(REFEREED RESEARCH)

YARN LOCATION DETECTION IN WOVEN FABRIC IMAGE USING AUTOMATIC MULTISCALE-BASED PEAK DETECTION

OTOMATİK ÇOKLU-ÖLÇEK TEMELLİ TEPE NOKTASI TESPİTİ KULLANARAK DOKUMA KUMAŞ GÖRÜNTÜLERİNDE İPLİK KONUM TESPİTİ

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ABSTRACT

In this study, an approach based on Automatic Multiscale-Based Peak Detection (AMPD) is proposed for detecting yarn locations in a woven fabric image with skew and noise. Finding yarn locations in a digital image of woven fabric can be defined as a problem of local maxima detection in a noisy signal of a periodic or a quasi-periodic signal. In this approach, projection profiles of woven fabric images in vertical and horizontal directions are calculated and local peaks are detected by using the AMPD algorithm where local maxima indicate yarn center positions along the woven fabric width or length. The method is tested with real woven fabric images and experimental results show that AMPD algorithm performs well for detecting yarn locations. Although the proposed method performs well on noisy images; detection accuracy is highly affected by the skewness. Therefore, woven fabric images are needed to be enhanced before obtaining signals.

Keywords: Image processing, woven fabric, automatic multiscale-based peak detection (AMPD), projection profiles, yarn locations

ÖZET

Bu çalışmada, iplik konumlarının eğiklik ve gürültü içeren dokuma kumaş görüntülerinde tespiti için otomatik çoklu-ölçek temelli tepe noktası tespitine dayalı bir yaklaşım önerilmektedir. Dokuma kumaşların sayısal görüntülerinde iplik konumlarının bulunması gürültü içeren periyodik veya yarı-periyodik sinyallerde yerel maksimum noktaların tespiti problemi olarak tanımlanabilir. Bu yaklaşımda dokuma kumaş görüntülerinin yatay ve düşey projeksiyon profilleri hesaplanır ve dokuma kumaş eni veya boyunca uzanan ipliklerin orta konumlarını ifade eden yerel tepeler otomatik çoklu-ölçek temelli tepe noktası tespiti algoritması ile tespit edilir. Metot gerçek dokuma kumaş görüntüleri ile test edilmiş ve deneysel sonuçlar algoritmanın iplik konumlarının tespiti için iyi sonuçlar verdiğini göstermiştir. Gürültü içeren görüntülerde iyi sonuçlar vermesine karşın eğikliğin varlığı tespitlerin doğruluğunu oldukça etkilemektedir. Bundan dolayı dokuma kumaş görüntüleri sinyallerin eldesinden önce düzeltilmelidir.

Anahtar Kelimeler: Görüntü işleme, dokuma kumaş, otomatik çoklu-ölçek temelli tepe noktası tespiti, projeksiyon profilleri, iplik konumları.

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1. Introduction

Measuring woven fabric density automatically in a non-contact manner by using computer assisted image analysis methods is a promising alternative to standard methods which are often tedious and time consuming. These image analysis methods can be classified into several approaches; statistical [1], spectral approaches [2, 3, 4, 5], model based approaches which are attempting to decompose yarns in a woven fabric to detect yarn locations either for counting the number of yarns or to calculate the average distance between yarns in periodicity.

Spatial gray level co-occurrence matrix (GLCM) is proposed for extracting image properties related to neighboring pixels in an image [1]. Among 14 statistics measurements [7] that can be calculated from the co-occurrence matrix, contrast texture feature [1] was used to measure the weaving density of a woven fabric. Density is calculated using the signal of contrast feature of distance pixels. The local maxima indicating yarn locations are detected and the average distance between neighboring maxima is used for calculations.

Several researchers proposed frequency domain analysis method for analysis, particularly Fourier transforms. In this approach general tendency is decomposing warp and weft yarns in spatial domain in a reconstructed image obtained by filtering power spectrum of the image in the frequency domain. Line-profile signals are obtained in order to detect yarn periodicity by selecting vertical or horizontal lines after reconstruction of the image. In the literature, model of time series [5] and 1-D FFT of the profile [4] are the proposed methods for calculating periodicity.

Gray line-profile method is an efficient method for woven fabric yarn density measurements [6, 8]. In this approach the gray line-profiles are obtained by calculating the means of rows and columns. Obtained profile signals contain information where local minima of the gray line-profiles correspond to the boundary positions between yarns and local maxima correspond to the locations of yarn centers. Sliding filter with a predefined size [6] is used for detecting local maxima and later an approach for optimum filter size detection is proposed [9].

