9 that was deeper than some study. 2D Haar WT was performed using the Matlab Wavelet Toolbox for image decomposition [13]. Standard deviations of wavelet decomposition detail coefficient (horizontal, vertical and diagonal) at different levels were extracted for wrinkling characterization. Four wrinkling features were as follows:

SH_i: standard deviation of horizontal detail coefficient cH_i,
SV_i: standard deviation of vertical detail coefficient cH_i,
SD_i: standard deviation of diagonal detail coefficient cH_i,
S_i: total of SH_i, SV_i and SD_i, where i is the level of wavelet decomposition, i=1….9

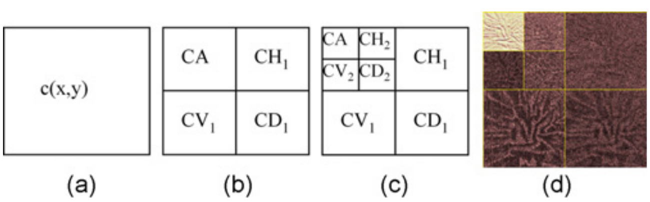

Figure 2. The principle of wavelet decomposition (a) image $c(x, y)$ (b) wavelet decomposition at level 1 (c) wavelet decomposition at level 2 (d) wavelet decomposition of wrinkled fabric at level 2.

Results and Discussion

Measured Wrinkle Recovery Angle

Figure 2 shows the wrinkle recovery angles (WRA) measured according to AATCC 66-2008. As there are too many data, only WRA in warp, weft directions and their mean value, as well as the mean value of the 25 directions (abbreviated as average WRA) were listed. From Figure 2, it can be seen that a fabric has different WRA in different directions. The mean value of warp and weft WRA differed greatly from that of the 25 directions. Of the 12 fabrics, F10 has the largest difference between the two mean values, about 25 ^{o}. Therefore, it is not scientific to characterize the comprehensive wrinkling behavior of a fabric by its WRA in warp and weft directions only.

Relationship between WRA and GLCM Variables

Energy, entropy, contrast and correlation represent textural homogeneity, the disorder of the texture, the local variations of texture and the linear dependency between gray levels in the texture, respectively. Figure 3-6 show the relationship between WRA and the GLCM variables (energy, entropy, contrast and correlation), in which the four GLCM variable values were the sum of energy, entropy, contrast and

Table 2. Wrinkle recovery angles in different direction (^{o})

Fabric	Warp	Weft	Mean value of warp and weft	Mean value of 25 directions
F1	73.67	84.33	79.00	89.66
F2	92.76	81.00	86.88	92.76
F3	130.43	148.00	139.22	135.43
F4	121.62	130.33	125.98	121.62
F5	77.46	93.33	85.40	87.46
F6	138.8	155.67	147.26	138.80
F7	129.17	120.67	124.92	127.17
F8	100.8	76.00	88.40	100.80
F9	135.66	157.33	146.50	131.49
F10	99.72	150.33	125.03	99.72
F11	134.74	135.00	134.87	134.74
F12	106.95	88.00	97.48	106.95

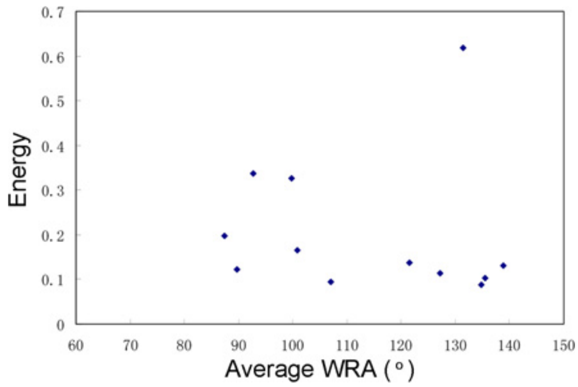

Figure 3. Relationship between energy and average WRA.

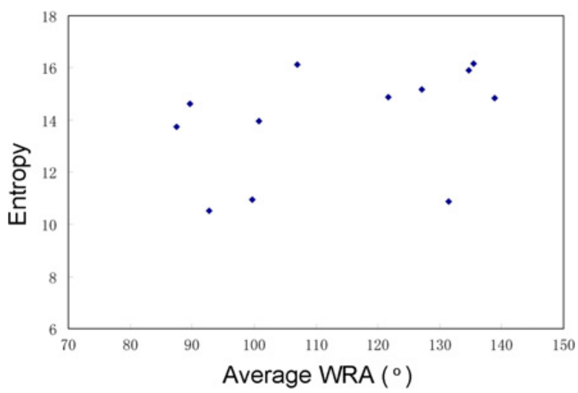

Figure 4. Relationship between entropy and average WRA.

