Optimal Morphological Filter Design for Fabric Defect Detection

K. L. Mak, P. Peng, H.Y.K. Lau
Department of Industrial and Manufacturing Systems Engineering,
The University of Hong Kong, Pokfulam Road, Hong Kong
Emails: makkl@hkucc.hku.hk, ppeng@hkusua.hku.hk

***Abstract*-This paper investigates the problem of automated defect detection for textile fabrics and proposes a new optimal morphological filter design method for solving this problem. Gabor Wavelet Network (GWN) is adopted as a major technique to extract the texture features of textile fabrics. An optimal morphological filter can be constructed based on the texture features extracted. In view of this optimal filter, a new semi-supervised segmentation algorithm is then proposed. The performance of the scheme is evaluated by using a variety of homogeneous textile images with different types of common defects. The test results exhibit accurate defect detection with low false alarm, thus confirming the robustness and effectiveness of the proposed scheme. In addition, it can be shown that the algorithm proposed in this paper is suitable for on-line applications. Indeed, the proposed algorithm is a low cost PC based solution to the problem of defect detection for textile fabrics.**

***Keywords:* Defect detection; Morphological filters; Gabor wavelet networks; fabrics; Mechatronics**

I. INTRODUCTION

In the textile industry, before any shipments are sent to customers, inspection is needed for assuring the fabric quality because defects in fabrics can reduce the price of a product by 45% to 65% [1]. Currently, the quality assurance of web processing is mainly carried out by manual inspection. However, the reliability of manual inspection is limited by ensuing fatigue and inattentiveness. Currently only about 70% of defects can be detected by the most highly trained inspectors [2]. Furthermore, textile industries are facing increasing pressure to be more efficient and competitive by reducing costs. Therefore, automated detection of defects in textile fabrics, which results in high-quality products at high-speed production is needed.

In fact the problem of automated inspection on plain fabrics has been investigated for over two decades. Wang et al. [3] contributed the success in this area to the fact that 90% of the defects in a plain fabric could be detected simply by thresholding. Therefore, in recent years, researchers have begun to investigate the automated inspection of more complicated fabric, including twill and denim fabrics [4, 5].

Numerous approaches have been proposed to address the problem of detecting defects in woven fabrics, which can be categorized into three classes, namely, statistical, spectral and model based methods. This paper proposes a morphological filter based algorithm for detecting defects. Since morphological filtering methods can be counted as a statistical detection method, in this paper, only algorithms related to statistical analysis are reviewed.

Chetverikov et al. [6] used two fundamental structural properties of texture, i.e., structural regularity and local anisotropy, to detect the structural defects in regular and flow-like patterns. Bodnarova et al. [7] analyzed the suitability of the common detection methods for weaving defects by using two criteria: accuracy and computational efficiency. The compared methods included spatial grey level co-occurrence, normalized cross-correlation, texture blob detection and spectral approaches. After comparison, they concluded that the correlation approach was the most promising method. However this method would be computationally demanding when large-size templates were used. Muller et al. [8] successfully designed two morphological filters to detect fabric defects, i.e. thread drags and oil spot respectively. Zhang et al. [9] successfully combined morphological operators and autocorrelation functions to inspect fabric defects, knot and slub. Other methods based on edge detection [10], cross-correlation [11], co-occurrence matrix [12] and neural networks [4] were also reported in foregoing research.

This paper presents an optimal morphological filter design approach for fabric defect detection, which is further developed into a defect segmentation algorithm. In particular, the proposed scheme provides a low cost PC-based solution to the problem of defect detection for textile fabrics. The paper is organized as follows: Section II introduces the architecture of Gabor Wavelet Network (GWN) and its application as a feature extractor. In Section III, the defect detection scheme based on mathematical morphology is described in detail. Section IV evaluates the performance of the methodology by using a variety of textile images. Finally, the conclusions from the work are summarized in Section V.