Many approaches for woven fabric density measurement using image processing methods involve signal analysis in order to detect local peaks or valleys which are used for indicating the locations of the yarns and boundaries between adjacent yarns. So far there is no generally accepted method for detecting true minima or maxima of projection profile signals obtained from woven fabric images. In this paper, an algorithm based on Automatic Multiscale-Based Peak Detection (AMPD) Method, which is proposed for peak detection in noisy periodic and quasi-periodic signals [10], is applied to detect local maxima in projection profiles for detecting yarn locations. Effects of noise and skew on the performance of the method are also investigated. Experimental results show that the AMPD method works well for real woven fabric images. It is also shown that algorithm can deal with noisy profiles as well.

2. Theoretical consideration

The proposed algorithm can be summarized as follows

1- Start with a grayscale image

2- If the input image has skewness, rectify the image

3- Calculate the projection profiles in warp and weft direction, store profile vectors

4- Find the local maxima of warp and weft profile signals using AMPD, store the peak locations in vectors

5- Detected peak locations correspond to the yarn locations in the woven fabric.

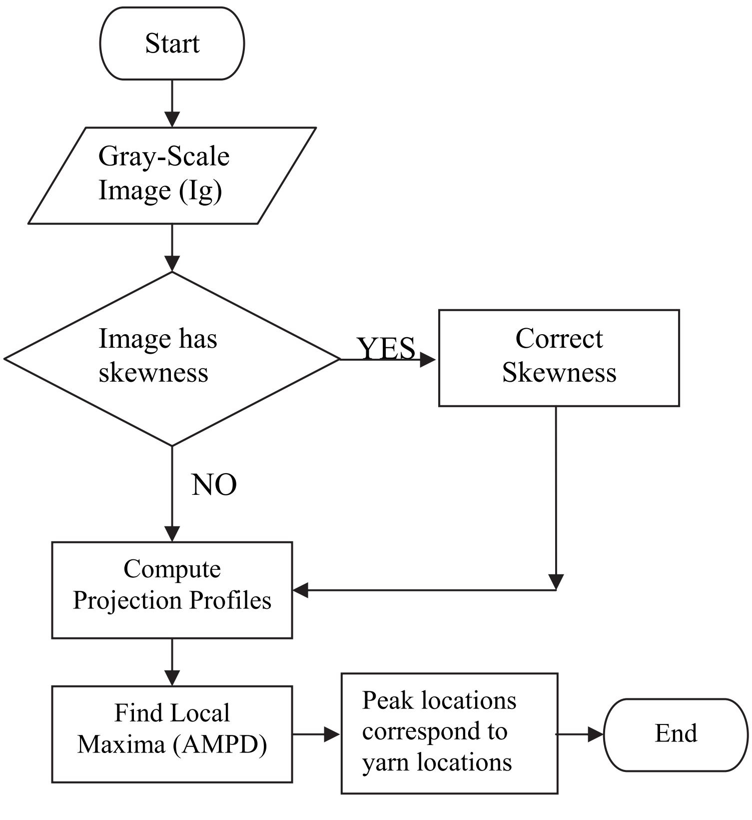

Figure 1. The proposed algorithm flowchart

2.1 Skewness effect

Woven fabric images can include some skewness due to either skewness of real fabric or misalignment of the sample during image scanning process [12]. In both cases, the projection profiles will include noise which might lead the analysis unsuccessful. Therefore, skewness of the woven fabric images should be rectified before the analysis. There are two methods in the literature for woven fabric skewness detection, Hough Transform [12, 13, 14] and projection profile analysis [15]. In this approach the projection profile analysis for estimating the skew angle of the woven fabric image is used The flow chart of the approach (Figure 2) and the algorithm is as follows [15];

1. Input gray-scale image (Ig)
2. Ig is rotated at angles through (-10, 10)
3. Each rotated image is cropped
4. Horizontal projection profiles (HPP) of cropped images are computed at each angle.
5. Differences between adjacent elements (HPPd) of HPP are computed at every angle
6. The standard deviation (SD) of HPPd is computed at every angle
7. The angle which maximizes the SD value is regarded as the estimated skew angle.

The same algorithm is valid for vertical alignment of the images and realized by computing vertical projection profile instead of horizontal projection profile.

