Computer Vision Aided Fabric Inspection System for On-Circular Knitting Machine

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Abstract

This paper describes a computer vision-based fabric inspection system accomplished on a circular knitting machine to inspect the fabric under construction. This paper consists of two parts. In the first part, knitted fabric defects detection was performed and performance of three different spectral methods including discrete Fourier transform, Wavelet and Gabor were evaluated off-line. It was found that the Gabor transform method has the highest efficiency value among the other methods.

In the second part, knitted fabric defect detection and classification were implemented on-line. Having been synchronized to the motion of the circular knitting machine, the developed system first acquires images of the fabric using front lighting. The captured images were subjected to a defect detection algorithm, which was based on the concepts of Gabor wavelet transform, and a feed forward back propagation Neural Network (as a classifier). The system was used to acquire and analyze more than 8100 images of fabrics knitted with 36 yarn feeders during production. The performance of the system was evaluated as an operator encountering defects. The fabric images were broadly classified into 14 classes including seven main categories: cracks or holes, vertical stripes, horizontal stripes, vertical soil stripes, horizontal, neps or slubs and defect free as well as seven combined defects. The results of the designed system were compared with those of human vision. The overall success rate of the proposed method was 96.57% with a localization accuracy of 2 mm and a false alarm rate of 1.4%.

Keywords

Computer Vision, Fabric Inspection, Circular Knitting Machine, Neural Network, Fourier Transform, Wavelet Transform, Gabor Transform.

1-Introuduction

There are three principal methods of mechanically manipulating yarn into textile fabrics: interweaving, intertwining, and interlooping [1]. Knitting is the most common method of interlooping and is second only to weaving as a method of manufacturing textile structure. In this case, circular knitting is one of the easiest and fastest ways (20 million stitches per minute) of producing cloth and textile pieces such as garments, socks, and gloves. Fabric faults, or defects, are responsible for nearly 85% of the defects found by the garment industry. An automated defect detection and identification system enhances the product quality and results in improved productivity to meet customer demands, and to reduce the costs associated with off-quality. Higher production speeds make the timely detection of fabric defects more important than ever. Presently, inspection is done manually; when a significant amount of fabric is produced, the fabric roll is removed from circular knitting machine, and then sent to an inspection frame. An optimal solution would be to automatically inspect the fabric as it is being produced and to alert maintenance personnel to prevent production of defects or to change process parameters automatically and consequently improve product quality. Also if inspection is done on the machine, the need for 100% manual inspection is eliminated [2].

It has been reported [3] that knitted fabric defects can be classified in two main categories: horizontal and vertical variations [4,5]. While the first category is mainly due to the yarn, the second category is related to the knitting elements. In order to deal with these problems, various studies have been conducted and a few specialized systems are developed, which can detect abnormalities in the fed yarn, defects in the knitted fabric, and defects in the knitting elements [4,6]. It is claimed that these systems are very specialized and usually do not provide any further information related to the knitting process and the cause of a defect. Araújo *et al.* [3], proposed an approach to investigate process control for total quality in circular knitting machine based on yarn input tension analysis. By using this method it is possible to observe the whole process of loop formation, thus enabling the detection of abnormalities along with their position in the appropriate knitting element and possible cause diagnosis.

The existing defect detection techniques can be classified into three different categories: statistical, spectral, and model-based. Defect detection approach by Zhang [7] is based on first order statistics such as mean and standard deviation. The fabric image is divided into sub-blocks with the use of information obtained by auto-correlation. The use of gray-level co occurrence matrix of the image is based on second order statistics [8]. However, these statistical techniques are not useful for the detection of those textured defects whose statistical features, i.e. first- and second-order moments, are significantly close to that of defect-free textured regions [9]. High level of quality assurance requires identification of such defects, and therefore the techniques based on spectral features have been investigated in the literature [10-20].

