AUTOMATED FABRIC DEFECT INSPECTION FOR QUALITY ASSURANCE SYSTEMS

Raluca Brad, Remus Brad

ABSTRACT

Existent industrial applications of computer vision systems are directly connected to quality assurance requirements. The task of fabric defect detection is carried out by human visual inspection, in most of the traditional textile industry. The possibility of automated defect detection is investigated and a solution leading to improved productivity and high quality in the weaving process is proposed. We are introducing an unsupervised and robust system for the inspection of textured materials, based on multi-channel filtering. The Gabor function is employed for the filter bank and a cost function is used for filter selection. An appropriate thresholding of the filtered image followed by segmentation accomplishes the defect detection. Real image tests shows that our algorithm is robust and computationally efficient for the inspection of textured materials.

1. INTRODUCTION

The textile industry and especially the ready-to-wear clothing segment are nowadays the less automated production sectors. Due to the fact that all operations are hand-made, high productivity and quality can be achieved only by intensive quality inspection before and between the manufacturing stages. The high production speed and the large flexibility required by customers' urge to automated defect detection of the quality assurance system. In the traditional textile industry, this task is carried out by human visual inspection.

In the case of the weaving sector, inspection is performed at the end of the manufacturing stage. Large batches of fabric rolls are manually inspected and actions are performed off-line of the production system. Employing computer vision automation directly on the production stage will improve the on-line reaction of the manufacturing staff and reduce the number of defects.

In the clothing industry, defect detection is performed between manufacturing stages and is strictly dependent of the model and production markers. It is carried-out by manual measurements and visual examination of markers and texture. The final inspection validates the output and has no feedback in the preceding stages. A computer vision system could replace human inspection and provide several benefits. Besides the high processing speed, computer vision systems can offer robust detection and large flexibility. Automation based on image processing does not suffer of human limitations and could entirely replace traditional methods.

Automated visual inspection relies on material properties as texture. Texture analysis techniques for fabric defect detection allows determining texture features and statistically segment defects. Gray-levels texture properties and statistics (Liu et al. 1998) are employed for local segmentation. Characterizing the fabric texture using a Markov random field model in Özdemir et al (1996), detection is derived by hypothesis testing. In Campbell et al. (1996), model-based clustering is used for woven fabric defects.

Since texture can be defined as a function of spatial variations in pixel intensities and possess a high level of periodicity, Fourier transforms and Fourier-domain analysis (Tsai et al. 1999), (Chan et al 2000) are convenient tools for discriminating texture variations. Multi-resolution approaches are decomposing fabric images in several scales using a bank of filters. Gabor function based filters are popular in the area of web defect detection (Kumar et al 2002) and texture inspection.

In the present paper, textile defect detection is investigated through a bank of Gabor filters. In section 2, the Gabor function and filters are presented. In Section 3 our algorithm for texture inspection and defect detection is introduced. Section 4 reports our experimental results, followed by conclusions and future work.

2. GABOR TEXTURE FILTERING

During the last years, the Gabor filters resulted from a modulation product of a gaussian and sinusoidal signals, are the bases of many computer vision algorithms. Gabor has introduced these elementary signals as optimal transmitional signal in telecommunication. Application of Gabor filters starts from edge detection and ends with texture classification and image compression.

In the two-dimensional plane, the Gabor function has the following general form:

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right]\exp(2\pi j u_0 x) \tag{1}$$

where u_0 is the radial frequency of the filter and σ_x, σ_y are constants defining the gaussian envelope along x and y axis.

Using function in equation (1) as a base, similar filter bank can be obtained by dilatation and rotation of $f(x,y)$ by way of the following expression:

$$f_{pq}(x,y) = \alpha^{-p} f(x^{'}, y^{'}) \tag{2}$$

where

$$x^{'} = \alpha^{-p}(x\cos\theta_q + y\sin\theta_q) \text{ and } y^{'} = \alpha^{-p}(-x\sin\theta_q + y\cos\theta_q) \qquad (3)\ (4)$$