2.2 Projection Profiles

Projection profiles can be calculated after rectification of the woven fabric images. Projection profiles are averages of gray levels of the image pixel in horizontal and vertical directions denoted by $G_2(x)$ and $G_1(y)$ respectively. For profile calculations, equations

$$G_1(y) = \frac{\sum_{x=1}^{M} I_{x,y}}{M} \qquad y = 1,2,..., N \qquad (2)$$

$$G_2(x) = \frac{\sum_{y=1}^{N} I_{x,y}}{N} \qquad x = 1,2,..., M \qquad (3)$$

can be used where $I_{x,y}$ is the intensity of gray level at pixel coordinate (x, y).

2.3 Automatic Multiscale-Based Peak Detection (AMPD)

Although woven fabrics possess a periodicity due to the structure and weave repeats, projection profiles obtained from woven fabric images are rarely perfect periodic signals and generally involve noise. Therefore, the signals to be examined can be better described as noisy periodic and quasi-periodic signals. Scholkmann et al (2012) proposed a novel method for automatic detection of peaks in noisy periodic and quasi-periodic signals which consist of three main steps [10]. The algorithm is applied on a real woven fabric sample shown in Figure-3(a) for demonstration purposes. Decolorized 8-bit gray level image, the horizontal and vertical projection profiles of the gray level image are shown in Figure-3(b), Figure-3(c) and Figure-3(d) respectively.

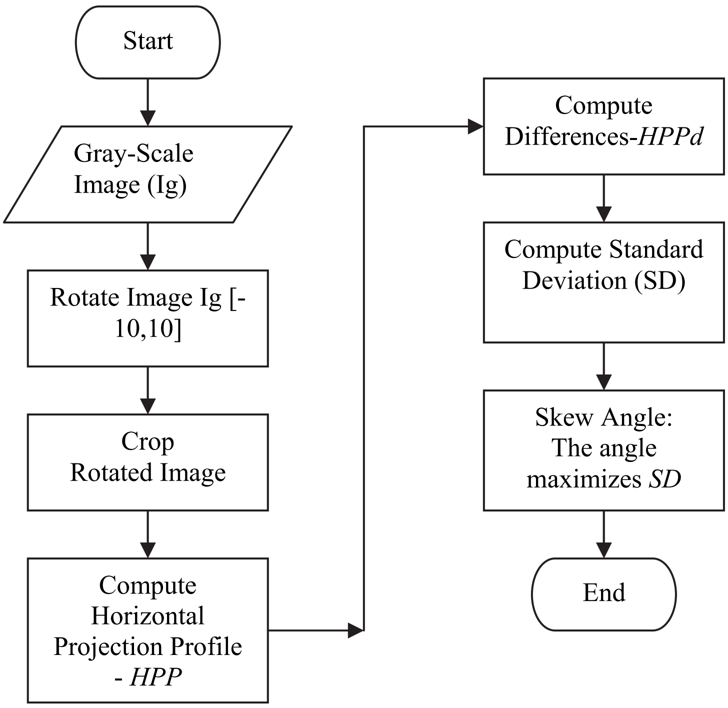

Figure 2 Skew angle estimation flowchart

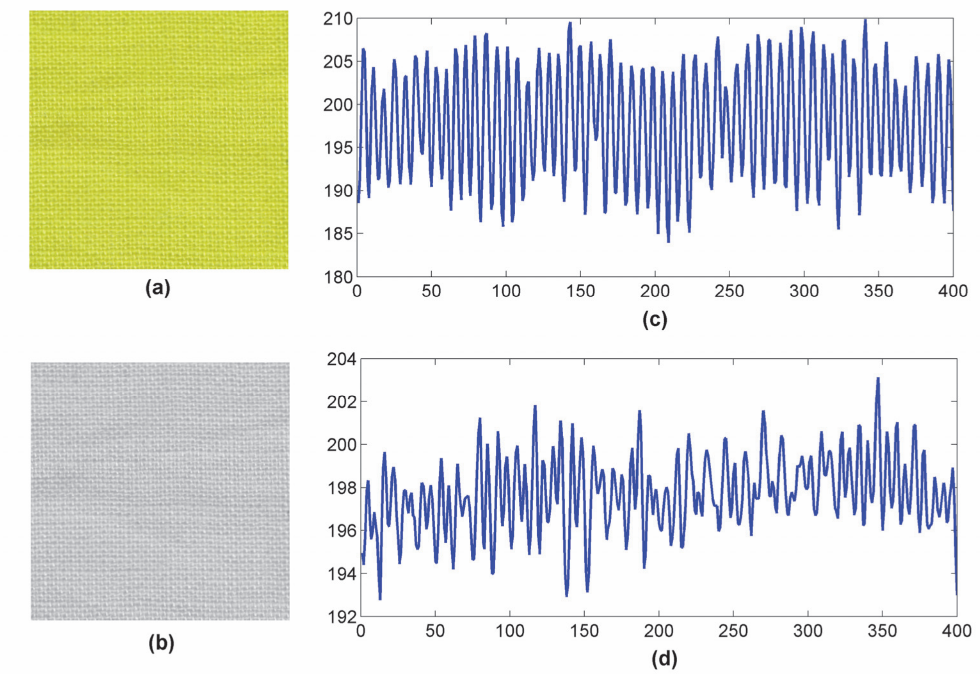

Figure 3. Sample woven fabric image a-original true color image b- gray level image c- horizontal projection profile d-vertical projection profile

