Detecting Fabric Density and Weft Distortion in Woven Fabr Using the Discrete Fourier Transform

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ABSTRACT

Fabric density and distortion offer important information on fabric attributes and quality during the manufacturing process. However, most current procedures require human effort, which is often inefficient, time-consuming, and imprecise. In this paper, we propose to use an automatic method using the 2D Fast Fourier Transform (2D-FFT) to count the number of yarns and determine the angle rotation of weft yarns in fabric images. First, we explain the mathematical background of Fourier Transform and 2D-FFT. Then, we use a customized and optimized software package to apply a 2D-FFT to extract image magnitude, phase, and power spectrum. We apply the inverse 2D Fast Fourier Transform (2D-iFFT) on selected frequencies corresponding to periodic structures – basic weave patterns – to reconstruct the original image and extract warp and weft yarns separately. Finally, we use a local adaptive threshold process to convert reconstructed images into binary images for the counting and calculating process. For the weft rotation, we apply a mathematical calculation on the frequency domain to collect the angular distribution and then figure out the major rotation of weft yarns. Our experiments show that the proposed method is highly accurate and capable of inspecting different patterns of fabric. We also observe that the processing time of our proposal method is practical and time-efficient.

CCS CONCEPTS

• **Computing methodologies** → **Image processing**; **General and reference** → *Measurement*.

KEYWORDS

Fabric Density, Weft Distortion, FFT, Computer Vision

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1 INTRODUCTION

Fabric density and weft distortion are important fabric attributes that are widely used for quality control during fabric production. Fabric density helps explain the balance and evenness of fabric, and measure base weight. Weft distortion angle is also constantly checked to make sure that fabric flows evenly from machine to machine during process, and moves through rollers correctly. Any inconsistency and distortion can cause permanent damage to fabric, deteriorating its value.

Such important information is still measured manually and incorrectly in many cases. Factory workers count warp (vertical threads) and weft yarns (horizontal threads) by using old-fashioned and outdated methods. Such methods not only take a long time but also do not guarantee accurate results. Therefore, a better automatic method needs to be developed to solve the problem faster and more accurately.

One efficient approach to this problem is using the *Fourier Transform* method. It can easily separate the fabric image into two distinct images: warp-only and weft-only images. Then, by applying local adaptive threshold processing, we can achieve reconstructed binary images. We can compute simple steps to count number of warps and wefts in the original fabric image by running through reconstructed images.

This paper begins with providing the background of Fourier Transform and explaining how to generate reconstructed binary warp-only and weft-only images from the original fabric image. We then explain the proposed method to calculate the fabric density and the weft rotation of fabric. Next, we show our experiment setup and results for our dataset. Three basic patterns of weave fabric (plain, twill, and satin pattern (Figure 1)) are collected to test the accuracy and efficiency of our proposed method. Finally, we discuss and analyze the results.

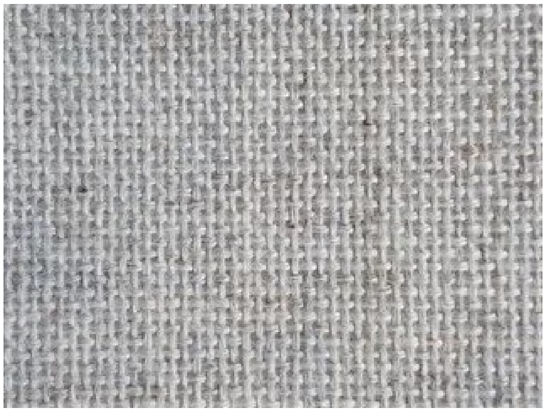
2 BACKGROUND

Fourier transform is a powerful image-processing tool as it offers an efficient way to extract the periodic characteristics of a spatial-domain image. Using Fourier transform, the image can be decomposed into its sinusoidal components in the frequency domain, thus it is possible to analyze certain frequencies and reconstruct the image in the spatial domain with high accuracy. [4]

