ON-LINE FABRIC DEFECT DETECTION AND FULL CONTROL IN A CIRCULAR KNITTING MACHINE

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Abstract:

This study has shown that image analysis has great potential to provide reliable measurements for detecting defects in knitted fabrics. Using the principles of image analysis, an automatic fabric evaluation system, which enables automatic computerised defect detection -(analysis of knitted fabrics) was developed. On-line fabric defect detection was tested automatically by analysing fabric images captured by a digital camera. The results of the automatic fabric defect detection correspond well with the experimental values. Therefore, it is shown that the developed image capturing and analysis system is capable of on-line detection of fabric defects and full control in the knitting machine (for example, by stopping the circular knitting machine as soon as a defect is acquired by the digital camera).

Keywords:

Fabric defect detection, control, circular knitting machine

1. Introduction

Any variation to the knitting process needs to be investigated and corrected. Defects fall into this category. As soon as they appear, repair is needed; this is time-consuming and sometimes results in the fabric's rejection. Fabric defect detection has been a long-felt need in the textile and apparel industry. Surveys carried out as early as 1975 [1] show that inadequate or inaccurate inspection of fabrics has led to fabric defects being missed, which in turn has had great effects on the quality and subsequent costs of the fabric finishing and garment manufacturing processes.

Circular knitting is one of the easiest and fastest way (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 both 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 the circular knitting machine, and then sent to an inspection frame. An optimal solution would be to automatically inspect fabric as it is being produced, and to encourage maintenance personnel to prevent the production of defects or to change the process parameters automatically, consequently improving product quality [2].

The study of this problem has led to the identification of two main categories of defects in knitted fabrics: horizontal and vertical variations [3,4]. While the first category is mainly linked to the yarn (quality and management), the second category is related to the knitting elements: needles, sinkers, feeders, and so on. The solutions to these problems are, for the first category, a careful selection and management of the yarn, and for the second, the correction or substitution of the defective elements. In order to deal with these problems, various studies have been conducted and some specialised systems were developed which can detect abnormalities in the yarn being fed, defects in the knitted fabric and defects in the knitting elements [4,5].

In a previous work [6], neural network methods were applied to images of simple circular knitted fabrics for classifying faults. The result showed the successfulness of the methods, but this approach is not useful in industry because the process is time-consuming and there are no ways to determine the fault's location and area. To prevent the problem, in current research [7], the wavelet transform was applied to process the image of circular knitted fabrics.
Depending on the knitted structure, defects can be categorised into three types of vertical, horizontal and regional defects [8,9].

This paper presents a method and the instruments developed at the Textile Faculty for the automatic detection and identification of defects on flat fabrics. The work was intended to develop a monitoring system for random processes based on video images during the production phase. The system we developed consists of hardware equipment [10-12], data evaluation implemented in software and determination of acceptable tolerances related to final product quality. Applications of the methods developed were investigated in a paper production process, a carding process and a weaving process.

Many researchers in the field of image analysis have used neural networks as a classifier [13-18]. In these approaches, the data of the images is reduced, in one form or another, to accelerate the processing time. Techniques used to extract image features include statistical procedures [14,16,19], timefrequency domain transforms such as the discrete cosine transform [14,19], the Fourier transform [14-16,20,21,22] and the wavelet transform [21].

