

Weaving Density Evaluation with the Aid of Image Analysis

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Abstract

This paper deals with the efficiency evaluation of selected methods for automatic assessing of weaving density based on image analysis for different kinds of fabrics. A set of woven fabrics samples in plain, satin and twill weave and patterned fabrics were selected for assessing weave density. Images of samples were captured by a flat scanner followed by preprocessing for the enhancement of images. The methods selected included the gray line profile method, a method based on image decomposition with a Wiener and median filter, a method based on the co-occurrence matrix and one using the 2 dimensional discrete Fourier transform. The results show that any of these methods is suitable for all kinds of fabrics in general.

Key words: woven fabric, weaving density, image processing, automatic assessing.

Introduction

In the textile branch it is standard practice to measure the weaving density of woven fabric by manual operations, which is a time consuming manual operation requiring the permanent attention of the measurer. Therefore the textile industry is concerned with replacing human inspection by suitable automated assessing and monitoring of weaving density. The automated system would use resources of computer vision and image analysis tools for objective and independent weaving density assessment.

Recently several studies have dealt with the automatic measurement of weaving density based on image analysis. Several approaches to the automatic assessing of weaving density with the aid of direct image analysis are known. The authors in [1] introduced the Gray Line

Profile Method, which is computationally simple and can be applied for various weaves. However, the direction of warp and weft yarns must be parallel with the axes of the fabric image, which can be achieved, for instance, with the aid of the Hough transform for detecting lines in images [2, 3]. Automatic inspection of weaving density based on the co-occurrence matrix algorithm was presented in [4]. The co-occurrence matrix for several displacements was counted from gray level images of woven fabrics. A feature contrast was obtained from such matrices and the weaving density was calculated from the figure where the contrast against the distance pixel is plotted. Several more papers deal with the spectral approach based on 2D DFT, which is suitable for the description of periodic patterns in monochromatic images due to the relationship between the regular structure in the spatial domain and its

Fourier spectrum in the frequency domain. Significant frequencies correspond to structure parameters e.g. weaving density [5, 6]. The application of Wiener and median filters for the assessment of weaving density is introduced in works [7, 8]. In this paper the efficiency and comparison of selected methods based on work [9] is presented.

Woven fabric is, as a rule, composed of two sets of mutually perpendicular and interlaced yarns. The weave pattern or basic unit of the weave is periodically repeated throughout the whole fabric area with the exception of the edges. The general principle of automatic measurement of weaving density is based on finding the periodicity of warp and weft yarns in woven fabric images. Weaving density D in cm^{-1} can be determined from the number of pixels in a cycle according to [1]

