Rofidatunnissa, 2025, 13:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Automated Fabric Density Measurement via FFT and Intensity Gray Profile Analysis

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Abstract- Woven fabrics are formed by the interlacing of warp (vertical) and weft (horizontal) yarns, with yarn density (threads per inch) being a critical parameter in textile quality assessment. This study aims to develop an automated yarn density measurement system using the Fast Fourier Transform (FFT), which analyzes periodic texture patterns in the frequency domain. The method involves frequency filtering and density estimation based on gray line profile intensity and was tested on 25 images for each weave type. Results show high accuracy for plain (0.96% warp error; 1.14% weft error) and twill (1.02% warp error; 1.57% weft error) weaves. However, satin weave exhibits a significant discrepancy between warp (31.98%) and weft (1.99%) errors, attributed to its unique structural characteristics—high yarn density, overlapping warp threads that obscure the weft, and a glossy surface that causes uneven light reflections, which affect image acquisition. While the method proves effective for most fabrics, accurately measuring warp density in satin remains a challenge. Nonetheless, the proposed approach has potential for industrial application to improve production efficiency in the textile industry.

Keywords: Fast Fourier Transform, Fabric Density, Gray Profile Line Intensity.

I. INTRODUCTION

Textile fabrics play a significant role as body protection and as a medium of aesthetic expression[1]. Woven fabrics are constructed from the interlacing of warp yarns (vertical) and weft yarns (horizontal), where the warp forms the structural base and the weft acts as the binder[2]. Based on the weaving pattern, basic weaves are classified into three types: plain, twill, and satin[3]. The textile industry must analyze fabric parameters such as yarn content, fabric weight, yarn number and yarn density to meet market demands[4].

Fabric density is defined as the number of warp/weft yarns per inch[4], and it serves as a quality indicator that affects textile properties such as air permeability[5]. Fabric density also determines the overall quality—the denser the weave, the stronger the fabric, but the less breathable it becomes [6]. The conventional approach to recognizing woven patterns in textile laboratories relies on visual inspection by humans, often assisted by the use of pins fabrics[7]. However, manual measurements are prone to errors and inefficient [8]. Automated fabric density measurement is essential to reduce testing time and produce more accurate analysis results. Jing et al.[8] also stated that automated methods play an important role in reducing labor costs while improving the performance of textile companies. With the advancement of computer technology, many textile researchers have developed image-based methods to analyze fabrics automatically. Several previous studies, such as those conducted by Pan and Gao[9], demonstrated that image processing methods are capable of extracting low-level features from yarns in woven fabrics, including texture, color, shape, edges, and various other information. One of the image processing techniques widely used in fabric texture analysis is the Fourier Transform.

Fourier Transform (FT) is a mathematical tool that enables the conversion of data from the spatial domain to the frequency domain, making it highly effective for analyzing periodic patterns such as the woven yarn structure in fabrics[5]. In the context of textiles, FT can identify yarn density by detecting the repetitive patterns of warp and weft interlacing through frequency spectrum analysis. Automated methods such as Fourier transformation in the frequency domain have been shown to accurately measure fabric density by analyzing texture periodicity[10]. This technique has also proven effective in other fields, such as early detection of Alzheimer's disease through MRI image analysis[11]. The FFT can be used to denoise a noisy ECG signal using a bandpass filter [12]. Zhang et al[10] applied Fast Fourier Transform and binary analysis to measure fabric density, but only for solid fabrics.

II. LITERATURE REVIEW

Fourier Transform

A transformation is a mathematical tool that simplifies the representation of signals and extracts relevant information[13]. Fourier analysis, introduced by French scientist Jean Baptiste Joseph Fourier in the 1800s, allows the representation of any periodic signal—regardless of its complexity—using harmonic series [14][15]. The Fourier Transform is a classical analytical method that represents signals as a linear combination of sine and cosine functions [13]. It is also a powerful method for decomposing functions into sine and cosine components with relatively low computational complexity.