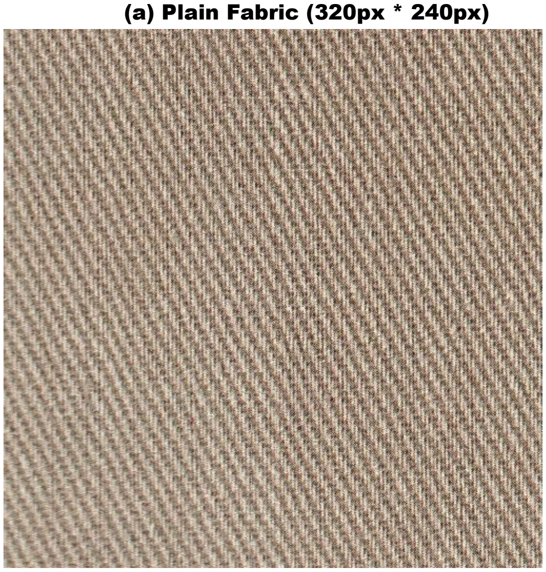
The complex form of a one dimension Fourier Transform on a continuous function $f(x)$ is defined as:

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi ux} \, dx \tag{1}$$

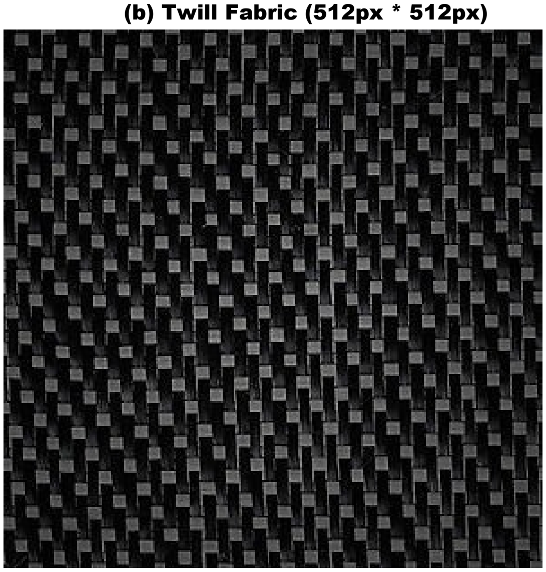
where u is the variable frequency and $j^2 = -1$. If the real and imaginary components of $F(u)$ are denoted by $F_r(u)$ and $F_i(u)$,



(a) Plain Fabric (320px * 240px)



(b) Twill Fabric (512px * 512px)



(c) Satin Fabric (300px * 300px)

Figure 1: Common Fabric Patterns

then the magnitude $M(u)$ and phase $\Phi(u)$ can be calculated below [6]

$$\begin{aligned} M(u) &= |F(u)| = \sqrt{F_r^2(u) + F_i^2(u)}, \\ \Phi(u) &= \tan^{-1} \frac{F_i(u)}{F_r(u)}. \end{aligned} \tag{2}$$

Note: $\tan^{-1}$ is the 4-quadrant arc tangent function.

The Inverse Fourier Transform is defined as:

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{j2\pi ux}\, du \tag{3}$$

Equivalently, Fourier Transform for two-dimensional function $f(x, y)$ is [6]

$$\begin{aligned} F(u, v) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x, y) e^{-j2\pi(ux+vy)}\, dxdy \\ f(x, y) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(u, v) e^{j2\pi(ux+vy)}\, dudv \end{aligned} \tag{4}$$

where u and v are the frequencies corresponding to x and y in spatial domain. The magnitude $M(u, v)$ and phase $\Phi(u, v)$ are also computed as one dimension.

As we focus on the digital images only, we limit our work to the Discrete Fourier Transform (DFT). Suppose M columns and N rows of data points are sampled from a two-dimensional function $f(x, y)$ at evenly spaced intervals in both directions. The DFT pair for this $M \times N$ data array is: [1, 7]

$$F(u, v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(\frac{ux}{M} + \frac{vy}{N})} \tag{5}$$

for $u = 0, 1, 2, \ldots, M-1$ and $v = 0, 1, 2, \ldots, N-1$, and

$$f(x, y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) e^{j2\pi(\frac{ux}{M} + \frac{vy}{N})} \tag{6}$$

for $x = 0, 1, 2, \ldots, M-1$ and $y = 0, 1, 2, \ldots, N-1$. As the DFT is an extremely slow process especially when the data set is large, Danielson and Lanczos [8] developed an algorithm to enhance the efficiency and robustness of the Cooley-Tukey Fast Fourier Transform (FFT) algorithm [2]. As we focus on the digital images only, we will limit this paper to the FFT.