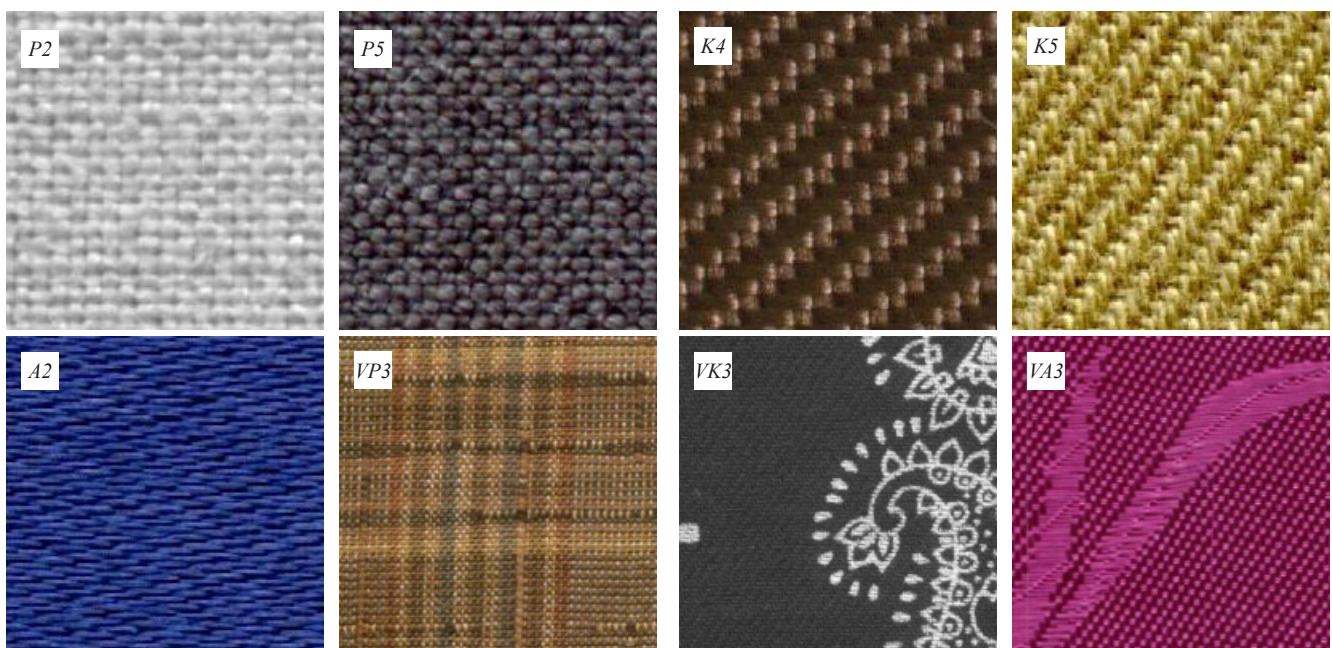


Figure 1. Representative set of image samples.

Table 1. Parameters of the representative set of samples.

Sample	Weave or pattern	Ravelling method (average of 5 measurements)	
		D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹
P2	Plain	24.3	22.5
P5	Plain	28.7	25.4
K4	Twill O4	22.6	23.4
K5	Twill O4	42.2	27.4
A2	Satin O8	48.8	45.4
VP3	Check	21.2	18.8
VK3	Printing	26.6	19.0
VA3	Woven pattern	26.2	26.6

$$D = \frac{R/2.54}{(N_2 - N_1)/N_v}, \quad (1)$$

where:

R is the image resolution in dpi ,

N_1 the initial pixel,

N_2 the final pixel, and

N_v is the number of repetitions.

Experimental details

42 kinds of woven fabric with different weaves, density, colours and patterns were used for evaluation [9]. In this paper experimental samples are represented by a selected set of 8 samples of woven fabric: 2 samples in plain weave (P2, P5), 2 samples in twill weave (K4, K5), 1 sample in satin weave (A2), and patterned fabrics: 1 sample in plain (VP3), 1 sample in twill (VK3), and 1 sample in satin weave (VA3). The woven structure, pattern, and warp and weft yarns density obtained by ravelling are summarised in **Table 1** as an average of 5 measurements.

Images of the woven fabrics selected were obtained by a flat scanner and stored as image matrices with a resolution of 600 dpi , which showed better results in contrast to those with a smaller resolution [9]. The preprocessing of im-

ages includes conversion from RGB to the gray level scale and equalisation for contrast enhancement. A representative set of image samples with an area of 200×200 pixels (unicolour fabrics) and 1000×1000 pixels (patterned fabrics) can be seen in **Figure 1**.

Gray line profile method

The *Gray Line Profile Method (GLPM)* is based on the function $G_r(k)$ and $G_s(k)$ as the average gray value of rows and columns of an image matrix. Function $G_s(k)$ is the average gray value of the k -th horizontal line for the warp and function $G_r(k)$ is the average gray value of the k -th vertical line for the weft, defined in [1]

$$G_r(k) = \frac{\sum_{x=1}^M I(k, x)}{M}, \quad (2)$$

$$G_s(k) = \frac{\sum_{y=1}^N I(y, k)}{N}, \quad (3)$$

where:

$I(k, x)$ is the intensity of gray levels in coordinates (k, x) ,

$I(y, k)$ is the intensity of gray levels in coordinates (y, k) ,

M is the number of rows, and

N is the number of columns in the image matrix.

Peaks and valleys in the figure of $G_r(k)$ and $G_s(k)$ represent yarns and spaces between yarns. The main principle is based on finding average distances between peaks or valleys. Local maximums are found between peaks in the graphs, where each value of $G_s(k)$ and $G_r(k)$ is compared with its neighboring values, and if it is larger than both of its neighbors ($n = 2 \times 2$), it is a local peak. The pixel's distances between particular positions of local maximums are converted to the pixel's distances in centimeters according to the following equation [1]:

Table 2. Statistical characteristics for spacing between warp yarns.