II. GABOR WAVELET NETWORKS

A. The network

On the basis of wavelet networks [13], Kruger and Sommer proposed the concept of Gabor Wavelet Networks (GWN) for solving the problems in pattern recognition [14]. GWN is a three-layer neural network, and uses the imaginary part of a Gabor function as the transfer function of the hidden layer. The mapping form of the network is expressed in the following form:

$$f(x,y)=\sum_{i=1}^{N} w_i g_o{}^i(x,y)+\overline{f}\ , \qquad (1)$$

where w_i is a network weight from the i-th node in the hidden layer to the node in the output layer, and $\overline{f}$ is introduced to eliminate the DC value of the objective function. The imaginary part of the Gabor function used, the transfer function, is expressed as:

$$g_o{}^i=\exp\left\{-\frac{\left[(x-t_x{}^i)\cos\theta^i-(y-t_y{}^i)\sin\theta^i\right]^2}{2\left(\sigma_x{}^i\right)^2}-\frac{\left[(x-t_x{}^i)\sin\theta^i+(y-t_y{}^i)\cos\theta^i\right]^2}{2\left(\sigma_y{}^i\right)^2}\right\} \times\sin\left(2\pi\omega_x{}^i\left[(x-t_x{}^i)\cos\theta^i-(y-t_y{}^i)\sin\theta^i\right]\right), \qquad (2)$$

where $t_x{}^i$, $t_y{}^i$ are the translation parameters of the i-th Gabor wavelet, and $(\sigma_x{}^i,\sigma_y{}^i)$, θ^i and $\omega_x{}^i$ are the radial frequency bandwidths, the orientation and the central frequency respectively of the i^{th} hidden node. In fact, the network proposed in [14] has only two input nodes and one output node. In the network, the input vector $[x\ y]$ is the position of a pixel in the studied image IM, and the output is the grey level of the corresponding pixel. Fig. 1 displays the architecture of Gabor wavelet networks. For each Gabor wavelet in the network, there are seven parameters which need to be determined by the network learning process. These include the translation parameters, the orientation, the radial frequency bandwidth, the centre frequency, and the corresponding weight. The objective function of the learning process is defined as:

$$E=\min_{\forall w^i,t_x{}^i,t_y{}^i,\sigma_x^i,\sigma_y^i,\theta^i,\omega_x{}^i}\left\|IM-\sum_i w_i g_i\right\|_2^2 . \qquad (3)$$

The network learning process is carried out by optimization, which is based on the LM algorithm.

In order to simplify the explanation, imaginary Gabor wavelet is used to represent the imaginary part of a Gabor function.

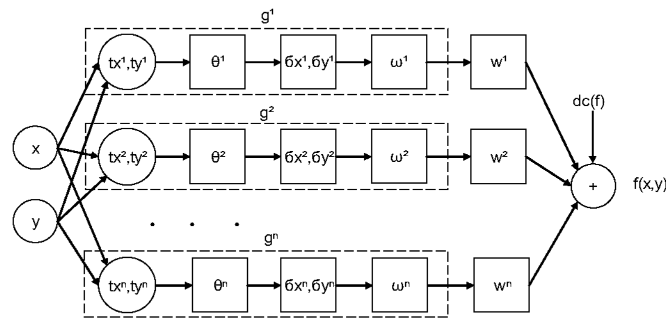


Fig. 1. Architecture of a Gabor wavelet networks.

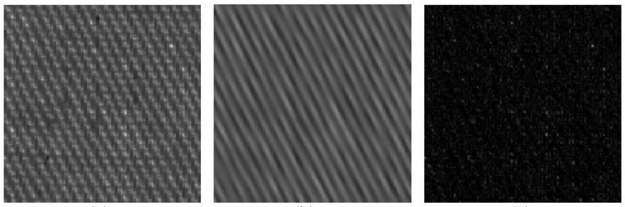
B. Feature extraction

GWN is a combination of feed forward network (FFN) and Gabor wavelet decomposition. Various experiments [15, 16] showed that a GWN is an efficient and task-specific feature extractor. It can be shown that any function f ($f\in L^2(\mathbb{R}^2)$) can be perfectly reconstructed if enough Gabor wavelets are put into the network.

Fig. 2(a) and (b) show a twill fabric image and its reconstruction result using a GWN respectively. Fig. 2(c) displays the difference between the original image and its reconstruction result, in which the energy is so small that there is no obvious difference that can be noticed. However, the image concerned is reconstructed with more than one hundred imaginary Gabor wavelets, and the reconstruction process is very time-consuming. Actually it can be found that one imaginary Gabor wavelet is sufficient to obtain the basic yarn information of a textile fabric. Fig. 3 shows the reconstruction result by the GWN with only one imaginary Gabor wavelet in the hidden layer. The network also captures the local texture information of a template fabric image, such as the yarn orientation and the yarn width, which can be approximately expressed by the Gabor wavelet parameters as follows:

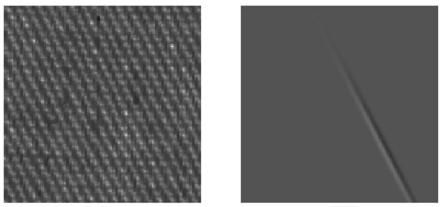
$$\begin{cases} w_y=4\sigma_x \\ \theta_y=\theta-\dfrac{\pi}{2} \end{cases}, \qquad (4)$$

where w_y and θ_y are the yarn width and the yarn orientation respectively.