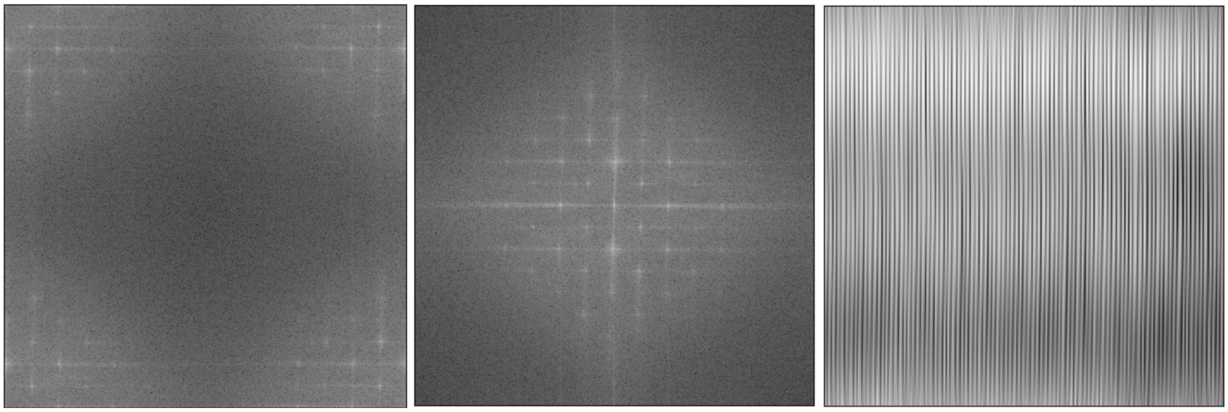
3 METHOD PROPOSAL

To reconstruct periodic weave patterns in fabric images, we propose to use both the 2D Fast Fourier Transform (2D-FFT) and the 2D inverse Fast Fourier Transform (2D-iFFT) techniques, combined with the local adaptive threshold method. The ultimate goal of this process is two-fold: 1) to locate and separate the warp and weft yarns into different images for the counting process, and 2) to eliminate non-periodic elements, noises, and background from the fabric images.

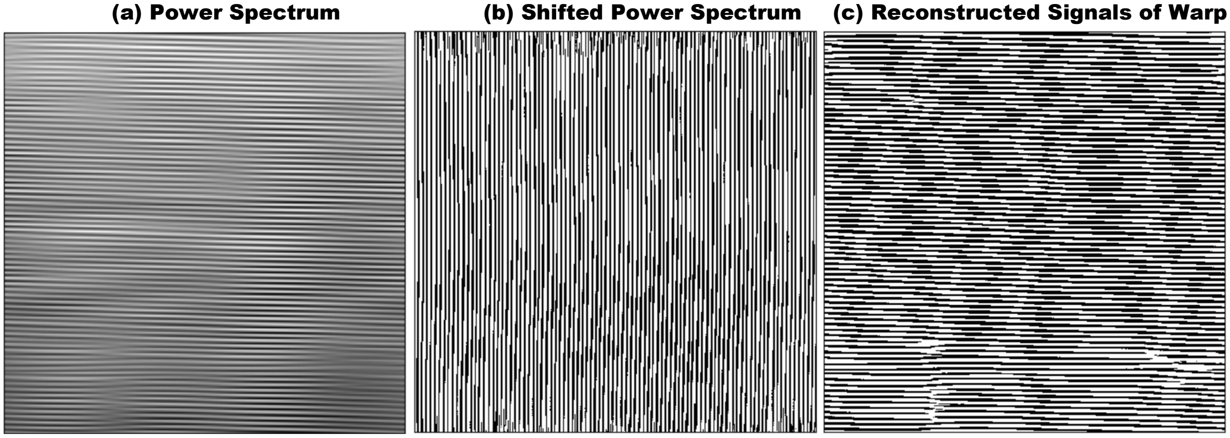
3.1 Fourier Transform

Using the 2D-FFT, we can get the frequency domain magnitudes and phases[1] of the input images. Power is the square of the magnitude $M(u, v)$, and is often displayed against frequency to show

[1]The magnitude and phase is the polar representation of a complex number.