Textured materials, such as woven and knitted fabrics, possess strong periodicity due to the repetition of basic weaving pattern. Therefore spectral techniques using discrete Fourier transform [10, 11], Optical Fourier transform [12], and windowed Fourier transform [13] have been used to detect woven fabric defects. Escofet et. al. [21] have used the angular correlation of the Fourier spectra to evaluate fabric web resistance to abrasion. Sari-Saraf *et al.* [19], Chan and Pang [10] have used Fourier transform to detect fabric defects. Ravandi and Toriumi [22] have also used Fourier transform analysis to measure fabric appearance. Escofet *et al.*[14] have used a bank of multi scale and multi orientation Gabor filters for the detection of local fabric defects. Ajay and Pang [15] have demonstrated another approach for the fabric defect detection using real Gabor functions. Jasper *et al.* [16] have shown that the texture information can be adapted into Wavelet bases. Such an adapted Wavelet bases offer high sensitivity to the abrupt changes in the surface texture caused by the defects, enabling their detection. Several works also demonstrate several approaches for the detection of surface defects using Wavelet basis functions [17-20]. The Markov random field (MRF) model is a model based for describing local statistical dependence of the image [23, 24].

It is reasonable to conclude that the existing defects detection and classification techniques are mostly concentrated on woven and other textile webs. Thus, there is no comprehensive work to inspect on-circular knitting machine using computer vision system and defects detection and classification techniques. Therefore, in this paper, we focus on defect detection and classification on-circular knitting machine during processing using spectral method including discrete Fourier transform, Wavelet and Gabor.

2-Hardware Description

2-1-Knitting Machine Specifications

A Single Jersey Mini-Jacquard circular knitting machine with a 30" cylinder, gauge 24 and 72 feeders is used. On this machine, a plain knitted fabric is produced using viscose/polyester yarn (30 Ne). Due to some operational limitations for mounting camera and in order to capture full fabric surface image, only 36 yarn feeders are utilized.

2-2-Image Acquisition System

The implemented image acquisition system shown in Figure (1) The system consists of a 640×320 element CMOS (Complementary Metal Oxide Semiconductor) camera, which is synchronized to the moving fabric by means of an incremental encoder, a microcontroller board, and a personal computer based AMD Athlon XP 1800+ processor. The custom-made component in this system is the microcontroller board, which is used to extract the forward movement of the fabric and to enable accurate image-capture of camera. These components are used to acquire images of the fabric under construction and to store them on the computer.

3-Experiments

3-1-Laboratory Developed Experiments

The aim of this test is to evaluate and compare the performance of three different spectral methods including discrete Fourier transform, Wavelet and Gabor for fabric faults detection. In order to control the image acquisition process, a program under Lab-View® software has been developed. The program is responsible for on-line capturing and storing of received digital images received from the CMOS camera according to microcontroller commands. Defect detection and classification is performed off line using a program under MATLAB software. The knitting machine has been run with different speeds (2/3 to 17 rpm) and different fabric faults including vertical strip, vertical soil strip, horizontal strip, horizontal soil strip, crack or hole, nep or slub are created. Images of these fabric samples have been acquired under front lighting. Figure (2) shows different fabric defects considered in this experiment.

The dimension of individual image is 3.7*3.4 cm (176 ☐ı☐☐ pixels), with 256 gray levels. In general, 2315 fabric images are captured and then the fabric faults detected off-line. As shown in figure 2., because of front lighting method, there are not considerable different between vertical faults resulting from various causes. For this reason these faults are classified under vertical strip category. Similar situations have been found between the loop length variation and double yarn faults so that they are classified as horizontal faults group.

In this experiment, 20 images corresponding to six different categories of fabric defects and 20 images of defect free fabrics are used. In general, 50% images of each category employed for training and remaining images are used for testing.

3-2-The Fourier Transform Method

In this section, a method nearly similar to that of Ribolzi *et al.*,[12] and Tsai et al.,[26] is used. The I(0,0), I(0,1), and I(1,0) are used to neural network training. The I(0,0) is central peak intensity and I(0,1) and I(1,0) are corresponding intensities of neighborhood points in x and y directions.