(a) (b) (c)

Fig. 2. (a) A fabric image, (b) reconstruction result with a GWN, (c) the difference image.



(a) (b)

Fig. 3. (a) A fabric image, (b) reconstruction result by the GWN with only one imagery Gabor wavelet.

III. MORPHOLOGICAL FILTERS

Morphology was presented as a method of image analysis first in 1967 by Matheron in the study about porous materials [17]. Morphological operations are based on the comparison of an object being analyzed with another object with a known shape and size, named structuring elements, such as a line, a square or a hexagon etc. The shape and size of a structuring element is usually chosen according to some priori knowledge about the geometry of the relevant and irrelevant image structures. For a 2D discrete image, a structuring element is a set of $\mathbb{Z}^2$. In morphology, some complex transformations can usually be achieved by combining some simpler transformations. Therefore, morphological filters can become a chain of operations.

A. Morphological Operations

Erosion and dilation are the most basic morphological operators, which can serve as the fundamental elements in the expressions of other complicated operators. The erosion of an image IM by a structuring element B is denoted by $\varepsilon_B(IM)$, which is defined as the minimum value of the image in the window of the structuring element when its origin is at x:

$$\left[\varepsilon_B\left(IM\right)\right]\left(x\right) = \min_{b\in B} IM\left(x+b\right). \tag{5}$$

The dilation of an image IM by a structuring element B is denoted by $\delta_B(IM)$, which is defined as the maximum value of the image in the window of the structuring element when its origin is at x:

$$\left[\delta_B\left(IM\right)\right]\left(x\right) = \max_{b\in B} IM\left(x+b\right). \tag{6}$$

From the above definitions of erosion and dilation, it can be noted that when an image is eroded or dilated by a structuring element, some information in the original image will be lost. In order to recover the lost information caused by erosion and dilation, two extra transformations, opening and closing are introduced, with the following definitions:

$$\text{Opening: } \gamma_B\left(IM\right) = \delta_{\breve{B}}\left[\varepsilon_B\left(IM\right)\right] \tag{7}$$

$$\text{Closing: } \phi_B\left(IM\right) = \varepsilon_{\breve{B}}\left[\delta_B\left(IM\right)\right] \tag{8}$$

where $\breve{B}$ is the reflected structuring element of B and is defined by $\breve{B} = \{-b \mid b \in B\}$. According to the literature [18], an opening is suitable for removing a salt type of noise whereas a closing is good at eliminating a pepper type of noise. With a combination of openings and closings, an alternating sequential filter can be constructed, which is one of the most important filters in mathematical morphology.

B. Filters

According to the results in obtained in Section II, the approximate yarn orientation and yarn width of a twill or denim fabric can be obtained by the Gabor Wavelet Network with one wavelet function in the hidden layer. In fact, based on the yarn information obtained, an optimal structuring element can be constructed, which will be introduced in detail in the following paragraph. Fig. 4 depicts the proposed scheme for detecting defects in woven fabrics. The scheme first uses a pair of opening and closing to smooth the texture features in textile images, which can make yarns look less obvious. The process aims at attenuating texture backgrounds. Fig. 5 gives an example, which shows an original image and the corresponding results after filtering with a linear opening and closing. In the figure, the filtering result shows little texture background, whereas the defective area in the original image is left. In other words, the contrast between the defect and the background is enhanced, which is the function of the defect segmentation algorithm. In order to further eliminate the noise left in the above filtering result, the image is filtered by a 3×3 median filter subsequently. As a post-processing step, the image is then closed by a 3×3 square structuring element. The last step of the scheme is thresholding, which produces the final binary detection result.