(a) Power Spectrum **(b) Shifted Power Spectrum** **(c) Reconstructed Signals of Warp Yarns**



(d) Reconstructed Signals of Weft Yarns **(e) Reconstructed Warp Yarn** **(f) Reconstructed Weft Yarn**

Figure 2: Reconstruction Steps of Plain Fabric Image P9

the relative contribution of each frequency to the original spatial function in the sample interval. Usually, the dynamic range of the power spectrum is much larger than the range of a typical gray scale image pixel, which is 0 to 255. Therefore, the power spectrum is typically displayed on a logarithmic scale:

$$P_l(u, v) = \log[aP(u, v) + b] \qquad (7)$$

where a and b are scaling constants, which are often assigned to one [10].

Initially, the peaks corresponding to periodic structures of the fabric images, such as yarns and interstices, are in the low frequency regions which are on the borderline of the power spectrum. Meanwhile, the peaks in the center represent high frequency regions corresponding to non-periodic elements such as edges and noise. Using the property of conjugate symmetry of the Fourier Transform, we apply a shifting process to exchange the first quadrant of the spectrum with the third one, and the second quadrant with the forth one to display a centered power spectrum [3]. By shifting the quadrants this way, low frequency regions move close to the center and high frequency peaks move to the borderline of the spectrum. This step isolates low frequency peaks for further steps of reconstructing images and illustrates the power spectrum as a two-dimensional Cartesian system for inspections of weft rotation.

Figure 2 gives an example to illustrate the power spectrum of a fabric image acquired by using the 2D-FFT. Figure 2a and 2b represent the power spectrum and shifted power spectrum, respectively, of image 1a.

3.2 Separating Warp Yarns and Weft Yarns

The power at the origin $P_l(0, 0)$ is the average brightness of the original image, and the pixels on the same radius from the origin represent the same frequency term spreading in the original image. We separate weft and warp by keeping only frequencies that are on the principal horizontal line (line that passes through the origin horizontally) and the principle vertical line (line that passes through the origin vertically), while all other frequencies are set to zero. In a weave spectrum, peaks on the principle horizontal line are associated with the warp yarns, and those on the principle vertical line are related to the weft yarn. Therefore, we reconstruct the image from the magnitudes and phases of the selected peaks using 2D-iFFT. The images acquired from this process show either warp yarns only, if the peaks in the principal horizontal line are kept, or weft yarns, if peaks in the principal vertical line are kept. Figure 2c displays the warp yarns while Figure 2d displays the weft yarns of image 1a.

After the Fourier Transform process, we can separate warp yarns and weft yarns into two individual images. To locate the yarns more accurately, local adaptive threshold process is applied to reconstruct acquired images into binary images. Local adaptive threshold is a technique to convert an image consisting of gray scale pixels to just black and white scale pixels. It chooses different threshold values for every pixel in the image based on an analysis of its neighboring pixels, thus results in binary images with high precision [5]. In specific, periodic structures representing warp or weft yarns are converted to 255 (white), while structures corresponding to interstices between yarns are converted to 0 (black).

For this process, we use the Gaussian's adaptive threshold function from the OpenCV library. The results are shown in Figure 2. Figure 2e displays reconstructed binary warp-yarn image and Figure 2f displays reconstructed binary weft-yarn image of image 1a.

3.3 Performing Thread Counting

After obtaining the reconstructed binary images, we count the number of yarns by traversing from left to right for warp-yarn image and from top to bottom for weft-yarn image. Since white (pixel value 255) represents weave yarns and black (pixel value 0) represents interstices between two yarns, each time the pixel value changes when we traverse through the reconstructed images, that means we cross through one yarn or interstice. When one yarn and the corresponding interstice are traversed, we increase the number of yarns by one.