A three-layer Perceptron neural network with feed-forward back-propagation algorithm was used to classify fabric images. The best results are obtained with the following configuration of the neural network: 3 neurons in the first layer, 10 neurons in the second and 7 neurons in the third layer, learning rate of 0.025 and 3750 epoch. The maximum sum-squared error of the neural network is 10^{-5}. The results of the Wavelet transform method are presented in Table I.

3-3- Wavelet Transform Method

In this method, a Wavelet transform based Daubechies [25], second classes (Equation 2) is used. The experimental results indicated that an appropriate classification could be achieved using the third level of this transform. In this way, the detailed image is used to calculate the mean and variance of its pixel intensities in order to train neural network training.

$$G(\omega) = \frac{1}{4\sqrt{2}}\left[(1+\sqrt{3})e^{j3\omega} + (3+\sqrt{3})e^{j2\omega} + (3-\sqrt{3})e^{j\omega} + (1+\sqrt{3})\right] \quad (2)$$

where, $G(\omega)$ is Daubechies function and ω is variable.

A three-layer Perceptron neural network with feed-forward back-propagation algorithm was used to classify fabric images. The best results are obtained with the following configuration of the neural network: 30 neurons in the first layer, 8 neurons in the second and 7 neurons in the third layer, learning rate of 0.275 and 2250 epoch. The maximum sum-squared error of the neural network is 10^{-5}. The results of the Wavelet transform method are presented in Table I.

3-4- Gabor Transform Method

In this section, a Gabor Wavelet transform has been designed with the following general and special parameters:

General parameters:

-Number of Wavelet scales: 4

-Number of filter orientations: 6

-Wavelength of smallest scale filter: 3

-Scaling factor between successive filters: 4

-Ratio of the standard deviation of the Gaussian describing the Gabor filter's transfer function in the frequency domain to the filter center frequency: 0.35

-Ratio of angular interval between filter orientations and the standard deviation of the angular Gaussian function used to construct filters in the frequency Plane: 1.9

Special parameters:

-Orientation = 1, 3, 4, 6

-Scale = 2

A three-layer Perceptron neural network with feed forward back propagation algorithm was utilized to classify fabric images. The best results are obtained with the following configuration of the neural network: 15 neurons in the first layer, 8 neurons in the second and 7 neurons in the third layer, learning rate of 0.475 and 7350 epoch. The maximum sum-squared error of the neural networks is 10^{-5}. The results of the Gabor transform method are presented in Table I.

3-5- Summery of Laboratory Experimental Results

The laboratory experimental results of three spectral methods are presented in Table I. As shown, we conclude that the Gabor transform method with a success rate of 78.4% has the highest efficiency value among the three methods. Therefore, the Gabor transform method is selected to continue the experiment in an industrial system.

3-6-On-line Implementation on an Industrial System

In this part of work, the whole process of the image capturing, defects detection and classification are performed on-line. A schematic diagram of the experimental set-up is shown in Figure 3. In order to capture, store and process of image on line, at a rate of 13 frames per second (fps), two computers with similar specifications have been used. The first computer receives and detects images using two linked programs (Lab-View for image capturing and MATLAB for image detection). The second computer is utilized for fabric defect classifications and grading using two linked programs (Lab-View for computer communication and fabric grading and MATLAB for defect classifications).

The Gabor transform, is employed to implement fabric defect detection. A three-layer Perceptron neural network with feed forward back propagation algorithm is used to classify fabric images. The best results are obtained with the following configuration of the neural network: 20 neurons in the first, 38 neurons in the second and 7 neurons in the third layer, learning rate of 0.475 and 5200 epoch. The maximum sum-squared error of the neural networks is 10^{-5}.

In this experiment, 50 images corresponding to individual six different categories of fabric defects (Figure 2.) and also 50 images of defect free fabrics out of 2315 images are applied for neural network training. Then, the Knitting machine run again at speed of 2/3 to 10 rpm and 8135 images including different types of defects and defect free are captured and analyzed using proposed program. To precisely investigate and maintain the efficiency of this program, all 8135 images are visually inspected and finally the images corresponding to defect types are categorized and classified. The results of the designed program are compared with those of human vision inspection and then the success rate of the system was determined (Table II).