As described above, a linear opening and a linear closing are used in the proposed scheme, which shares the same linear structuring element (linear segment). In the detection scheme, the length of the linear structuring elements is set a value equal to the yarn width obtained by the GWN. The orientation of the linear segment is set to different values for different fabrics. This paper only considers detecting those defects that are found on the most commonly used fabrics, i.e. plain, twill and denim fabrics. In the actual textile industry, most fabric defects appear in some specific orientations, either in the direction of motion (i.e. warp direction) or perpendicular to it (i.e. weft direction) [18] because of the weaving process. Therefore, for the fabric without the obvious yarn information like plain cloth, the orientation of the linear segment is set to $\pi/4$, whereas for the rest of the textile images captured from twill and denim fabrics, the orientation of the linear segment can be set perpendicular to the yarn orientation obtained by the GWN.

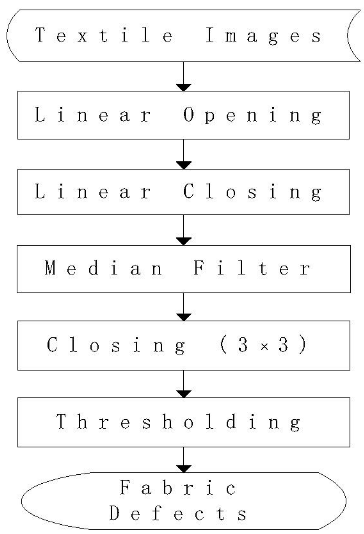
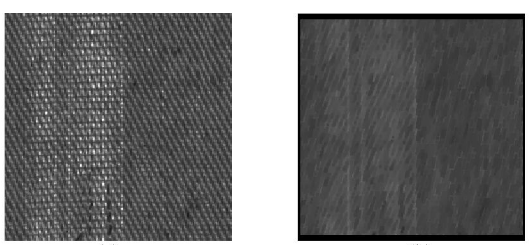


Fig. 4. Morphological filtering algorithm for fabric defect detection.



(a) (b)

Fig. 5. (a) A textile image with a fabric defect called netting multipliers (b) image after filtering with only linear opening and closing (b).

Equations (7) and (8) define the opening and closing operations in morphology. In addition, the computation effort of the opening and closing operations can be reduced by using the fast recursive algorithm detailed in [19] and the moving histogram technique can reduce the computational effort for the median filter [20].

IV. EXPERIMENTS AND RESULTS

The performance of the proposed detection scheme is evaluated by using a test database consisting of 78 fabric images, in which 39 images are defect-free and the rest is with different fabric defects. In the database, the fabric samples contained differ in detect types, resolution and texture background. In total, 32 types of commonly appeared fabric defects are tested in the study. The testing images of textile fabric samples are 256×256 pixels in size (8-bit grey level).

The performance of the algorithms is determined by visually assessing the binary output images. True detection (TD) is recorded when the white zone overlaps the defective area in the original image and at the same time there is no other white areas appearing in the non-defective region. Detection with false alarm (FA) is recorded when the defective zone is overlapped and white areas appear significantly distant from the defective area. Overall detection (OD) is the sum of TD and FA. Misdetection (MD) means that the defective area is totally lost. A Pentium III-450 MHz PC with 512M RAM is used to run the developed defect detection software. The test results are summarized in Table I.

Table I
The overall test results of the proposed detection scheme

The detection scheme	Performance
Overall Detection (OD)	76 (97.4%)
Misdetection (M)	2 (2.6%)
False Alarm (FA)	2 (2.6%)

Some of the experimental results are displayed in Fig. 6. Fig. 6(c), (g) and (k) show fabric images with small defects, i.e., colorfly, fuzzyball and burl respectively, which is difficult to visualize. The defects are successfully segmented by the proposed scheme as shown in Fig. 6(d), (h) and (l). Fig. 6(e) shows an example in which a defect, harness breakdown. only alters the spatial arrangement of neighboring pixels and not the mean gray level. The alteration is also increased by the scheme, and finally the defect is segmented as shown in Fig. 6(f). For these two types of situation, that is, a bright defect with a dark texture background in Fig. 6(a) (foreign fiber) and a dark defect with a bright texture background in Fig. 6 (c) (colorfly), (i) (water damage), the scheme performs equally well.