Arithmetic mean, cm	0.0421
Median, cm	0.0423
Modus, cm	0.0339
Max, cm	0.0508
Min, cm	0.0339
Lower quartile, cm	0.0339
Upper quartile, cm	0.0339
Variance	4.738e-005
Standard deviation, cm	0.0069
Variation coefficient	0.1635
Interquartile range, cm	0.0169
Density of warp, count of yarns/1 cm	23.754

$$DistC = \frac{2.54}{R * DistP}, \quad (4)$$

where:

R is the image resolution in dpi ,

$DistP$ the pixel's distances between particular positions of local maxima, and N is the number of distances between positions.

Thereafter the woven density D is defined as:

$$D = \frac{1}{\frac{1}{N} \sum_{x=1}^N DiffCm}, \quad (5)$$

where $DiffCm$ are distances between local maxima positions in centimeters.

Method *GLPM* is illustrated in **Figure 2**, and an image of a sample in plain weave P2 is shown in **Figure 2.a**. The gray line profile for warp yarns and weft yarns of sample P2 are illustrated in **Figure 2.b**, **2.c**, where blue lines display profiles of warp and weft yarns, and red stars represent local maxima with neighbors $n = 2 \times 2$.

Exploratory data analysis is made for distances between yarns (**Table 2**) and the arithmetic mean is taken as an estimation

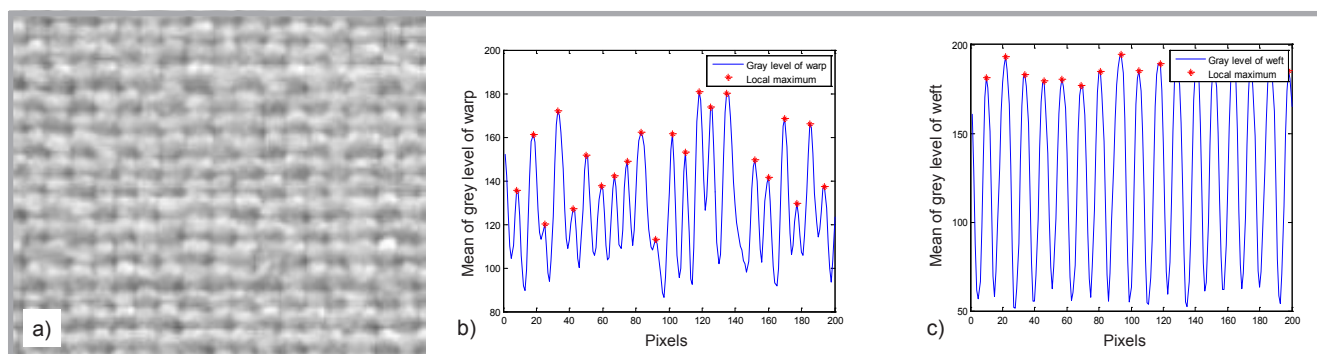


Figure 2. Application of method *GLPM* to sample P2; a) Image of sample P2, b) gray level profile for warp yarns, c) gray line profile for weft yarns.

Table 3. Results of weaving density obtained by GLPM.

Sample	Ravelling method		GLPM method	
	D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹	D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹
P2	24.3	22.5	23.8	21.7
P5	28.7	25.4	26.7	24.9
K4	22.6	23.4	21.9	20.0
K5	42.2	27.4	39.6	28.7
A2	48.8	45.4	44.3	45.6
VP3	21.2	18.8	28.4	23.2
VK3	26.6	19.0	26.5	25.3
VA3	26.2	26.6	22.6	22.4

Table 4. Results of weaving density obtained by DIDWF with suitable filter size for each sample.

Sample	Wiener filter	Ravelling method		DIDWF method	
		D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹	D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹
P2	16 × 2	24.3	22.5	20.1	18.3
P5	16 × 1	28.7	25.4	26.8	26.1
K4	12 × 1	22.6	23.4	21.1	24.4
K5	12 × 2	42.2	27.4	40.8	27.1
A2	16 × 1	48.8	45.4	40.6	29.3
VP3	12 × 1, n = 4.4	21.2	18.8	19.9	19.0
VK3	12 × 1	26.6	19.0	26.1	17.1
VA3	16 × 2	26.2	26.6	25.3	27.6

of yarn spacing. The value of 1 pixel corresponds to 0.0042 centimeters.

Comparison of results between the GLPM method and those obtained by ravelling is summarised in **Table 3**. Results showed that method GLPM provides the most accurate results for the set of plain and twill weave structures.