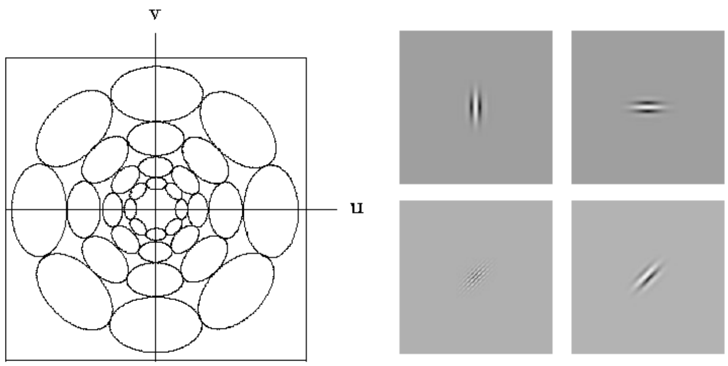
and $\alpha > 1$; p=1, 2, ..., S; q=1, 2, ..., L

The scale parameter p controls the dilatation of the original function to the maximum number of S scales and the rotation parameter q defines the number of possible orientations. For every value of q, the orientation angle is defined by:

$$\theta_q = \frac{\pi(q-1)}{L} \tag{5}$$

It has been proved that all filters in the bank have the same energy independently to their scale or orientation. In most applications, symmetric filter having $\sigma_x=\sigma_y$ are employed but one can imagine the use of an asymmetrical form.

The feature detection characteristic of the Gabor filters relies on the possibility of tuning the orientation of his frequency selectivity. Thus, choosing different values for p (scale) and q (orientation) will generate a series of filters. As shown in figure 1, 4 scales and 8 orientations have been used. The four images are synthetic three-dimensional views of filter shapes, where white/dark levels represents positive/negative amplitude values.



a) b)

Figure 1. a) The Gabor filters bank representation in 2D space. The four images in b) represent filters at different scales and orientations

As resulted from equation (1), each filter has a real and imaginary part. For a given image $I(x,y)$, the filtered image $I_{pq}(x,y)$ is obtained as follows:

$$I_{pq}(x,y) = \sqrt{\left[f_{pq}(x,y)_r * I(x,y)\right]^2 + \left[f_{pq}(x,y)_i * I(x,y)\right]^2} \tag{6}$$

where $f_{pq}(x,y)_{\mathrm{r}}$ and $f_{pq}(x,y)_{\mathrm{i}}$ are the real and imaginary parts of the filter in equation (2).

3. TEXTURE DEFECT DETECTION

Texture defect detection can be defined as the process of determining the location of various defects based on the textural properties of the input image. A quality control system implies an unsupervised process for defect detection, dealing especially with unknown texture defective patterns. As presented in section 2, Gabor filters have a special feature that allow to texture tuning and consequently to respond in a different manner to texture irregularity. Unsupervised inspection is achieved by both local and global investigation.

A bank of Gabor filters processes the input image. Some authors are producing a 25 filter bank by convolution, using a set of Law vectors (Grigorescu et al. 2002). Each filter is chosen in order to respond on a small frequency and scale domain. In our method, the filter bank is generated using equation (1) and (2).

In order to perform the convolution in equation (6), the required S x L number of filters (real and imaginary parts) are computed in an M x M matrix form. The original image $I(x,y)$ is divided in N regions of k x k pixels. Each filter in the bank is applied to the each of the N regions and the filtered result is obtained using equation (6). Figure 2 presents the results of a defect texture filtering using different scale and orientation generated Gabor filters.