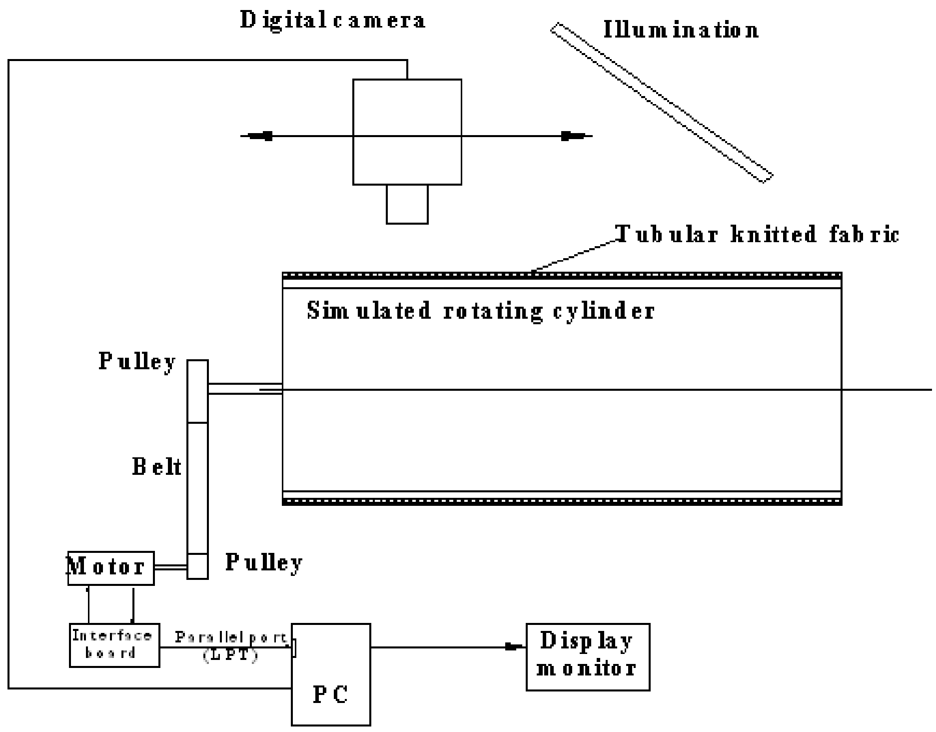


Figure 1. The hardware components used in the inspection system

It has been reported [18] that knitted fabric defects can be classified in two main categories including horizontal and vertical variations [23,24]. 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 some specialised systems were developed, which can detect abnormalities in the yarn being fed, defects in the knitted fabric and defects in the knitting elements [23,25]. It has been claimed that these systems are very specialised and usually do not give further information related to the knitting process and the cause of a given defect. The objective of this research is the development of a computerised system capable of detecting defects in knitted fabrics during the knitting process. Further, this system should be able to identify the type and potential source of the defect, providing the operator with information on how to correct the problem. The developed systems are capable of identifying defects with greater accuracy than experts in the knitting industry, which promises significant improvements in quality. In addition, this system is capable of stopping the circular knitting machine as soon as the defect is acquired.

2. Experimental work

2.1. Sample and tested defects

In this study, we used two types of fabric structure, such as plain single jersey and rib, with different densities. With respect to the tested fabrics, four kinds of common defects were chosen and created in these fabrics. These defects are needle line, dropped stitch, hole and oil spots. From each of the three kinds of fabric defects, a large number of samples were acquired by image-capture equipment.

Each type of defect is imaged many times from random different locations. The images of these defected samples were analysed by a computer program.

The samples for each kind of fabric defect were divided into two groups. The first group had many samples and was used for training, and the other group was used for testing.

2.2. Fabric image acquisition

The experimental materials include plain single jersey and rib structures, twenty specimens for each weave pattern acquired from different areas of the same knitted fabrics. The illumination consists of a fluorescent lamp, inclined at 45° to the specimen surface 5 to 13 cm apart, and the magnification was 6×. The captured images of knitted fabrics consists of RGB 24 (320×240) pixels, and each pixel has 256 levels of grey. The area of a knitted fabric sample was 6.5 × 4.8cm.