Scholkmann et al (2012) explained the algorithm in detail [10], and here it will be summarized. First step is to calculate Local Maxima Scalogram (LMS) matrix M of the linearly detrended signals $G_2(x)$ and $G_1(y)$ of the horizontal projection profile for illustration purposes in this part. Local maxima of the signals $G_2(x)$ and $G_1(y)$ are determined by using a moving window of varied length w_k. Here k is the scale of the signal $\{w_k = 2k | k = 1,2,...,L\}$ and $L = \lceil N/2 \rceil - 1$. Local maxima scalogram matrix M

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,N} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ m_{L,1} & m_{L,2} & \cdots & m_{L,N} \end{bmatrix} = (m_{k,i}) \quad (4)$$

can be obtained for every scale k and for $i = k+2,..., N-k+1$ according to

$$m_{k,i} = \begin{cases} 0, & x_{i-1} > x_{i-k-1} \wedge x_{i-1} > x_{i+k-1} \\ r+\alpha & oteherwise \end{cases} \quad (5)$$

where r is a random number in the range [0,1] and α=1. The obtained Local Maxima Scalogram matrix M is shown in Figure 4

The second step is row-wise summation of LMS matrix in order to calculate scale dependent distribution of local maxima in a vector ɣ by using equation 6 and the obtained vector is shown in Figure-5

$$\gamma_k = \sum_{i=1}^{N} m_{k,i} \; for \quad k \in \{1,2,...,N\} \quad (6)$$

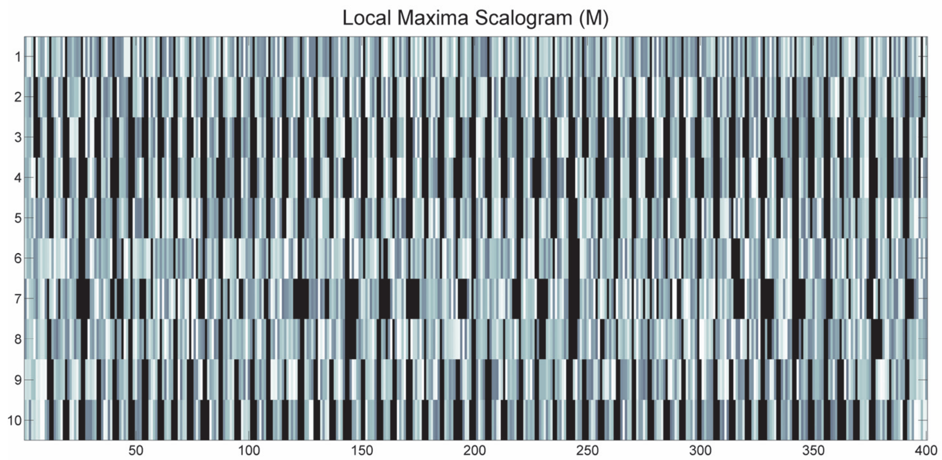

Figure 4. Application of AMPD algorithm, local maxima scalogram (M)