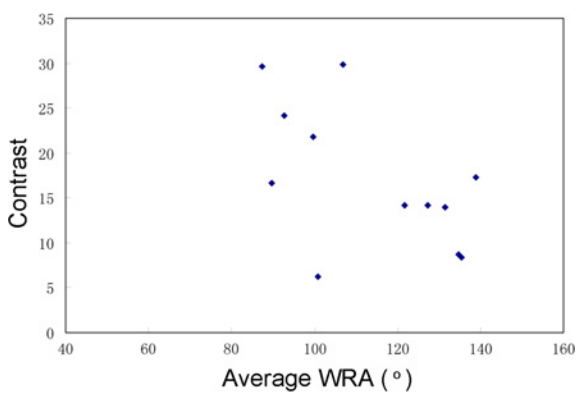

Figure 5. Relationship between contrast and average WRA.

correlation at direction of 0 °, 45 °, 90 ° and 135 °. From Figure 3-6, we can see that there is not significant linear correlation between the above four variables and WRA, especially energy and entropy. It is mainly because these variables are not appropriate to show small differences in surface texture [15].

Comparison of WRA and Standard Deviation of Wavelet Decomposition Detail Coefficient

Figure 7 shows the Pearson's correlation coefficient

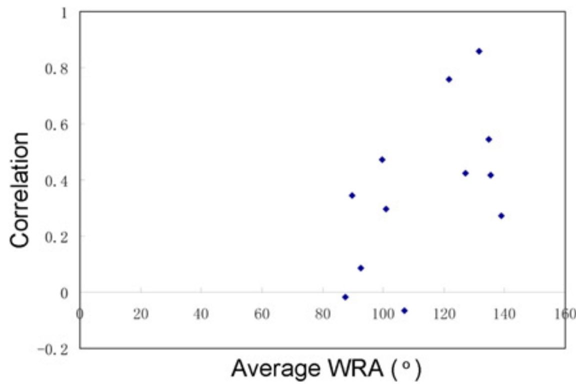

Figure 6. Relationship between correlation and average WRA.

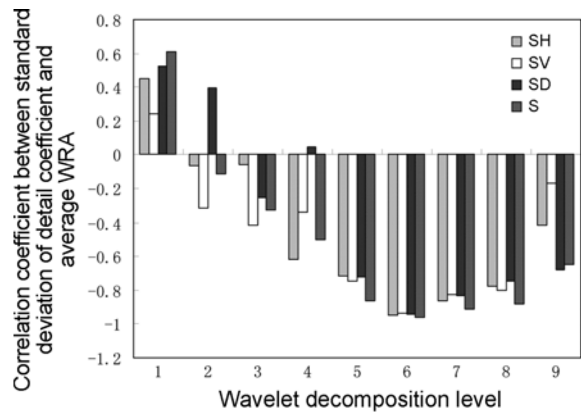

Figure 7. Correlation coefficient between average WRA and standard deviation of detail coefficient at different wavelet decomposition level.

between average WRA and detail coefficient standard deviation at different wavelet decomposition. From Figure 7, it is clear that different detail coefficient standard deviations have different correlation coefficients with average WRA. From decomposition level 1-9, the absolute value of correlation coefficient increases first and decreases subsequently. The detail coefficient standard deviation at decomposition level 6 has the highest correlation coefficient value (about −0.95) with average WRA, including all the horizontal, vertical, diagonal detail coefficients. It can possibly be explained as 6 may be the optimum level of wavelet decomposition that can express the wrinkling features to the most extent. Figure 7 also indicates that detail coefficient standard deviations have negative correlation with average WRA, except level 1 and SD_2 at level 2. In other words, the higher the WRA is, the lower the wavelet decomposition coefficient standard deviation is.

Figure 8-11 show the quadratic polynomial results between average WRA and four detail coefficient standard deviations at wavelet decomposition level 6. The four equations can be used to predicate average WRA of a fabric conveniently, instead of measuring the WRA in different directions many

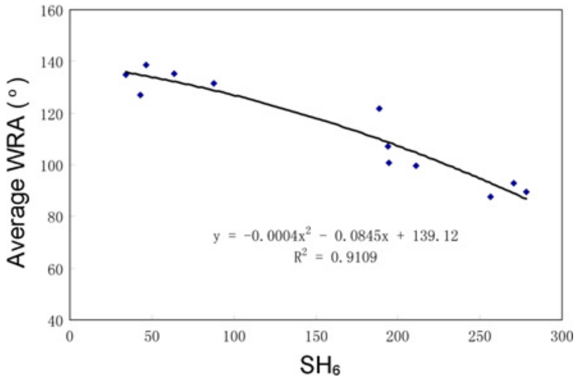

Figure 8. Relationship between average WRA and SH_6.