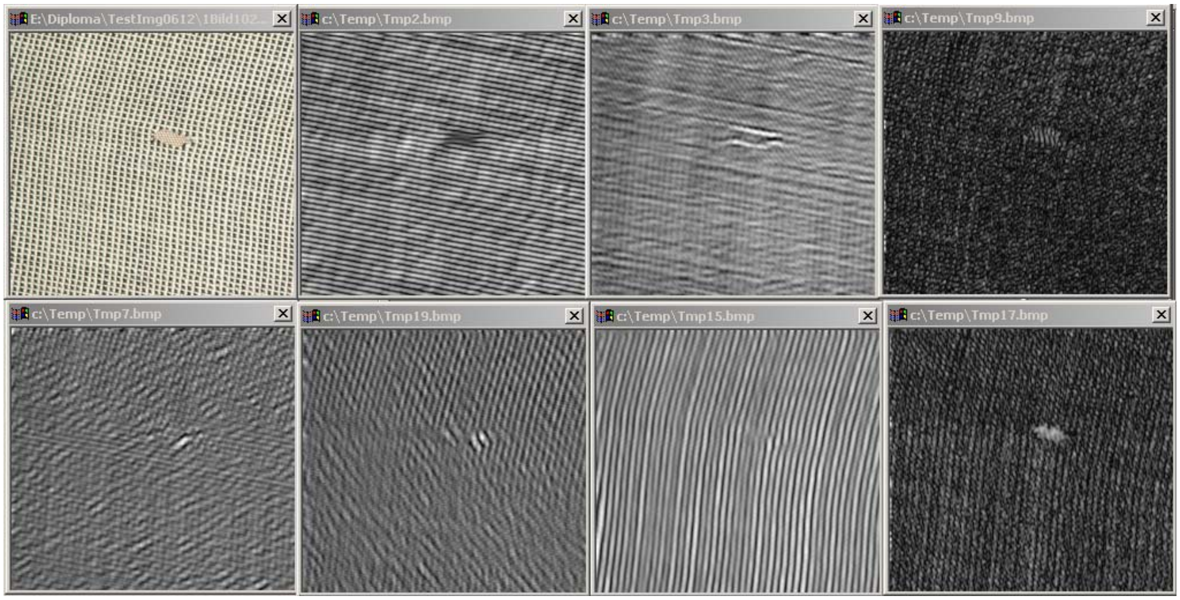


Figure 2. Results of texture filtering for different orientations and scales

The average result for every *i*th filter in the bank for any region *n* in *N* is computed by the following:

$$A_n^i = \frac{1}{kxk} \sum_{(x,y)\in n} I_{pq}(x,y) \tag{7}$$

For every *i*-th filter among the *N* regions, a maximum $A_{\max}^i$ and minimum $A_{\min}^i$ average value is retained. The cost function will be the normalized difference between the two values:

$$C(i) = \frac{A_{\max}^i - A_{\min}^i}{A_{\min}^i} \tag{8}$$

The filter having the highest cost function will be selected for defect detection and the original image will be subject to filtering. Then, a thresholding operation is required for the final segmentation of texture defects, as shown in figure 3.

Segmentation of the filtered image will perform defect detection. Choosing the appropriate filter represents the key to correct results. An unsupervised algorithm can be developed for the selection of the filter that performs large outputs in the case of defect texture and small output for defect-free. A cost function (Kumar et al. 2002) is required for the discrimination of the filters bank results.

Selecting the threshold has been another challenging task. Some authors recommend using the maximum value resulted on the filtered image, having as original a defect free sample. In order to eliminate the pre-processing of a defect-free image, we are proposing an original method using as a threshold, the median value of maximum values obtained by applying the selected filter on all image regions:

$$Th = median(m_1, m_2, ..., m_N) \tag{9}$$

where m_i is the maximum value of the *i*th filtered block in the partitioned image. As shown in the next section, our original method succeeds in emphasizing defects on the resulted binary image.

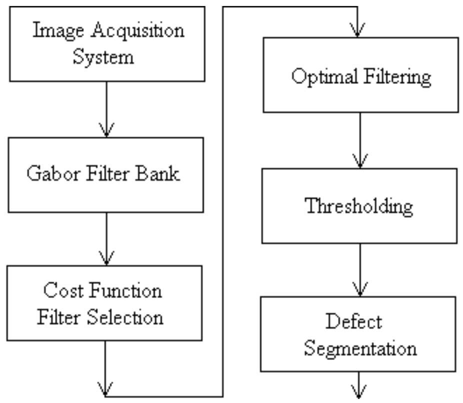


Figure 3. The defect detection scheme

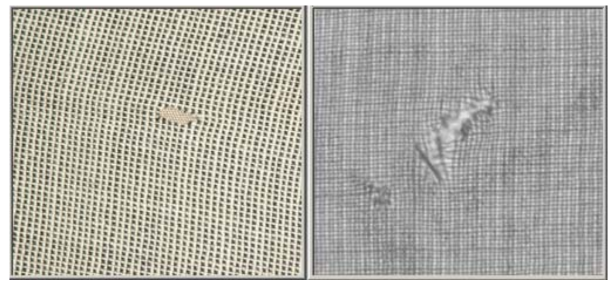
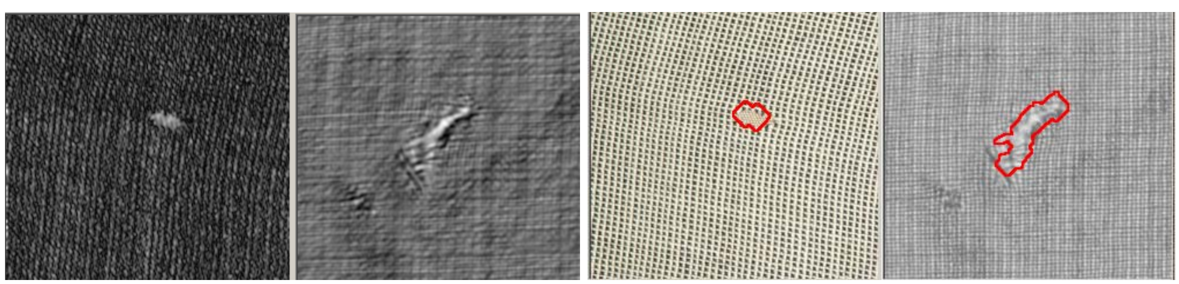