We do this for every left-most pixel of the reconstructed warp image and for top-most pixel of the reconstructed weft image, then calculate the average of the yarns counted as below.

$$y_{warp} = \frac{\sum_{i=0}^{l} y_i}{l} \qquad y_{weft} = \frac{\sum_{j=0}^{w} y_j}{w} \tag{8}$$

where y_{warp} and y_{weft} is the number of warp and weft yarns in the original fabric images, l is image length, w is image width, y_i is individual numbers of warp yarns from left to right, y_j is individual numbers of weft yarns from top to bottom.

3.4 Calculating Weft Yarn Rotation

A power spectrum image $P(u, v)$ can be treated as an ordinary image that can be processed by spatial operations such as traversing and filtering. Any periodic structure in the spatial domain, such as warps, wefts, and diagonal lines made from intersections of yarns, can cause a peak on the power spectrum at a perpendicular angle. As a result, the rotation of weft yarns can be obtained by computing angle distributions in $P(u, v)$ and selecting the highest angle in the distribution. An angular distribution P(α) refers to the average values of pixels along a line whose angle relative to the principle horizontal line is equal to α, that is:

$$P(\alpha) = \frac{\sum P(u_i, v_i)}{K} \,|\, \forall u_i, \forall v_i, \tan^{-1}\left(\frac{v_i}{u_i}\right) = \alpha \, (0 \le \alpha \le 2\pi) \tag{9}$$

where K is the number of pixels counted on a specific line.

Since $P(u, v)$ is always perpendicular to the orientation of the original image, three most common spikes that occur at 0°, 180° and 90° correspond to the wefts and warps, respectively (0° and 180° both indicate weft yarns) [9]. The logarithm of angular distributions for all three sample fabric images P9, T1, and S1 are shown in Figure 3. There are other major spikes that occur at different degrees indicate diagonal structures of intersections. For twill and satin weave patterns, those diagonal lines are usually more visible than weft yarns, thus dominating the major spike at 90°. As a result, for practical purposes of finding weft distortion in all types of weave patterns in real industry, we narrow the range for inspection of weft rotation into 80° - 100°. If weft yarns are rotated, the primary vertical line in the power spectrum is also rotated for the same degree to the left or right based on the direction of weft rotation. In other words, the highest spike within that range helps us calculate the weft rotation in the original image as follows:

$$\alpha = |90^\circ - max(P(\alpha))| \tag{10}$$

where $max(P(\alpha))$ is the highest spike within the boundaries that we are discussing. Moreover, we can figure out the direction of weft rotation from (10) Weft yarns are rotated clockwise if $max(P(\alpha))$ is less than 90° and counter-clockwise if $max(P(\alpha))$ is greater than 90°. Otherwise, there is no rotation for weft yarns if $max(P(\alpha))$ is equal to 90°.

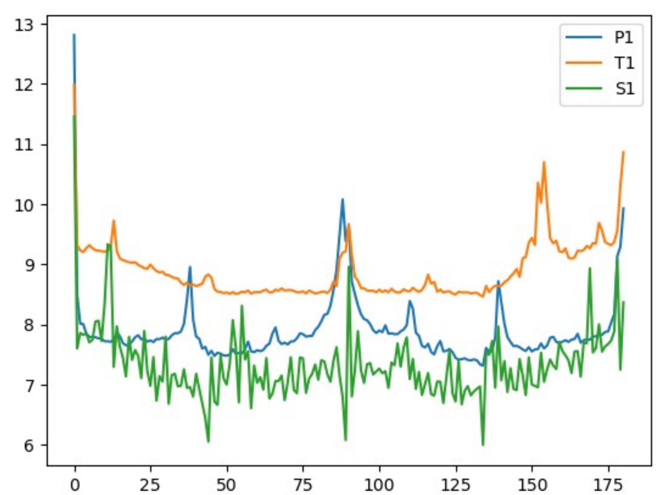


Figure 3: Angular Distributions of Sample Image P9, T1, and S1

In Figure 3, the highest spikes of P9, T1, and S1 within the boundaries that we are discussing occur at 88°, 90°, and 90°, respectively. As a result, weft yarns in P9 are rotated 2° clockwise, while in T1 and S1 there is no rotation for weft yarns. Other major spikes beyond the boundaries indicate the orientation of diagonal lines.