The Fourier Transform converts a signal from the spatial domain to the frequency domain, making it one of the most fundamental tools in the fields of signal and image processing [16]. Fourier Trasnform is widely utilized across various domains such as transformation analysis, fault detection, optimization, and feature extraction [11]. In image processing, the frequency components obtained through Fourier Transform are commonly employed in filtering processes to reduce noise and enhance image sharpness[17], [18]

A digital image of size M × N is represented by a grayscale function f(x,y) As the period T approaches infinity, the Fourier series converges to the continuous Fourier Transform. Since processing infinite discrete data is impractical, the Discrete Fourier Transform (DFT) is used to convert it into a finite series [13]. The function f(x,y)is transformed into the frequency domain as F(u,v) and can be converted back to the spatial domain using the Inverse Fourier Transform to retrieve f(x,y) [14], [19].

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

$$f(x,y) = \frac{1}{MN} \sum_{u=0}^{m-1} \sum_{v=0}^{n-1} F(u,v) e^{j2\pi({ux}/_{m}+{vy}/_{n})} \tag{2}$$

Where variables u and x = 0,1,2,...,N-1 also v and y = 0,1,2,...,M-1, representing frequency domain variables, and M and N representing the pixel dimensions (rows and columns) of the image, the Discrete Fourier Transform (DFT) can be computed. However, conventional DFT calculations have a high computational complexity of ($O(P^2)$). To address this, the Fast Fourier Transform (FFT) was developed as an optimization algorithm that reduces the complexity to O(P log P) [20], enabling faster and more efficient analysis, especially in textile industry applications that require real-time measurements. Power spectrum analysis in the frequency domain is key to this method. Energy peaks in the frequency spectrum correlate directly with the yarn density in the fabric structure [10].

$$P(u,v) = log(1 + |F(u,v)|^2 \tag{3}$$

Thus, the intensity and distribution of spectral peaks can be used as quantitative indicators for evaluating the density and regularity of yarn interlacing.Fabric density analysis using Fourier Transform leverages frequency domain manipulation through filtering[14]. The fabric image is transformed using FFT to identify the frequency components representing the yarn structure [10]. Selective band-pass filters are applied to the frequency spectrum to isolate the vertical (warp) and horizontal (weft) frequencies[21], and the image is then reconstructed back to the spatial domain using Inverse FFT (IFFT)[20].

Gray Line Profile Intensity

The reconstructed image is analyzed using the gray profile line intensity method, which involves counting the number of peaks in the grayscale intensity waveform. This method works by projecting the grayscale levels of the image onto the horizontal axis, allowing the number of warp yarns to be determined based on the number of local peaks in the gray line profile that are separated by a predefined threshold. To calculate weft yarn density, the fabric image is rotated 90 degrees, and the same method is reapplied from the beginning[22]. In a previous study, Jeong and Jang[23] demonstrated that the gray line profile method yields good results for both patterned and non-patterned fabrics and offers an advantage by not

requiring any pre-processing or additional filtering techniques. However, a limitation of this method is that its effectiveness is highly influenced by the size of the filter used to identify local minimum points in the profile graph.

III. METHODOLOGY

Fabric density identification using MATLAB was performed by testing 25 images for each basic weave pattern: plain, twill, and satin. The process begins with image acquisition using a camera with 5× magnification. The captured image is then imported into MATLAB, where it is converted from RGB to grayscale and resized to 640×640 pixels, representing a 10×10 mm area. The analysis continues by transforming the image from the spatial domain to the frequency domain using the Fast Fourier Transform (FFT)