4-Results and Discussions

The experimental results presented in Table I demonstrate that the application of Gabor transform method applied in this paper are highly promising in the identification of knitted fabric defects with the overall success rate of 78.4%. In the case of vertical and horizontal strips, horizontal soil strips and nep/slub defects, the success rate is more than 90%. However, the vertical soil strip is detected at a lower rate (20%) because the intensity of this defect is closed to that of fabric surface (so it is hard to be distinguished from a defect free fabric). In the case of defect free samples, the success rate is 60% presumably due to low sample numbers used for training the neural network.

Analyzing 8135 images through industrial system for both fabric types (defect and defect free) as shown in Table II, resulted in the overall success rate of 96.57% with a localization accuracy of 2 mm and a false alarm rate of 1.4%. It should be noted that the false alarm rate is computed as the total number of false detections divided by the total number of processed images.

Several typical photos of fabric images are shown in Figures 4 to6. In each figure, the top image refers to gray captured image of fabric (defect or defect free). The first, second, third and forth columns are related to the filter output, binary image, dilated and threshold results respectively. Moreover, the first, second, third rows refer to vertical, closed curved and horizontal defects respectively.

It can be observed that for the most common and the most serious defects, such as vertical, horizontal and horizontal soil, neps/slubs, horizontal-vertical strips, horizontal strips-holes and horizontal strips-neps defects, the system performance is acceptable with the success rates of 75% to 95.87%. On the other hand, other defects such as vertical soil strips, vertical soil strips-neps, vertical strips-neps, and horizontal strips-holes are detected at a lower success rate of 50%-60%. In the case of holes defects, they appeared at the edge of captured image and mis-identified as other defect types. Because the intensity of vertical soil strips is closed to that of defect free fabric surface, it is detected at a low rate of 58.77%. This result in turn causes the success rate of vertical soil strips-neps defects to be low too (50%). In addition, since position of vertical strip and nep defects in some images are too close, these defects have been mixed together leading to a low success rate of 57.14%. For the case of vertical strip-hole defect, the number of samples was too low and needs further investigation.

5-Conclusion

We have described a computer vision aided fabric inspection system for on-circular knitting machine. Two experimental approaches, laboratory-developed experiment, and industrial system have been investigated.

In the case of laboratory experimental method, three different spectral methods (discrete Fourier transform, Wavelet and Gabor transforms) in order to detect sample images of fabric faults are employed. It is found that the Gabor transform method with a success rate of 78.4% has the highest efficiency value among three methods.

In the case of industrial system, the knitting machine run at speed of 2/3 to 10 rpm and 8135 images including different types of defects and defect free have been captured and analyzed using proposed program. The captured images are then detected using Gabor transform and classified using a neural network system. To precisely investigate the efficiency of this program, all 8135 images are inspected under human vision and finally these images corresponding to defect type are classified in 14 categories. The results of proposed program are compared with those of visually and then the success rate of designed machine vision system is calculated. The overall success rate of the proposed approach is found to be 96.57% with a localization accuracy of 2 mm and a false alarm rate of 1.4%.

This paper has opened a new approach for the detection of online-knitted fabric defects using the Gabor transform. Since this research is limited to speed of knitting machine, further studies are needed to investigate the fabric defects in higher speed of knitting machine.

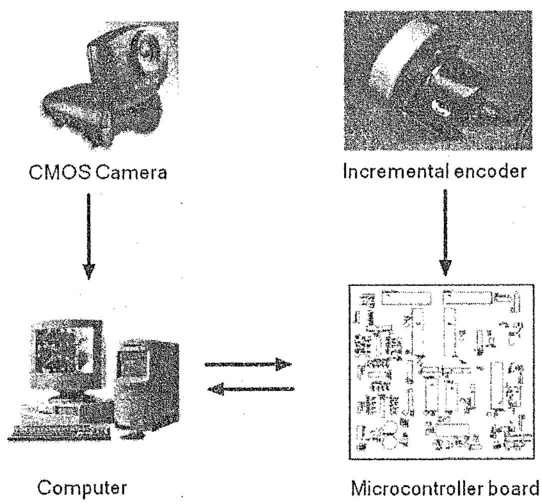

Figure (1) Image Acquisition System.