4 EXPERIMENTAL SETUP

We implemented the proposed method in Python 3.8.1 with a Fourier Transform package from OpenCV library on a PC (Ubuntu 18.04, an Intel® Core™ i5-8250U CPU, 1.6GHz, RAM: 8GB).

Our test fabric images are color weave fabric images for three different types of basic weave patterns: plain, twill, and satin. We collected more than 200 sample images that meet our requirements from textile industry websites. For this paper, we use five plain images (a-e), labeled P1 - P5, from Benchmark Catalog, five plain images (f-h), labeled P6 - P10, from Vervedc company, four twill images (k-n), labeled T1 - T4, from Cotton Inc., and two satin images (o-p), labeled S1 - S2, from Thayercraft Inc. All images were converted to gray scale using a converting function from OpenCV for the experiments.

5 RESULTS AND ANALYSIS

5.1 Thread Counting

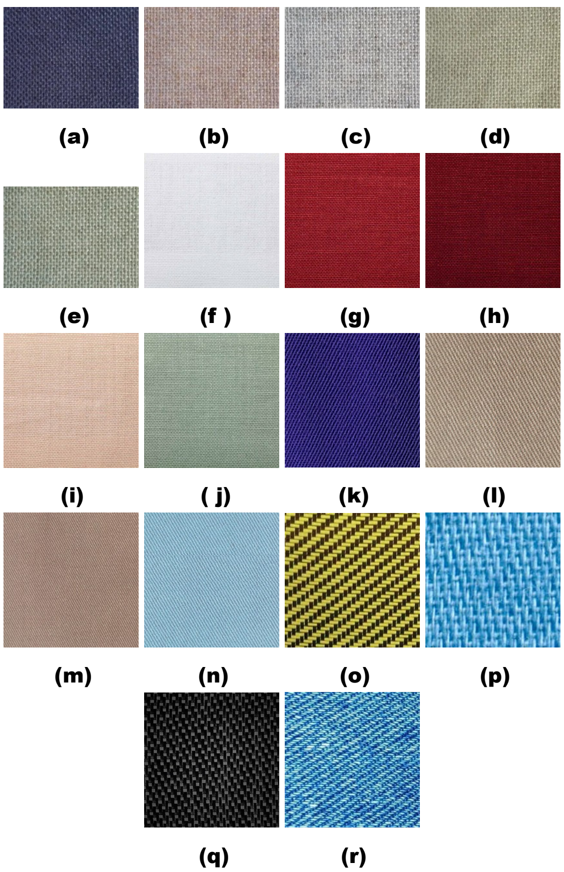


Figure 4: Sample Fabric Images of Three Weave Patterns

Table 1 compares the manual method and our proposed method. The measurement is conducted for both warp yarns and weft yarns, then the difference in two methods are collected and displayed in number of yarns and percentage error. The specific formula for percentage error is as follows:

$$error = |1 - \frac{y}{x}| * 100 \quad (11)$$

where x is the density measured manually and y is the density calculated from (8).

For plain weave fabric images, the error percentage in the fabric density inspected by our automatic method is always below 3%. The lowest and highest error percentage for warp yarns is 0.01% and 1.85%, respectively. The lowest and highest error percentage for weft yarns is 0.02% and 2.65%, respectively. The highest difference in number of yarns is about 1 yarn, thus our proposed method outperforms the manual method in counting plain weave fabric density in real-time production.

For twill and satin weave fabric images, however, we did not achieve the same level of accuracy as plain type fabrics. With twill weave images T1 - T4, the lowest error is 1.92% while the highest error is around 28% as shown in Table I. With satin images S1 - S2, the average error is much higher and unstable. The main reason for this low accuracy is that twill and satin fabric images have more complex structure. Since their fabric yarns are tightly bound together, it is difficult to completely locate the signal for both warps and wefts through the FFT process. Also, the diagonal line made from the intersections of yarns interfere into the overall signals in the frequency domain.