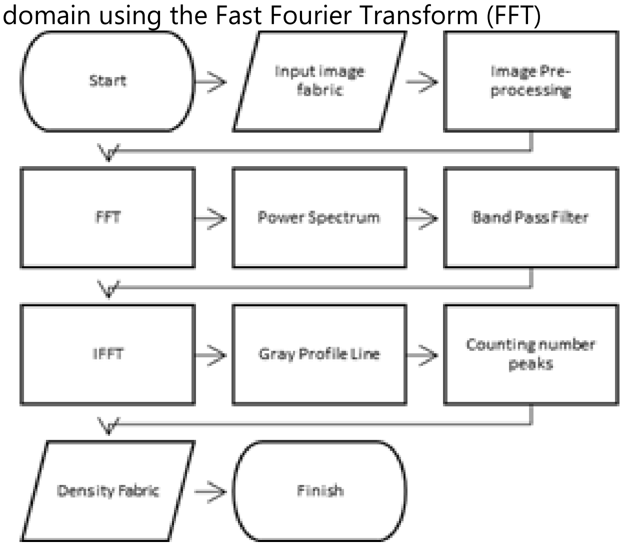

Figure 1: Flowchart FFT

This transformation produces a frequency spectrum that represents the frequency of intensity changes in the image and enables the identification of periodic patterns in the weave structure through frequency spectrum analysis. The frequency spectrum is then used to calculate the power spectrum, which represents the strength of each frequency component (frequency peaks). To separate the warp and weft yarn components, a band-pass filter is applied, preserving frequency components within a 9-pixel width around the center of the spectrum, while zeroing out the others. The filtered spectrum is then reconstructed back to the spatial domain using the Inverse FFT (IFFT), resulting in images that clearly highlight vertical lines (warp yarns) and horizontal lines (weft yarns) like Figure 2.

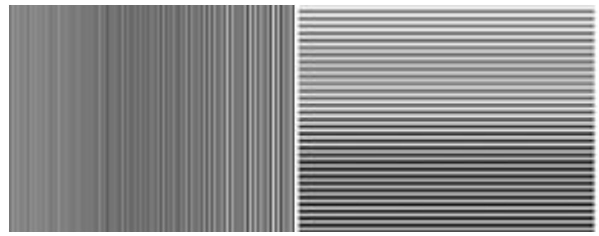

Figure 2: Image Reconstruction from Band Pass Filter

Once the images showing only vertical or horizontal lines are obtained, the warp and weft yarn densities are calculated by counting the number of peaks in the gray intensity profile graph. To calculate the warp yarn density, the grayscale intensity values along the central horizontal line of the image are extracted. This intensity profile is then smoothed using a Gaussian filter with a window length of 10 pixels to reduce noise that may interfere with peak detection. The smoothing process preserves the general wave shape while eliminating small, insignificant fluctuations.

Once the signal is smoothed, the findpeaks function is used to detect local maxima, each representing a detected warp yarn due to periodic intensity variation caused by the woven structure. To account for possible partial peaks at the beginning or end of the profile (which may be truncated due to image boundaries), a correction is applied by adding 0.5 peaks if the starting or ending value is higher than its neighbor.

The total number of peaks (including this correction) is then converted into the warp yarn density in threads per inch (TPI). The same procedure is applied to determine the weft yarn density, with the fabric image rotated 90 degrees so that the weft yarns align horizontally. The gray profile intensity method is then reapplied from the beginning to this orientation.

The number of peaks corresponds to the yarn density, which is then converted into the industry-standard unit of yarns per inch. The measurement error is calculated by comparing the results with manual methods, using the percentage error formula[24].

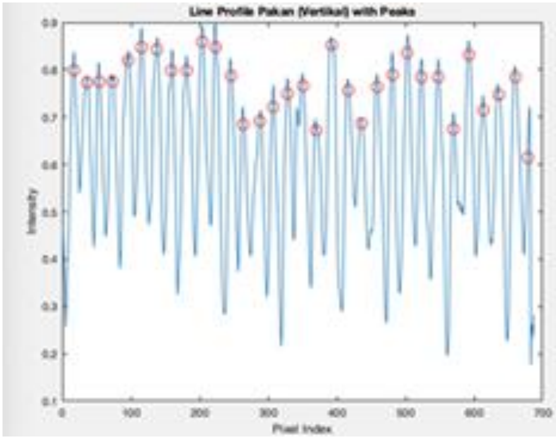

Figure 3: Line Profile with Peaks

$$Error\% = \frac{|N_O - N_M|}{N_M} x100\% \quad (4)$$

IV. RESULT AND DISCUSSION

Based on the measurement data of plain weave fabric density in Table 1, the error values in the automatic measurement of plain weave fabric density are generally low, indicating good accuracy. For warp yarns, the error ranges from 0.06% to 3.24%, with the majority of samples showing errors below 1%. The highest warp errors occurred in samples plain9 (3.10%) and plain19 (3.24%), while the lowest were found in plain8 (0.06%) and plain23 (0.13%). For weft yarns, the error ranges from 0.09% to 2.97%, with most values staying under 2%, except for plain3, which recorded the highest weft error at 2.97%.