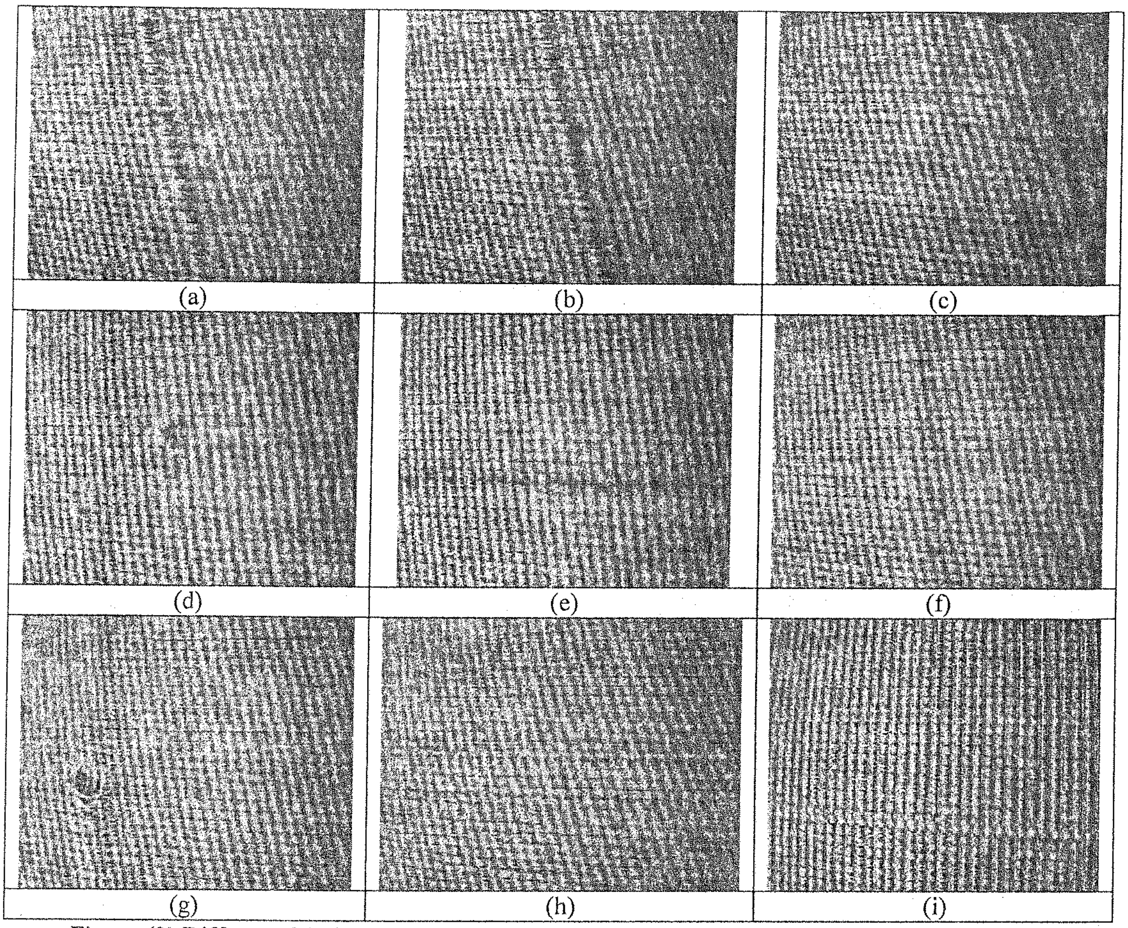

Figure (2) Different fabric defects created during circular knitting processing. Vertical strip: (a) Broken latch, (b) Closed latch, and (c) Broken hook. (d) Nep, (e) Horizontal soil strip, (f) Vertical soil strip, (g) Hole, Horizontal strip: (h) loop length variation, and (i) Double yarn.