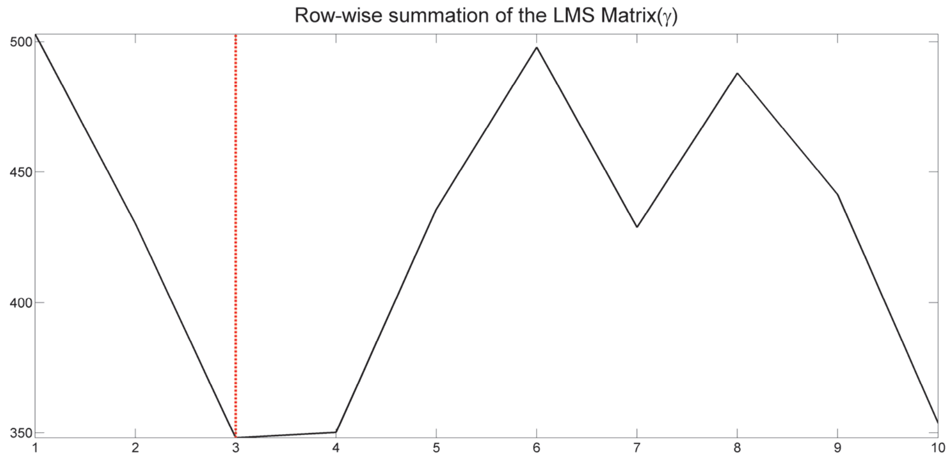

Figure 5. Row wise summation of the LMS matrix

All the rows of scales in LMS matrix bigger than the global minimum of the summation vector (γ) are removed from the LMS matrix leading to a new matrix M_r shown in Figure-6.

Finally peaks are detected by calculating the column-wise standard deviation of the new matrix (M_r) and determining zero values which are the detected peak points. Figure-7 shows the column wise standard deviation of the rescaled LMS and the zero values and in Figure-8 the detected peak points are shown which are the locations of the zero points.