Usually the defect detection algorithms can be categorized into two classes, i.e. supervised detection and unsupervised detection. In the supervised detection, the information about the defects which may appear in the automatic inspection is known, including the size, the shape etc. When a supervised detection algorithm is constructed, the known information about defects is used to facilitate the design of the detection method. However, when a piece of cloth gets off the production line, the locations and sizes of the generated fabric defects vary randomly. Therefore, the supervised algorithm that only deals with specific defects sometimes does not work satisfactorily in real applications. In this sense, an unsupervised approach is preferred. In the process of constructing an unsupervised detection method, the information of defects which may appear in the detection process is totally unknown and even the texture background of inspection is unknown. Therefore, the design of an unsupervised detection method needs to consider all the possible situations, which may occur in the inspection process. Usually, the design of such a type of detection algorithm is rather complicated and usually involves a bank of filters, which can result in the penalty of heavy computation. Therefore, to tackle the problem of detecting defects in textile fabrics, the deployment of an optimal filter is a good choice. Optimal morphological filters where the parameters are obtained from defect-free images, can be designed to detect a class of textile fabrics. The design of an optimal linear segment has a direct relation with the optimized output from the GWNs, which does not need any information about fabric defects. Those parameters are optimal and specific to a particular texture background. Based on this idea, an effective detection algorithm is proposed, which performs satisfactorily in most cases.

V. CONCLUSIONS

In this paper, a new morphological approach for detecting fabric defects is presented. The Gabor wavelet network with only one wavelet in the hidden layer is utilized to obtain basis texture information from a defect-free textile image, which provides heuristic knowledge to design an optimal linear structuring element. In view of this optimal linear segment, a new scheme of detecting defects in textile fabrics has been developed. The design of the morphological filters in the proposed scheme requires only a defect-free fabric image and no priori knowledge about fabric defects is needed. As such, the proposed scheme is semi-supervised.

The performance of the scheme has been extensively evaluated by using a variety of fabric samples, which differ in defect type, size and shape, texture background, and image resolution. The results obtained have shown that the scheme is effective and robust; and hence, suitable for online web inspection.

ACKNOWLEDGMENT

The authors gratefully acknowledge the financial support from the Research Grants Council of the Hong Kong Special Administrative Region, PRC under the grant HKU7382/02E for this project.

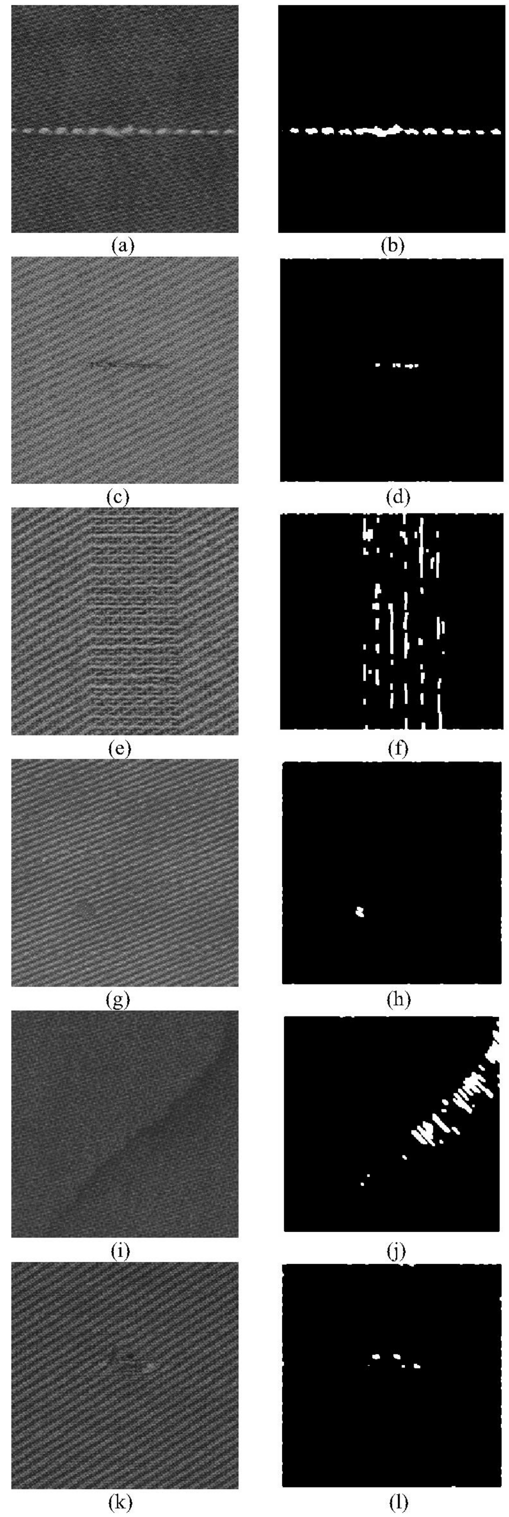


Fig. 6. Fabric samples with foreign fiber (a), colorfly (c), harness breakdown (e), fuzzyball (g), water damage (i), and burl (k) respectively; the final defect segmentation results with the proposed scheme in (b), (d), (f), (h), (j), and (l).