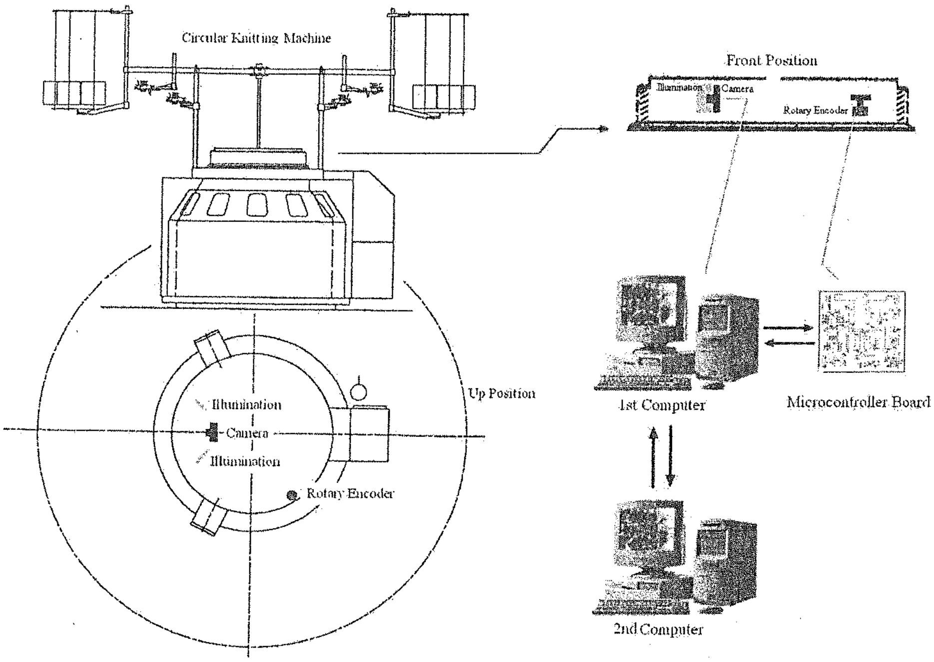

Figure (3) Experimental set-up for industrial system.

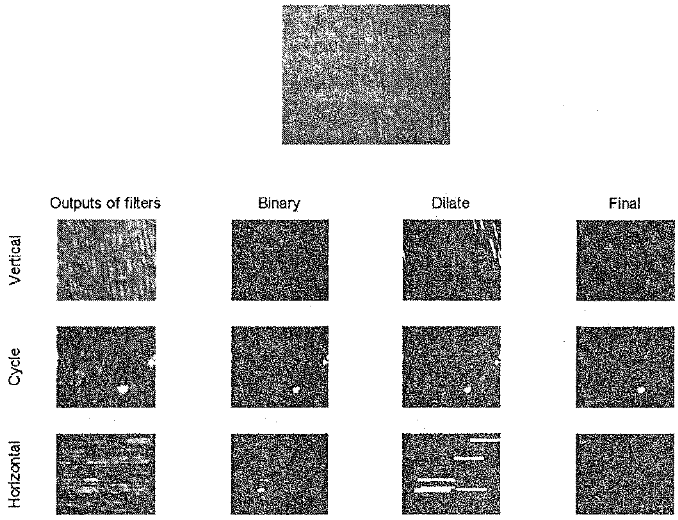

Figure (4) Fabric image with nep defect; with corresponding filters output (vertical, closed curve and horizontal defects), binary, dilation and threshold results.