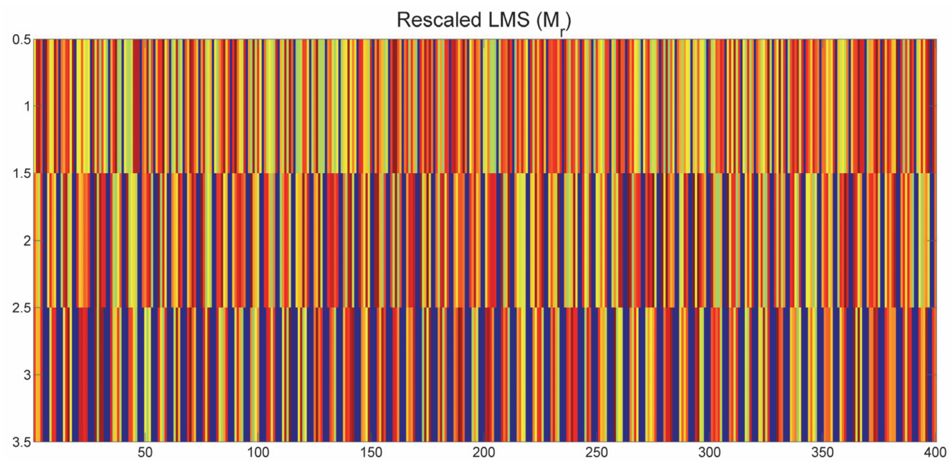

Figure 6 Rescaled local maxima scalogram

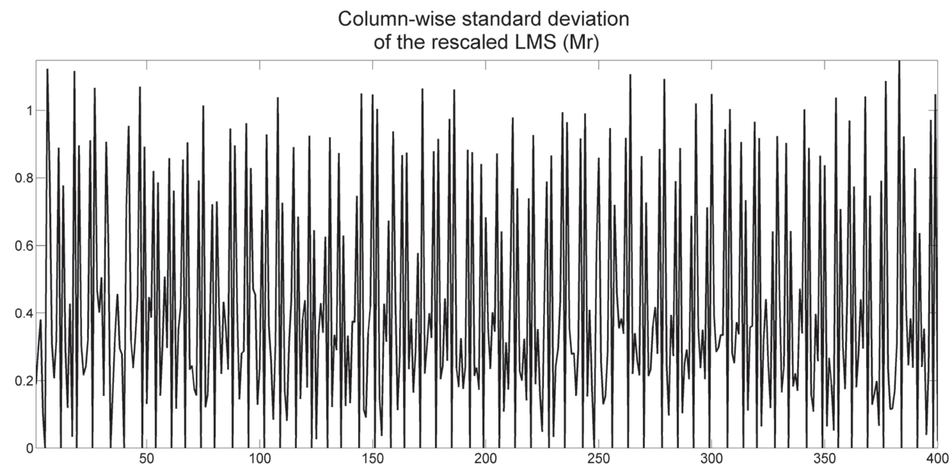

Figure 7 Column wise standard deviation of the rescaled LMS matrix

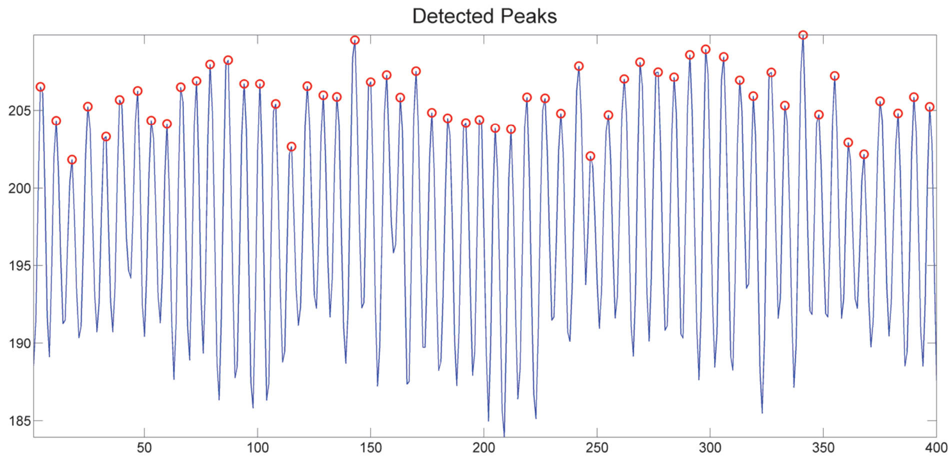

Figure 8 Detected peaks

3. Materials and Method

To examine the performance of the proposed method, 16 different woven fabrics are scanned by a HP flatbed scanner in resolution of 600 dpi in true colors. The scanned woven fabric image area with a size of 400×400 pixels are selected arbitrarily for investigation. Plain and twill woven fabrics are defined as P and T with indices; P1, P2, P3 unicolor fabrics (same yarn color for warp and weft), P4 double mélange (warp and weft yarns have two different colored yarns at the same time), P5, P6, P7 one system mélange (one colored yarns in weft direction and different color for the warp yarns), P8 is a printed fabric on a solid color woven fabric. Twill woven fabrics (T1, T2, T3, T4, T5, T6, T7) are double mélange fabrics and one sample (T8) is unicolor twill woven fabric.

The effectiveness of the method is evaluated by using the estimation error. Warp estimation error δ_1 can be calculated by using the following equation

$$\delta_1 = 100 * \frac{|NW_1 - NWM_1|}{NWM_1} \tag{7}$$

where NW_1 is the number of warp yarns detected by using proposed algorithm and NWM_1 is the number of warp yarns counted manually. Weft estimation error δ_2 can be calculated by using a similar equation

$$\delta_2 = 100 * \frac{|NW_2 - NWM_2|}{NWM_2} \tag{8}$$

where NW_2 is the number of weft yarns detected by using proposed algorithm and NWM_2 is the number of weft yarns counted manually.

The method is implemented with an algorithm written in MATLAB (MathWorks 2013) and tested on a computer with 3.20 GHz processor and 4 GB RAM.

4. Results and Discussion

4.1Test results

Table-1 and Table-2 present the number of yarns of tested woven fabrics obtained manually and number of yarns detected by the proposed method in those fabric samples. Mean and standard deviation of errors on each tested plain woven fabric images computed by using AMPD are shown in Table-1. The estimation accuracy for samples P1, P2 and P3 are the best of all samples in warp and weft direction which are unicolor plain woven fabrics. Sample P4 has the worst estimation error of %20 in plain woven fabrics in weft direction. Samples P5, P6, P7 and P8 have estimation error of average accuracy in both warp and weft directions.

Mean and standard deviation of errors on each tested twill woven fabric images computed by using AMPD are shown in Table2. When Table 2 is examined weft detection accuracy is worse than warp detection accuracy. This might be due to the woven fabric image samples are scanned from face side where warp yarn floats are longer than weft yarns. Floats of the warps might result in better projection profile signals while weft yarns are hidden in between.

4-2 Skew tolerance

To investigate how large a skew angle the proposed method can tolerate, all the zero-angle images are also rotated by (1, 2, 3, 4, 5, 6) degrees in clockwise and anti-clock wise directions. From the detection results shown in Figure 9, we can conclude that the proposed method is sensitive to skewness and the skew angle should be rectified before applying the algorithm.