Digital image decomposition of Wiener filter method

The *Digital Image Decomposition of a Wiener Filter (DIDWF)* method is based on the decomposition of an image by application of a Wiener filter [7]. A Wiener filter is a low-pass filter for grayscale images, used for the noise-removal filtering

of images. The filter is adapted for a woven fabric texture. The image of woven fabric is decomposed on horizontal and vertical sub-images by the Wiener filter, with the subimages containing warp and weft texture information. Function $f(x, y)$ represents the gray level of a pixel with coordinates (x, y) in the 2D image, whose local mean value μ and variance σ^2 are expressed in [11]

$$\mu = \frac{1}{MN} \sum_{x,y \in W} f(x, y), \quad (6)$$

$$\sigma^2 = \frac{1}{MN} \sum_{x,y \in W} f^2(x, y) - \mu^2, \quad (7)$$

where $M \times N$ is the size of filter W . Then the Wiener filter for determining the output value of every pixel based on the above two estimates can be written as [11]

$$g(x, y) = \mu + \frac{\sigma^2 - v^2}{\sigma^2} [f(x, y) - \mu], \quad (8)$$

where $g(x, y)$ means the output value of every pixel in coordinates (x, y) after using the Wiener filter and v^2 is the variance of noise. A patterned sample of satin weave VA3 with a Wiener filter of size 16×2 was chosen for illustration of application method DIDWF. **Figure 3.a** shows sample VA3. **Figure 3.b** shows a subwindow of the monochromatic image from **Figure 3.a** of size 200×200 pixels. **Figure 3.c** shows a filtered image from **Figure 3.c** and binary image de-

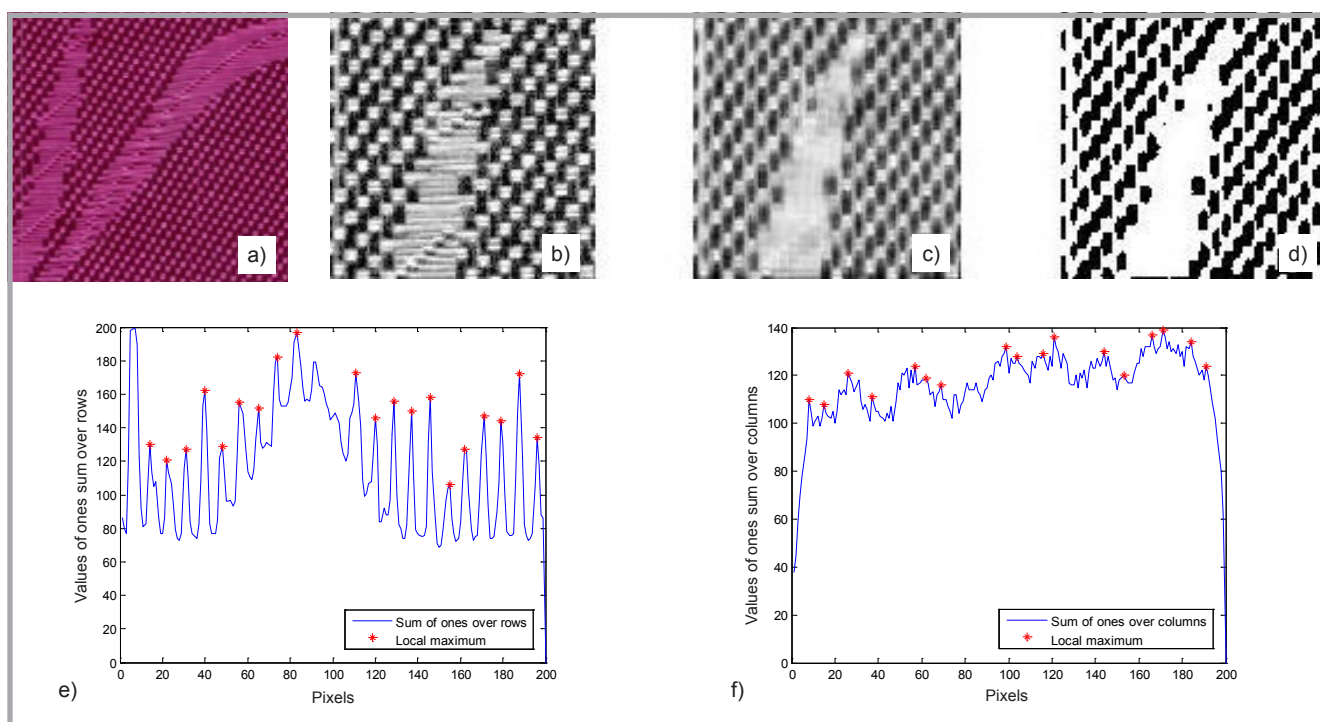


Figure 3. Application of DIDWF method to sample VA3; a) Image of sample VA3, b) monochromatic image of VA3, c) filtered image and d) decomposed binary image of sample VA3. Sums of all white pixels for warp e) and weft yarns f).