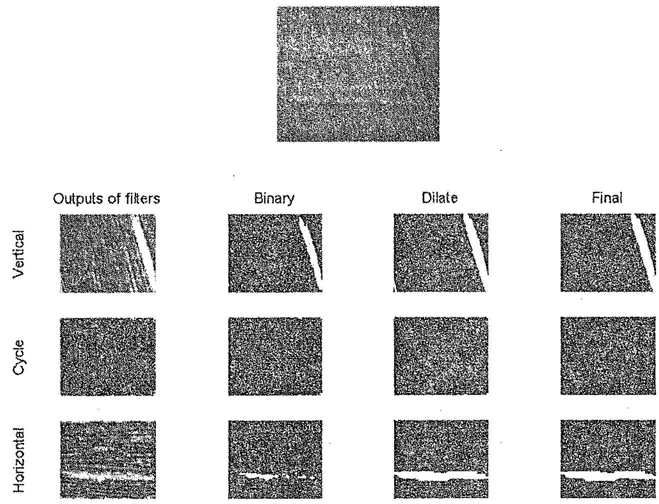

Figure (5) Fabric image with vertical-horizontal strips defect; with corresponding filters output (vertical, closed curve and horizontal defects), binary, dilation and threshold results.

Table (1) The success rate of fabric defect detection corresponding to different texture methods.

	Fourier transform	**Wavelet transform**	**Gabor transform**
Class type of fabric Image	**No. of detected images**	**No. of detected images**	**No. of detected images**
Vertical strip	1	7	10
Horizontal strip	5	5	10
Vertical soil strip	1	5	2
Horizontal soil strip	1	10	10
Nep/slub	3	5	9
Hole	0	4	8
Defect free	0	0	6
Overall success rate (%)	15.71	52.3	78.4

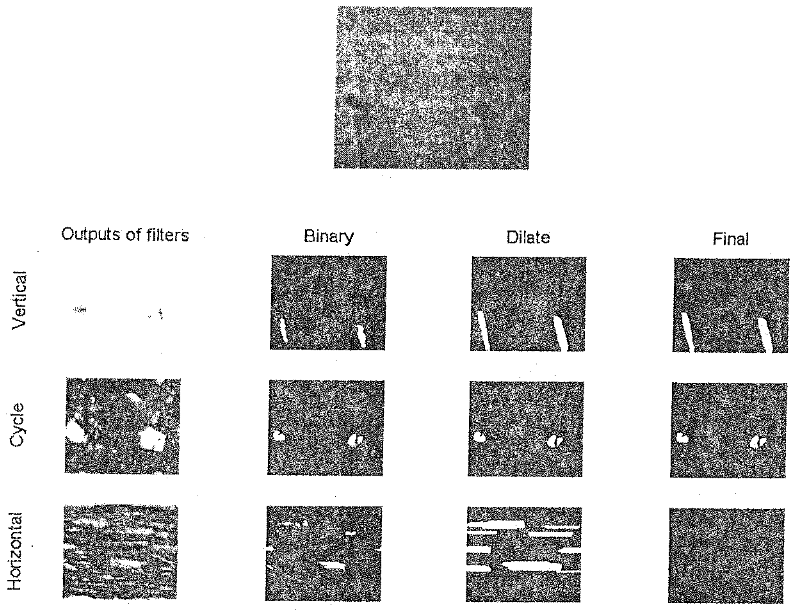

Figure (6) Fabric image with vertical strips-holes defect; with corresponding filters output (vertical, closed curve and horizontal defects), binary, dilation and threshold results.

Table (2) Final experimental results for industrial system.

Class type of fabric image	No. of images	No. of true detected images	No. of non-detected images	No. of false detected images	Success rate (percentage)
Vertical strip	163	132	1	30	80.98
Horizontal strip	127	104	0	23	81.88
Vertical soil strip	114	67	45	2	58.77
Horizontal soil strip	120	98	12	10	81.66
Nep/slub	1722	1651	10	61	95.87
Hole	14	9	3	2	64.28
Defect free	5791	5735	0	56	99.03
Vertical -Horizontal strip	19	16	2	1	84.21
Horizontal soil strip-nep	3	2	0	1	66.66
Vertical soil strip-nep	6	3	3	0	50
Vertical strip-nep	14	8	2	4	57.14
Horizontal strip-hole	28	21	1	6	75
Vertical strip-hole	4	2	1	1	50
Horizontal strip-nep	10	8	1	1	80
Total results	8135	7856	163	116	96.57

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