Table -1: Result Density Plain Fabric

Image	Auto Warp	Auto Weft	MN Warp	MN Weft	Error Warp (%)	Error Weft (%)
plain1	129,5	82,6	130	81	0,35	1,91
plain2	163,8	85,1	163	84	0,51	1,30
plain3	123,2	76,2	122	74	0,98	2,97
plain4	166,4	74,9	168	75	0,97	0,09
plain5	168,9	80,0	168	79	0,54	1,28
plain6	168,9	80,0	168	79	0,54	1,28
plain7	171,5	77,5	173	76	0,90	1,93
plain8	165,1	77,5	165	76	0,06	1,93
plain9	167,6	78,7	173	79	3,10	0,33
plain10	170,2	78,7	168	79	1,30	0,33
plain11	170,2	80,0	173	79	1,63	1,28
plain12	154,9	80,0	154	79	0,61	1,28
plain13	152,4	85,1	152	84	0,26	1,30
plain14	135,9	82,6	135	83	0,66	0,54
plain15	133,4	85,1	132	84	1,02	1,30
plain16	138,4	83,8	137	85	1,04	1,39
plain17	171,5	81,3	170	80	0,85	1,60
plain18	137,2	87,6	136	86	0,85	1,90
plain19	162,6	73,7	168	75	3,24	1,79
plain20	135,9	83,8	135	84	0,66	0,21
plain21	166,4	76,2	165	76	0,83	0,26
plain22	134,6	73,7	137	74	1,74	0,46
plain23	156,2	81,3	156	81	0,13	0,35
plain24	172,7	80,0	173	79	0,16	1,28
plain25	123,2	76,2	122	76	0,98	0,26

Auto : Automated measurement
MN : Manually measurement

In addition to the plain weave, the automated density measurement of twill fabrics also demonstrated strong performance, with error values generally remaining low and consistent. For warp yarns, the error ranged from 0.06% to 2.58%, with the majority of samples below 2%. The highest warp error was recorded in sample twill14 (2.58%), followed by twill15 (2.31%). Notably, several samples such as twill18 and twill21 exhibited extremely low errors of just 0.06%, indicating highly accurate warp detection.Weft yarn measurements also showed favorable results, with error percentages varying between 0.02% and 4.49%. Most of the weft errors were below 2%, although twill1 (4.42%) and twill22 (4.49%) showed relatively higher deviations, which may be attributed to texture complexity or minor inaccuracies during peak detection. Nevertheless, samples like twill4, twill11, and twill19 demonstrated near-perfect weft accuracy with errors close to 0.02%–0.66%.

Table -2: Result Density Twill Fabric

Image	Auto Warp	Auto Weft	MN Warp	MN Weft	Error Warp (%)	Error Weft (%)
twill1	100,3	141,0	102	135	1,64	4,42
twill2	142,2	80,0	145	83	1,90	3,60
twill3	97,8	80,0	99	79	1,22	1,28
twill4	123,2	94,0	122	94	0,98	0,02
twill5	113,0	86,4	114	86	0,85	0,42
twill6	125,7	90,2	127	91	1,00	0,91
twill7	100,3	81,3	99	84	1,34	3,24
twill8	100,3	81,3	99	83	1,34	2,07
twill9	105,4	91,4	107	91	1,49	0,48
twill10	161,3	99,1	160	102	0,81	2,88
twill11	119,4	94,0	119	94	0,32	0,02
twill12	120,7	88,9	119	90	1,39	1,22
twill13	128,3	102,9	128	102	0,21	0,85
twill14	133,4	102,9	130	102	2,58	0,85
twill15	127,0	100,3	130	102	2,31	1,64
twill16	111,8	78,7	112	81	0,21	2,79
twill17	110,5	85,1	109	84	1,37	1,30
twill18	99,1	76,2	99	76	0,06	0,26
twill19	101,6	135,9	102	135	0,39	0,66
twill20	101,6	55,9	100	57	1,60	1,96
twill21	99,1	76,2	99	77	0,06	1,04
twill22	97,8	82,6	98	79	0,21	4,49
twill23	80,0	99,1	81	99	1,22	0,06
twill24	81,3	108,0	81	107	0,35	0,89
twill25	141,0	77,5	140	79	0,69	1,94