composed in the vertical direction with a Wiener filter of size 16×2 (suitable size of the Wiener filter for the sample) in **Figure 3.d**. The sums of all white pixels for warp yarns and weft yarns are plotted in **Figure 3.e, 3.f**. A comparison of results between the *DIDWF* method (with a suitable size of Wiener filter for each sample) and those obtained by ravelling is summarised in **Table 4**. The results of method *DIDWF* show that it is suitable for the set of samples in plain and twill weaves, as well as for patterned woven fabrics in plain and twill weave.

Digital image decomposition of median filter method

The *Digital Image Decomposition of Median Filter* method (*DIDMF*) is based on median filtering. Median filtering is a nonlinear operation performing the median filtering of an image matrix in two dimensions. Each output pixel contains the median value in the neighborhood around the corresponding pixel in the input image [8]. Samples of plain weave with a check pattern showed the most accurate results in this set of samples, therefore sample VP3 with a median filter size of 16×2 was chosen for illustration of the application of method *DIDMF*. An illustration of sample VP3 is in **Figure 4.a**, a monochromatic image (**Figure 4.b**), a filtered image (**Figure 4.c**),

Table 5. Results of weaving density obtained by *DIDMF* with a suitable filter size for each sample.

Sample	Filter size	Ravelling method		DIDMF method	
		D_{wa}, cm^{-1}	D_{we}, cm^{-1}	D_{wa}, cm^{-1}	D_{we}, cm^{-1}
P2	16×1	24.3	22.5	15.9	22.2
P5	16×2	28.7	25.4	27.2	19.0
K4	12×2	22.6	23.4	21.1	22.2
K5	12×1	42.2	27.4	40.4	24.1
A2	12×1	48.8	45.4	46.8	31.9
VP3	$16 \times 2, n = 3.4$	21.2	18.8	20.6	19.2
VK3	16×1	26.6	19.0	29.7	18.0
VA3	12×2	26.2	26.6	34.1	27.3

and a binary decomposed image in the vertical direction with a median filter of size 16×2 (**Figure 4.d**). Sums of all white pixels for warp yarns and weft yarns are plotted in **Figures 4.e, 4.f**. Comparison of results for the *DIDMF* method and those obtained by ravelling is summarised in **Table 5**. The set of patterned samples and plain weave samples were the best sets for determining the weaving density by the *DIDMF* method.

Method based on gray level co-occurrence matrix

The *Gray Level Co-occurrence Matrix* method (*GLCM*) is based on the co-occurrence matrix [4]. It is possible to define a square matrix with the help of the two parameters d and θ . Parameter d means the distance between two neighboring pixels in an image and param-

eter θ represents the angle between two neighboring pixels with coordinates (x_1, y_1) and (x_2, y_2) . An element of *GLCM* is the number of times a pixel of gray level i occurs in the positions given with respect to parameters d and θ to a pixel having gray level j . In this study parameter θ is applied only in the vertical ($\theta = 90^\circ$) for the warp direction and in the horizontal ($\theta = 0^\circ$) for the weft direction. Experimental calculation of the density with the *GLCM* method was verified with the aid of the four most suitable features extracted from such matrices of values of the following features: contrast, correlation, energy and homogeneity. The best results of the weaving density assessment obtained by the *GLCM* method were shown by the sample of twill weave K4. Feature energy was used to calculate the density of sample K4. **Figure 5** shows an image of sample K4 (**Figure 5.a**), as