Figure 4. Samples of fabric defect images

4. RESULTS

In our experiments, we have employed images of fabric texture and defects acquired in the Computer Vision Laboratory. A bank of 24 Gabor filters has processed the 256 gray level image. We have considered 4 scales and 6 possible orientations for the convolution mask presenting the filter. After a series of experiments, the size of the filter was set at 9 x 9. Test images where grabbed at 256 x 256 resolution and partitioned in 32 x 32 pixels regions. Figure 4 shows an example of defects considered in our work (a break-out). Mispick, dirty-yarn and stains have also been investigated in Brad et al. (2003).



a) b) c) d)

Figure 5. a) and b) results of original images filtered by optimal Gabor filter; c) and d) deffect detection after thresholding and region growing

Original images have been partitioned in regions and the Gabor filter bank is applied. Using equation (7) and (8), the best characterizing filter for the given texture is then selected. Figure 5 a) b) shows the resulting filtered images for the two considered samples. A binary image is obtained using an appropriate threshold, selected by the method proposed in section 3. Defect is emphasized on the original image using a region growing algorithm and considering pixels in the binary image. Final results of fabric defect detection are presented in figure 5 c), d).

5. CONCLUSIONS

This paper presents an application of the Gabor function to texture inspection and especially to fabric defect detection. The main goal of the proposed method is the improvement of quality assurance techniques. A bank of Gabor filters have been generated and a cost function based on maximum filter response for the given texture is used. In order to eliminate pre-processing of a defect-free image, a novel method for threshold selection is introduced. Based on a region-growing algorithm, the segmented binary image provides defect identification and localization.

The results have shown successful detection of a variety of fabric defects. Even if it covers most of the common defects from the weaving and knitting industry, tests will be conducted on other possible situations. Being computationally feasible, PC-based implementations of on-line fabric inspections can be developed. Future work will include the application of the proposed framework to other types of textures and an extensive investigation on Gabor filter bank design. Furthermore, research on defect detection for printed fabrics or multi-colored textures will be intended.

6. REFERENCES

Brad R. and Brad R., “Quality Assurance by Automated Defect Detection of Textile Fabrics”, Proc. of XI-th Int. Symp. SINTES, vol. II, pp.487-491, Craiova Romania, 2003

Campbell J.G., Fraley C., Murtagh F. and Raftery A. E., “Linear flaw detection in woven textiles using model-based clustering”, Univ. Washington, Seattle, WA, Tech. Rep., 1996

Chan C.H. and Pang G., “Fabric defect detection by Fourier analysis”, IEEE Trans. Ind. Application, vol. 36, pp. 1267–1276, Sept./Oct. 2000

Grigorescu E., Petkov N., Kruizinca P., “Comparison of Texture Features Based on Gabor Filters”, IEEE Transactions on Image Processing, 2002

Kumar A. and Pang G., “Defect Detection in Textured Materials using Gabor Filters”, IEEE Trans. on Image Processing, vol. 38, no.2, pp.425-440, 2002

Liu H.S., Chan C.H., Kwan T. and Pang G., “Neural-Computing in fabrics inspection system”, Int. Symp. on Soft Comp. in Eng. Applications, Athens, Greece, June 22-25, 1998

Özdemir S. and Erçil A., “Markov random fields and karhunen-loève transforms for defect inspection of textile products”, Proc. IEEE Conf. EFTA, vol. 2, pp. 697–703, Nov. 1996

Sari-Sarraf H. and Goddard J. S., “Vision systems for on-loom fabric inspection”, IEEE Annual Conf. on Textile, Fiber and Film Industry, pp. 1-11, 1998.

Tsai D. M. and Heish C.Y., “Automated surface inspection for directional textures”, Image Vis. Comput., vol. 18, pp. 49–62, 1999

RESPONDENCE ADDRESS:
Dept. of Textile Technologies, "Lucian Blaga" University of Sibiu,
B-dul Victoriei 10, 550024 Sibiu, Romania