Auto : Automated measurement
MN : Manually measurement

In contrast to the plain and twill weave fabrics, the automated density measurements for satin fabrics exhibited significantly higher errors, particularly in the warp yarns. Warp error percentages ranged widely, from as low as 0.64% (satin25) to as high as 58.71% (satin9). More than half of the satin samples recorded warp errors exceeding 30%, indicating a considerable challenge in accurately detecting warp yarn density in satin fabrics using the current FFT-based method. Despite the high warp errors, weft density measurements remained relatively accurate. The majority of weft errors were below 3%, with the lowest error at 0.06% (satin19) and the highest at 8.26% (satin16). Several samples, including satin2, satin5, satin10, and satin23, exhibited exceptionally low weft errors under 1%, suggesting that the automated system can still reliably capture horizontal thread density even in complex satin weaves.

Table -3: Result Density Satin Fabric

Image	Auto Warp	Auto Weft	MN Warp	MN Weft	Error Warp (%)	Error Weft (%)
satin1	94,0	71,1	155	69	39,37	3,07
satin2	61,0	63,5	145	64	57,96	0,78
satin3	80,0	77,5	193	76	58,54	1,93
satin4	96,5	55,9	135	55	28,50	1,60
satin5	138,4	86,4	193	86	28,27	0,42
satin6	58,4	54,6	124	53	52,89	3,04

satin7	69,9	62,2	150	61	53,43	2,02
satin8	135,9	77,5	173	76	21,45	1,93
satin9	83,8	85,1	203	84	58,71	1,30
satin10	82,6	78,7	198	79	58,31	0,33
satin11	100,3	49,5	119	48	15,69	3,19
satin12	123,2	77,5	191	79	35,50	1,94
satin13	76,2	54,6	127	53	40,00	3,04
satin14	105,4	57,2	140	56	24,71	2,05
satin15	111,8	80,0	173	79	35,40	1,28
satin16	87,6	66,0	142	61	38,29	8,26
satin17	128,3	77,5	178	76	27,94	1,93
satin18	193,0	120,7	203	119	4,91	1,39
satin19	188,0	99,1	208	99	9,63	0,06
satin20	120,7	77,5	234	76	48,44	1,93
satin21	127,0	83,8	191	81	33,51	3,48
satin22	139,7	80,0	168	79	16,85	1,28
satin23	162,6	96,5	160	97	1,60	0,49
satin24	138,4	67,3	152	66	8,93	1,98
satin25	191,8	85,1	193	86	0,64	1,06

Auto : Automated measurement
MN : Manually measurement

The overall performance of the automated fabric density measurement system can be further evaluated through the Mean Average Error (MAE) across the three weave types. As shown in the table, plain weave fabrics yielded the lowest MAE, with0.96% for warp and 1.14% for weft, indicating a high level of accuracy and consistency in both directions. For twill fabrics, the system also demonstrated strong reliability, with slightly higher MAE values of 1.02% for warp and 1.57% for weft. These results confirm that the FFT-based method using Gray Line Profile remains effective even with the more complex interlacing pattern of twill weaves.