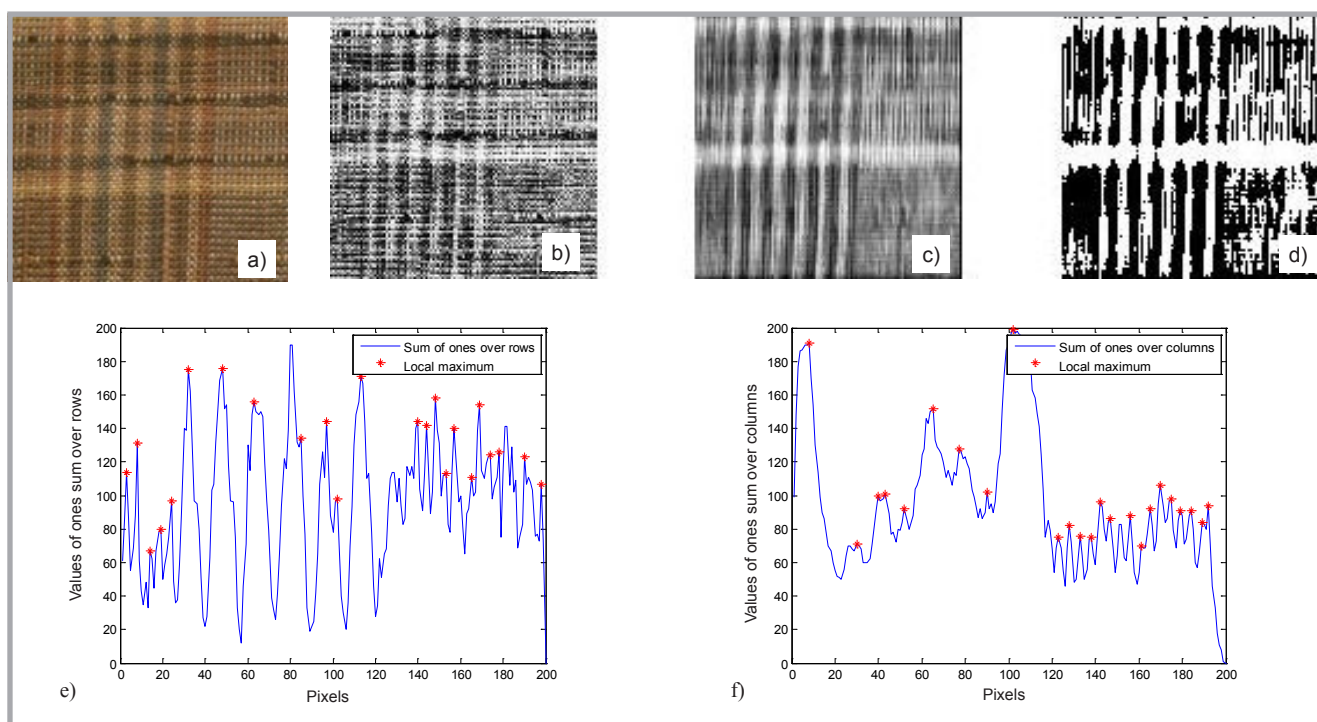


Figure 4. Application of *DIDMF* method to sample VP3; a) Sample VP3, b) monochromatic image, c) filtered image, d) binary decomposed image. Sums of all white pixels for warp yarns e) and weft yarns f).

Table 6. Results of weaving density obtained by GLCM.

Sample	Image resolution in dpi	Feature	Ravelling method		GLCM method	
			D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹	D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹
P2	600	Correlation	24.3	22.5	23.9	21.6
P5	400	Energy	28.7	25.4	29.5	23.6
K4	600	Energy	22.6	23.4	22.4	24.6
K5	600	Energy	42.2	27.4	29.4	19.4
A2	600	Energy	48.8	45.4	51.2	12.7
VP3	400	Correlation	21.2	18.8	19.5	19.6
VK3	600	Homogeneity	26.6	19.0	29.3	19.5
VA3	600	Energy	26.2	26.6	22.5	22.6

Table 7. Results of weaving density obtained by 2D DFT.

Sample	Ravelling method		2D DFT method	
	D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹	D _{wa} , cm ⁻¹	D _{we} , cm ⁻¹
P2	24.3	22.5	23.74	22.55
P5	28.7	25.4	27.30	23.74
K4	22.6	23.4	21.37	5.94
K5	42.2	27.4	40.36	27.30
A2	48.8	45.4	34.42	1.19
VP3	21.2	18.8	14.24	11.87
VK3	26.6	19.0	18.99	17.81
VA3	26.2	26.6	1.19	1.19

well as graphs obtained from values of the feature energy for warp (**Figure 5.b**) and weft (**Figure 5.c**). Comparison of results for the GLCM method with the most suitable features for individual samples and those obtained by ravelling is summarised in **Table 6**. The feature contrast did not give reasonable results. Results showed that the GLCM method is the least suitable for all samples in contrast with other methods.