Table 1 Estimation errors of plain woven fabric samples

Fabric Code	Number of Yarns Visual Counting		Number of Yarns Detected by AMPD		Estimation Error (%)	
	Warp	Weft	Warp	Weft	Warp	Weft
P1	13	12	13	12	0.00	0.00
P2	23	32	23	32	0.00	0.00
P3	49	44	48	44	2.04	0.00
P4	40	55	40	44	0.00	20.00
P5	26	21	25	20	3.85	4.76
P6	20	18	20	17	0.00	5.56
P7	30	22	28	21	6.67	4.55
P8	45	39	43	38	4.44	2.56
					2.12	4.68
					2.59	6.61

Table 2 Estimation errors of twill woven fabric samples

Fabric Code	Number of Yarns Visual Counting		Number of Yarns Detected by AMPD		Estimation Error (%)	
	Warp	Weft	Warp	Weft	Warp	Weft
T1	54	37	51	37	5.56	0
T2	77	58	76	61	1.30	5.17
T3	83	66	84	60	1.20	9.09
T4	41	36	42	28	2.44	22.22
T5	58	43	57	47	1.72	9.30
T6	44	43	43	42	2.27	2.33
T7	49	32	49	33	0.00	3.13
T8	37	53	38	54	2.70	1.89
					2.15	6.64
					1.62	7.13

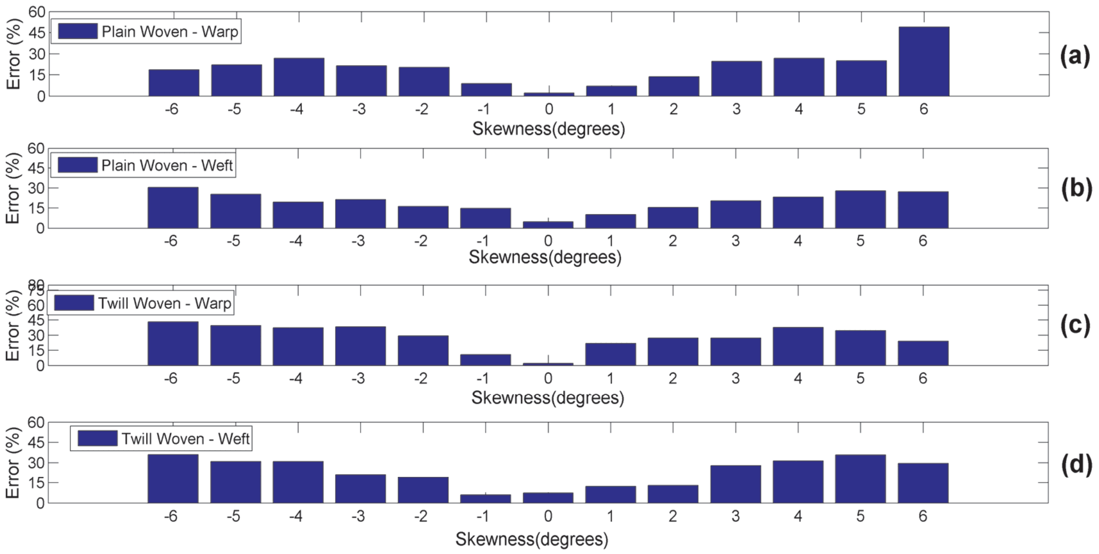

Figure 9. Skewness tolerance a-plain woven fabrics warp direction b-plain woven fabric weft direction c-Twill woven fabric warp direction d-twill woven fabric weft direction

4-3 Noise tolerance

Image noise is the random variation of brightness or color information in images [16]. The standard model of amplifier noise is uniform distributed white Gaussian noise. A noisy image corrupted with Gaussian white noise might be modeled as the noisy image formation model [16] provided in Equation 9,

$$I_n(x,y) = I_o(x,y) + n(x,y) \tag{9}$$

whereI_n is the image corrupted by additive noise, I_n is the uncontaminated original image and *n* is uniform distributed white Gaussian noise. In order to evaluate the effects of noise on results obtained by the proposed algorithm, the input image is contaminated by additive white Gaussian noise with standard deviations $\sigma = [0.0001; 0.005; 0.01; 0.02]$. One of the samples used for evaluation is shown in Figure-8, noisy images are obtained by using Matlab Image Processing Toolbox [11] using Gaussian noise with zero mean and varying standard deviations. Table 3 and Table 4 present the detection accuracy when the noisy images are used as input images instead of the original scanned versions. From Table 3 and Table 4 it can be concluded that the results of detection accuracy of proposed algorithm with noisy images is acceptable.