5.2 Weft Yarn Rotation

Table 1 also shows the weft distortion inspected by our proposed method. We collected the power spectrum of each sample image and then used 10 to figure out the rotation of weft yarns in each sample. Then, we verified the results by measuring each sample manually.

From our experiments, we observe that our proposed method provides the highest results with plain weave fabric image. The reason is that the weave structure for plain fabric is simple, thus angular distributions collected from the FFT clearly shows the highest spike which indicates the weft rotation of the images. On the other hand, twill and satin weave fabric images have more complex weave structure, thus the signals of the diagonal lines sometimes outnumber those of warps and wefts in the power spectrum. As a result, image resolution and quality are two important factors to ensure the high accuracy in determining the weft distortion using our proposed method.

5.3 Algorithm Analysis

The fabric image size is an important factor that influences the image reconstruction and segmentation results. The computation time for processing the fabric images with different sizes is calculated. The minimum computation time is 0.37s when the image size is 320 x 240 and the maximum computation time is 2.54s when the image size is 1000 x 1000.

Fabric pattern, on the other hand, does not affect the speed of inspection. Given images of the same resolution but different types and patterns, we conclude that computation time does not vary significantly for every phase. We also calculated the average computation time for each sample group by inspecting the groups ten times and measuring the average. From our experiments, the average computation time for small plain weave images P1 - P5 is about 0.37s while the average computation time for small satin weave images S1 - S3 is about 0.43s. Similarly, the average computation time for large plain fabric images P6 - P10 is about 1.74s while the

Table 1: Results for Samples Fabric Images

Data	Resolution	Warp, thread		Weft, thread		Warp Error		Weft Error		Weft Rotation °
		Auto	*Manual*	*Auto*	*Manual*	*Yarns*	*%*	*Yarns*	*%*	
P1	320px * 240px	46.46	47	35.78	36	0.54	1.16	0.22	0.61	1
P2	320px * 240px	42.99	43	32.65	33	0.01	0.01	0.35	1.05	0
P3	320px * 240px	42.20	43	32.39	33	0.80	1.85	0.61	1.84	1
P4	320px * 240px	44.93	45	32.80	33	0.07	0.15	0.20	0.60	1
P5	320px * 240px	41.68	42	31.15	32	0.32	0.77	0.85	2.65	1
P6	670px * 670px	96.25	96	76.64	77	0.25	0.26	0.36	0.47	2
P7	670px * 670px	91.43	91	76.99	77	0.43	0.48	0.01	0.02	1
P8	670px * 670px	93.27	94	76.98	78	0.73	0.78	1.02	1.31	2
P9	670px * 670px	92.28	91	73.07	74	1.28	1.41	0.93	1.25	2
P10	670px * 670px	93.85	94	77.07	78	0.15	0.16	0.93	1.19	0
T1	512px * 512px	136.33	139	100.78	77	2.67	1.92	23.78	23.60	3
T2	1000px * 1000px	119.00	127	68.34	58	8.00	6.30	10.34	17.82	1
T3	512px * 512px	206.20	183	154.15	125	23.20	12.68	29.15	23.32	4
T4	512px * 512px	165.90	138	104.85	108	27.90	20.20	3.15	2.92	0
S1	220px * 220px	34.68	36	16.07	16	1.32	3.67	0.07	0.44	2
S2	300px * 300px	49.82	43	50.92	47	6.82	15.86	3.92	8.34	4

average computation time for large twill weave images T1 - T4 is 1.46s.

6 CONCLUSION

This paper presents an automatic method applying the 2D-Fast Fourier Transform to overcome the limitations of the traditional method for inspecting fabric density and weft distortion. It separates and accurately locates the warp yarns and weft yarns from original fabric images for the counting process. It significantly eliminates non-periodic structures, noises, and background of the fabric image when specific peaks are selected in the frequency domain, which requires much more effort in the spatial, or time, domain. We demonstrate our experiment setup and implementation steps as well as analyzed the results on the accuracy by comparing number of yarns acquired from manual inspection and from our proposed method. We also represent the weft distortion results on different fabric weave patterns. The experiment results demonstrate that our proposed method can outperform the manual methods with higher accuracy and practicality for textile industry.

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