Method based on 2 dimensional discrete Fourier transform

Automatic evaluation of the density of woven fabric with 2D DFT (2 Dimensional Discrete Fourier Transform) is based on the restoration of the image.

One of the set yarns can be removed by determining the corresponding high frequency components in the Fourier spectrum with their setting at zero. Thereafter restored images of one set of yarns can be obtained from 2D DFT. Woven fabric density can be determined by finding the periodicity along horizontal and vertical directions in restored images. For better illustration of the application of this method, a patterned sample of twill weave VK3 was chosen. An illustration of sample VK3 (**Figure 6.a**), a selection from the spectrum for parameters $\varphi = 0^\circ$, $\varphi = 90^\circ$, $\Delta w = 7$ pixels (the most suitable cut-off width of high energy frequency components in the power spectrum corresponding to the set of yarns for sample VK3) based on paper [6] (**Figure 6.b, 6.e**), restored images after 2D DFT (**Fig-**

ure 6.c, 6.f), and the power spectrum (**Figure 6.d**) are shown in **Figure 6**. Graphs of gray levels as well as a time series model and gray line profile for warp (**Figure 6.g**) and weft (**Figure 6.h**) are displayed in **Figure 6**. Comparison of results between the 2D DFT method and those obtained by ravelling is summarised in **Table 7**. Method 2D DFT showed suitable results for samples in plain and twill weaves.

Conclusion

This paper presents a brief overview of known automatic methods for assessing fabric weaving density based on image analysis. Five selected methods were tested and compared with the real density of fabric samples. The GLPM method provided the most accurate results for the set of plain and twill weave structures. It turned out that DIDWF is applicable for the set of samples in plain and twill weaves, as well as for patterned woven fabrics in plain and twill weave. The DIDMF method showed the best results for the set of samples of patterned and plain weave fabric. The computation and time consuming method GLCM are not as effective as the other methods. The 2D DFT method provided correct results for samples in plain and twill weaves. Experimental results showed that any method is suitable for all kinds of plain and patterned woven fabrics, with more accurate estimations of weaving density being provided by less difficult methods: GLPM, DIDWF and DIDMF. Results showed that the algorithmically and computationally consuming methods do not always lead to more accurate results for woven density assessment. A universal method for the assessment of woven density was not found, but the work sug-

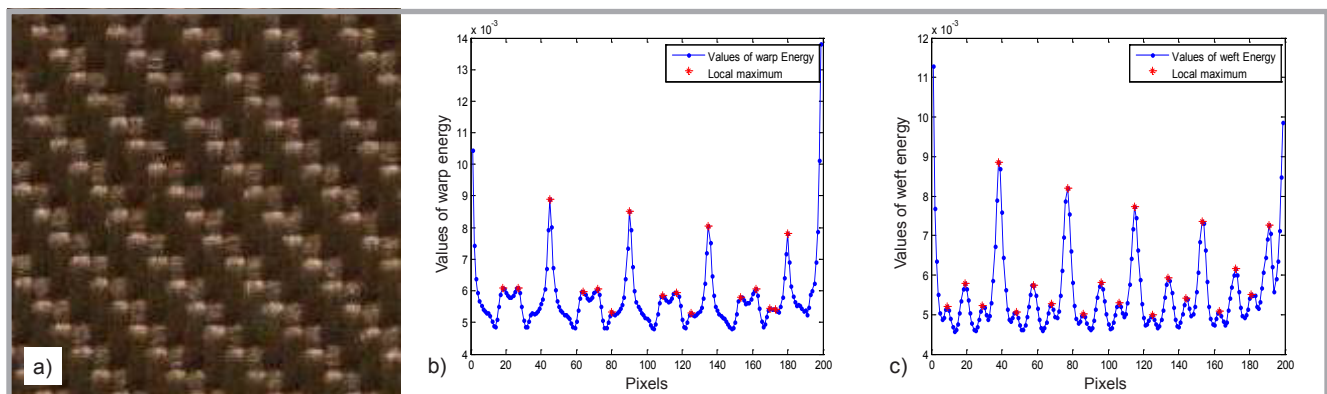


Figure 5. Application of the GLCM method on sample K4; a) Image of sample K4. The graphs for warp b) and weft c) from values of feature energy.