REFERENCES

[1] K. Srinivasan, P. H. Dastoor, P. Radhakrishnaiah, and S. Jayaraman, "FDAS: A knowledge-based framework for analysis of defects in woven textile structures", *J. Textile Inst.*, pt. 1, vol. 83, no. 3, pp. 431-448, 1992.

[2] H. Sari-Sarraf and J. S. Goddard, "Vision systems for on-loom fabric inspection", *IEEE Trans. Ind. Appl.,* vol. *35*, pp. 1252-1259, Nov-Dec. 1999.

[3] J. Wang, R.A. Campbell, and R.J. Harwood, "Automated inspection of carpets", in *Proc. SPIE*, vol. 2345, pp. 180-191, 1995.

[4] A. Kumar, "Neural network based detection of local textile defects", *Pattern Recognition*, vol. 36, pp. 1645-1659, 2003.

[5] J. Escofet, R. Navarro, M. S. Millan, and J. Pladelloreans, "Detection of local defects in textiles webs using Gabor filters", *Opt. Eng.*, vol. 37, pp. 2297–2307, Aug. 1998.

[6] D. Chetverikov and A. Hanbury, "Finding defects in texture using regularity and local orientation", *Pattern Recognition*, vol. 35, pp. 2165-2180, 2002.

[7] A. Bodnarova, M. Bennamoun, and K.K. Kubik, "Suitability analysis of techniques for flaw detection in textiles using texture analysis", *Pattern Analysis and Applications*, vol. 3, pp. 254-266, 2000.

[8] S. Muller and B. Nickolay, "Morphological image processing for the recognition of surface defects", in *Proc. SPIE*, vol. 2249 (automated 3D and 2D Vision), pp. 298-307, 1994.

[9] Y.F. Zhang and R.R. Bresee, "Fabric defect detection and classification using image analysis", *Text. Res. J.*, vol. 65, pp. 1-9, 1995.

[10] W.J. Jasper and H. Potapalli, "Image analysis of mispicks in woven fabrics", *Text. Res. J.*, vol. 65, pp. 683-692, 1995.

[11] A. Bodnarova, M. Bennamoun, and K.K. Kubik, "Defect detection in textile materials based on aspects of HVS", in *Proc. IEEE SMC'98 conference*, San Diego, CA., pp. 4423-4428, Oct. 1998.

[12] R.W. Conners, C.W. McMillan, K. Lin, and R.E. Vasquez-Espinosa, "Identifying and locating surface defects in wood: part of an automated lumber processing system", *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-5, pp. 573-583, 1983.

[13] Qinghua Zhang and Albert Benveniste, "Wavelet networks", *IEEE transactions on neural networks*, vol. 3, no. 6, pp. 889-898, November 1992.

[14] V. Krueger and G. Sommer, "Gabor wavelet networks for object representation", *DAGM Symposium*, Germany, pp. 13-15, September 2000.

[15] Volker Kruger and Gerald Sommer, "Gabor wavelet networks for efficient heard pose estimation", *Image and Vision Computing*, vol. 20, pp. 665-672, 2002.

[16] V. Krueger, *Gabor wavelet networks for object representation*, Ph.D thesis, Christian Albrechts University, Germany, 2001.

[17] G. Matheron, *Elements pour une theorie des milieux poreux*, Masson, Paris, 1967.

[18] H. Sari-Sarraf and J. S. Goddard, "Vision systems for on-loom fabric inspection", *IEEE Trans. Ind. Appl.*, vol. 35, pp. 1252-1259, Nov-Dec. 1999.

[19] V. van Herk, "A fast algorithm for local minimum and maximum filters on rectangular and octagonal kernels", *Pattern Recognition Letters*, vol. 13, pp. 517-521, 1992.

[20] G. Garibotto and L. Lambarelli, "Fast on-line implementation of two dimensional median filtering", *Electronic Letters*, vol. 15, no. 1, pp. 24-25, 1979.