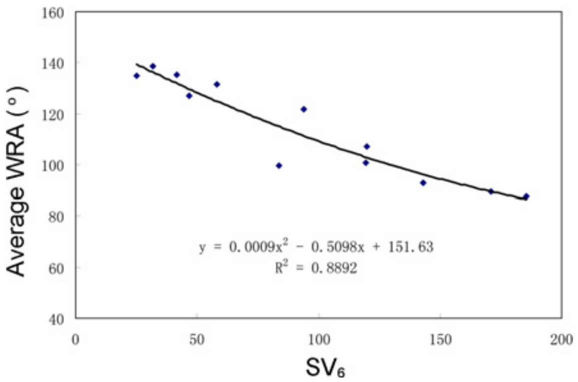

Figure 9. Relationship between average WRA and SV_6.

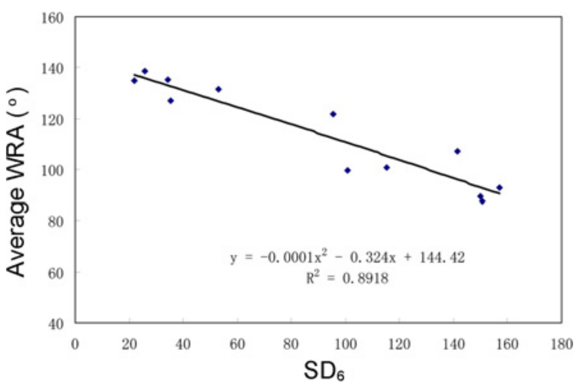

Figure 10. Relationship between average WRA and SD_6.

times. From R^2, it is revealed that we can get more accurate average WRA value by S_6 (total of SH_6, SV_6 and SD_6) compared with other standard deviation variables. Of the other three variables, SH_6 has the highest relation with average WRA and SV_6 has the lowest relation with average WRA.

Comparison of the Multidirectional Fabric Wrinkling Measurement and the AATCC Method

The now commonly used AATCC 66-2008 method and

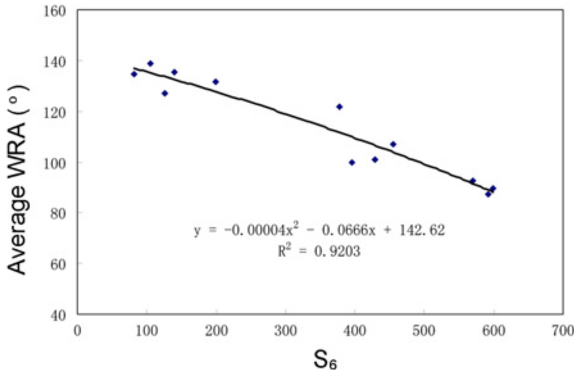

Figure 11. Relationship between average WRA and S_6.

AATCC 128-2004 method have some deficiencies in measuring fabric multidirectional wrinkling. To measure the multidirectional wrinkling behavior of a fabric, WRA in different directions has to be tested many times, which is time-consuming and troublesome. The AATCC 128-2004 method can't measure the multi-directional wrinkling behavior of a fabric very well because it produces slanting wrinkles in the diagonal direction mainly. The new method presented in this paper produces multi-directional wrinkles on fabrics simply and wavelet analysis are used to characterize fabric multidirectional wrinkling conveniently, as a result of which fabric multidirectional wrinkling behavior can be measured relatively precisely.

Conclusion

12 fabrics with different fiber contents and weave structures were prepared and wrinkled by the method presented in the study. GLCM variables and wavelet decomposition detail coefficients were used to characterize fabric wrinkling. It was shown that WRA does not have significant linear correlation with the GLCM variables (energy, entropy, contrast and correlation). The wavelet detail coefficient standard deviation at decomposition level 6 has the highest correlation coefficient value (about −0.95) with average WRA, including all the horizontal, vertical, diagonal detail coefficients. The quadratic polynomials between average WRA and standard deviations at wavelet decomposition level 6 can be used to predicate average WRA of a fabric simply and conveniently, avoiding the time and effort consuming testing of WRA in different directions.

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