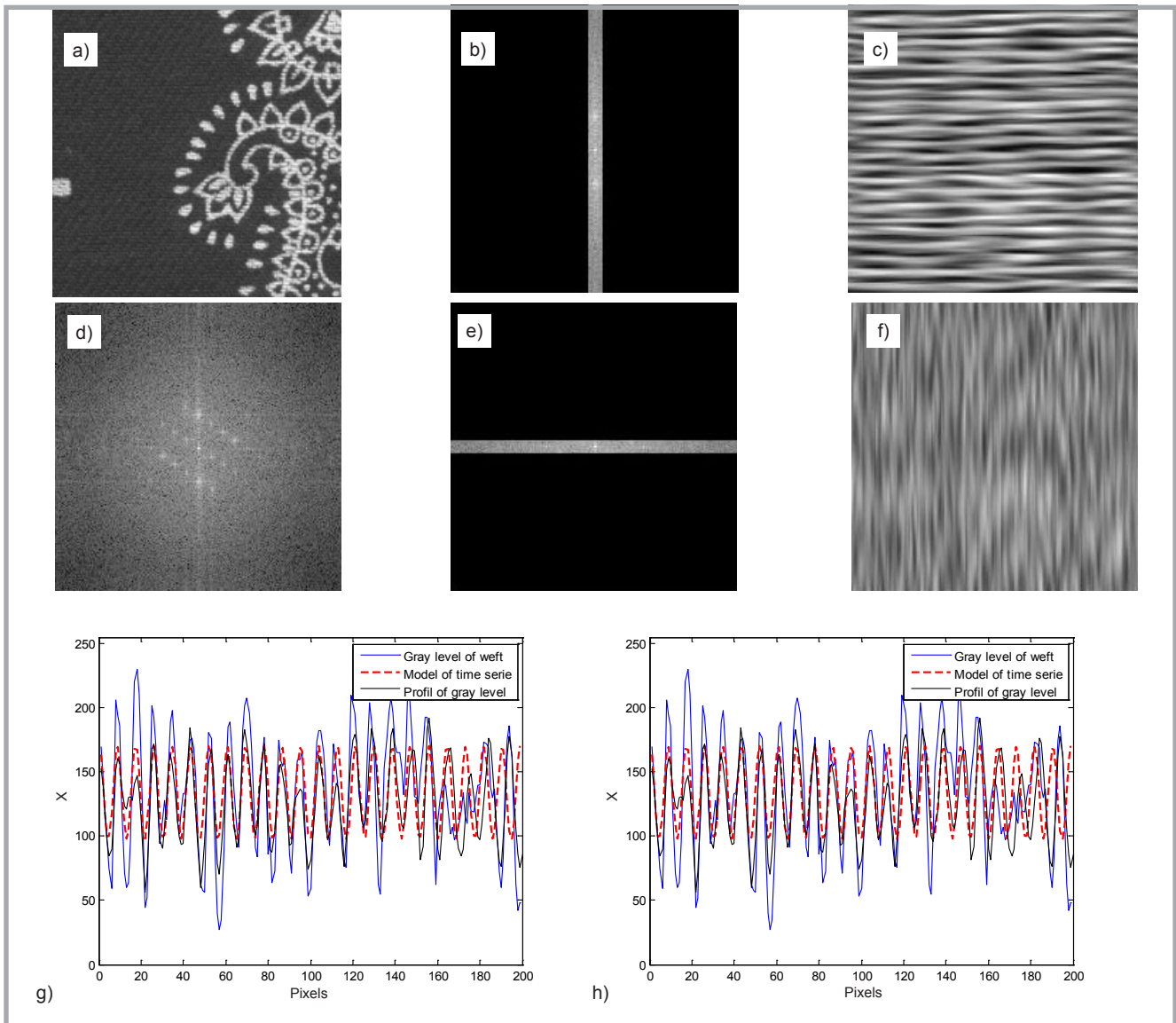


Figure 6. Application of 2D DFT method to sample VK3; a) Image of sample VK3, b), e) selection from spectrum for parameters $\varphi = 0^\circ$, $\varphi = 90^\circ$, $\Delta w = 7$ pixels, d) power spectrum, c), f) restored images after 2D IDFT. The gray level, time series model and gray profile line for warp g) and weft h).

gests optimal methods for various types of fabric weaves.



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