Table -4: Mean Average Error Fabric Density

Mean Average Error (%)	Plain	Twill	Satin
Warp	0,96	1,02	31,98
Weft	1,14	1,57	1,99

In contrast, the warp yarn density error for satin weave was considerably high at 31.98%, indicating that the automatic method is still less accurate in detecting warp density in satin fabrics. However, for weft yarns, the system performed much better, with errors mostly below 3%, and an average error of 1.99%. There is a significant discrepancy between the warp and weft density errors in satin weave, as well as when compared to the average errors observed in plain and twill weaves. This difference is likely due to the unique structural characteristics of satin fabrics, where the warp yarns tend to float over and obscure the weft yarns—especially in high-density fabrics (greater than 150 threads per inch). High yarn density can lead to overlapping and stacking of threads, making it difficult to accurately detect individual yarns. Moreover, satin fabrics typically have a glossy surface due to their floating yarn structure, which can cause uneven reflection during image acquisition. This reflective nature may introduce artifacts or highlights in the captured image, causing some yarns to appear blurred or partially missing, thereby reducing the accuracy of yarn detection. As shown in Figure 4, the red line highlights the repeating pattern consisting of 5 warp threads. However, the proposed method is only able to detect 3 to 4 of these threads, which explains the high error in warp density measurement for satin fabrics.

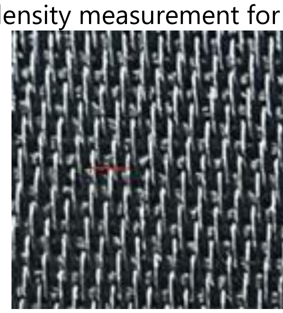

Figure 4: Satin Weave

These results demonstrate that the automatic method produces relatively small errors compared to manual measurement for plain and twill weaves, with most deviations remaining within an acceptable range. However, improvements in image acquisition and pre-processing are still needed for satin weaves.

The average error rates for plain, twill, and satin (warp) weaves are comparable to recent studies such as Zhang et al[5], who used backlight imaging; Tan & Wong[24], who used segmentation methods; and Meng et al[4], who applied Multi-scale Convolutional Neural Networks and Hough Transform—all reporting average errors below 2%. These results indicate that the FFT-based method developed in this study is as reliable as other state-of-the-art approaches in textile analysis.

Table -5: Previous Studies Comparison

Author	Method	Average Error
Zhang et al. [5]	backlight imaging	<1,5%
Tan & Wong [24]	segmentation methods	<1,5%
Meng et al [4]	Multi-scale Convolutional Neural Networks and Hough Transform	< 2%
Pan et al. [25]	FFT + Biner	0,98%
Wijayono [26]	Counting pixel	0,95%

This study reports slightly higher errors (ranging from 0.96% to 1.57%) compared to Pan et al[25] (0,98%) and Wijayono[26] (0,95%). However, this difference can be attributed to the fact that Pan's method was limited to single-colored fabrics, while the method proposed in this study utilizes FFT analysis based on intensity profile, which excels at detecting yarn structures even under low contrast and is more robust to color and lighting variations, making it suitable for multi-colored yarn-dyed fabrics. Other factors influencing the error rate include inaccurate boundary detection, uneven lighting distribution, and image blur. This highlights that the accuracy of fabric density measurement is highly dependent on the quality of image acquisition and pre-processing stages.

V. CONCLUSION

This study presents an automated fabric density measurement system based on FFT analysis using Gray Line Profile to evaluate warp and weft yarn density across three common weave types: plain, twill, and satin. The experimental results demonstrate that the proposed method achieves high accuracy for plain and twill weaves, with Mean Average Errors (MAE) consistently below 2% in both warp and weft directions. These findings are in line with previous state-of-the-art studies, confirming the reliability and robustness of the FFT-based approach. In contrast, satin weave fabrics present a notable challenge, especially in warp density detection, with an average error of 31.98%. This is due to the floating warp yarns that overlap and obscure the weft,making individual yarns harder to detect. For further refinement—such as adaptive preprocessing, improved thread boundary detection, or hybrid methods—is necessary to enhance accuracy for satin and other complex weave structures. Compared to previous works, the proposed method demonstrates competitive performance while offering greater robustness to multicolored and low-contrast fabrics. Despite slightly higher error rates than some conventional approaches that rely on controlled imaging conditions, this method proves effective in more realistic scenarios with diverse fabric types and colors. The FFT-based Gray Line Profile method is a viable and accurate solution for automated yarn density measurement in woven fabrics. It is applicable in the textile industry and can be further developed for other patterns or textile types, such as knitted fabrics

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