Table 3 Detection error with noisy images of plain woven fabric samples

	Variance 0.0001		Variance 0.005		Variance 0.01		Variance 0.02	
	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft
P1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P4	0.00	0.00	0.00	6.82	0.00	2.27	0.00	6.82
P5	0.00	0.00	0.00	5.00	0.00	0.00	0.00	0.00
P6	10.00	0.00	10.00	0.00	15.00	0.00	10.00	0.00
P7	0.00	0.00	3.57	0.00	3.57	0.00	3.57	0.00
P8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.63

Table 4 Detection error with noisy images of twill woven fabric samples

	Variance 0.0001		Variance 0.005		Variance 0.01		Variance 0.02	
	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft
T1	1.96	0.00	3.92	0.00	1.96	0.00	1.96	2.70
T2	1.32	0.00	1.32	0.00	1.32	0.00	0.00	0.00
T3	1.19	0.00	1.19	0.00	1.19	0.00	2.38	0.00
T4	0.00	0.00	0.00	3.57	0.00	3.57	0.00	0.00
T5	0.00	0.00	0.00	0.00	1.75	2.13	1.75	0.00
T6	9.30	2.38	2.33	2.38	0.00	2.38	6.98	0.00
T7	0.00	0.00	0.00	3.03	0.00	0.00	0.00	6.06
T8	2.63	0.00	2.63	1.85	2.63	0.00	2.63	5.56

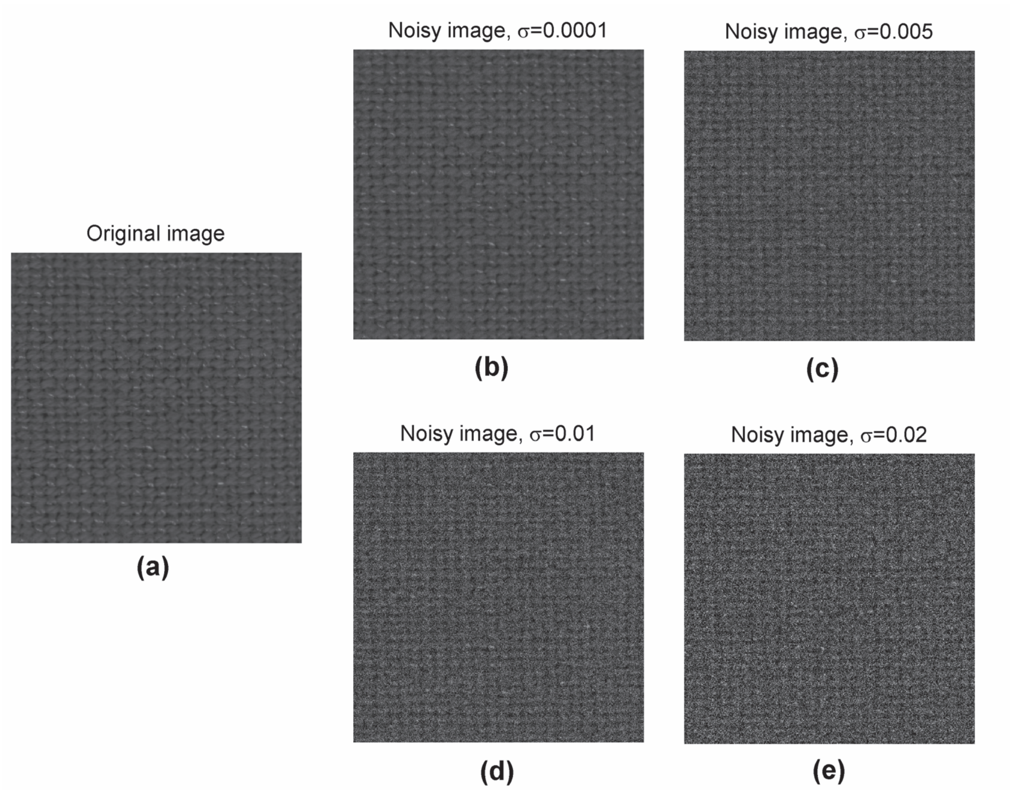

Figure 8. noisy images of sample P3 a-original image b- noisy image $\sigma = 0.0001$ c- noisy image $\sigma = 0.005$ d- noisy image $\sigma = 0.01$ e- noisy image $\sigma = 0.02 \frac{n!}{r!(n-r)!}$

5.Conclusions

Methods for detecting woven fabric density using image analysis can be divided into steps to be solved. First step is to decompose woven fabric images in order to obtain one set of yarns to be investigated. The second step is to obtain representing signal of decomposed yarns and detect local maxima or local minima of the signal. In this study Automatic Multiscale-Based Peak Detection (AMPD) method is researched for local maxima detection of the projection profile signals which indicate the yarn locations of the investigated direction. The trials on images of real woven fabrics with plain and twill weaves reveal that the method is capable of detecting the yarn locations. Effect of skewness and noise of the images on the detection accuracy are also investigated. Although method performs well on noisy images, detection accuracy is highly affected by skewness. Therefore, woven fabric images are needed to be rectified before obtaining the signals in order to apply further processes.

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