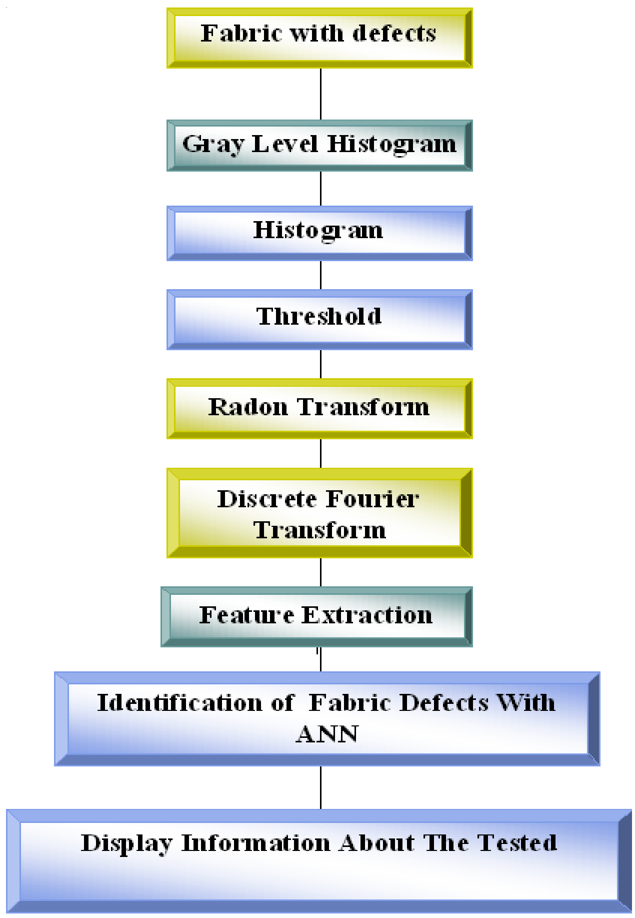
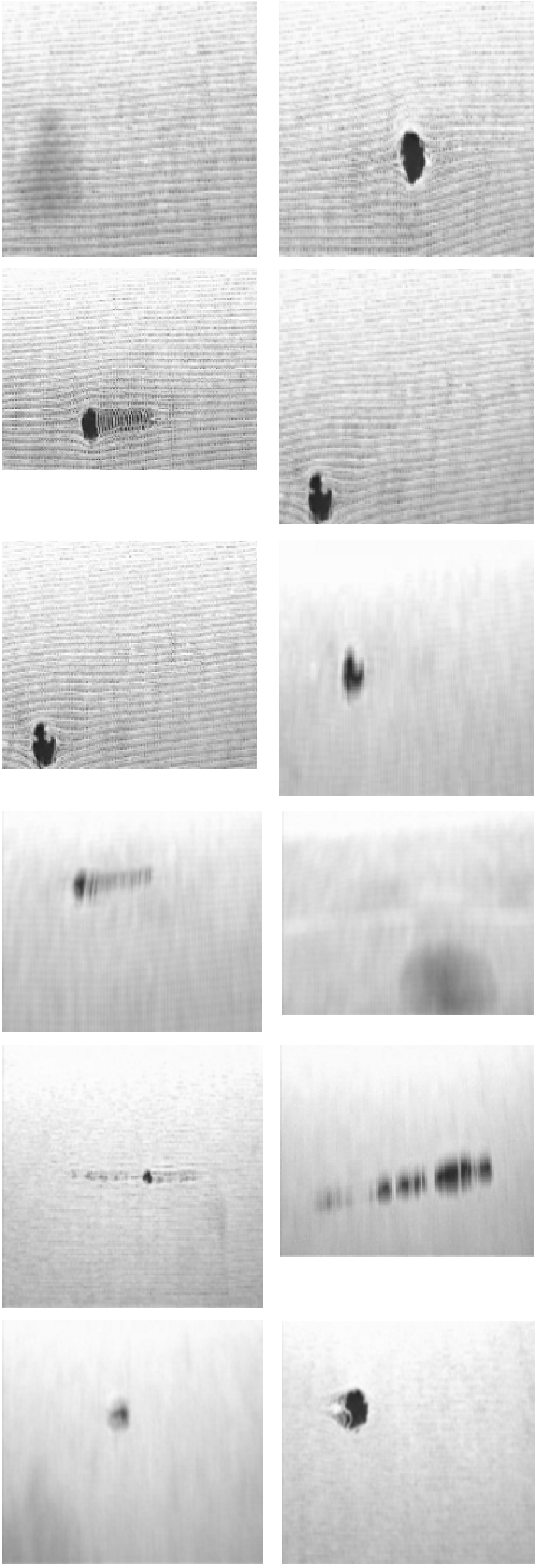


Figure 2. Flowchart of the presented defect segmentation. Scheme indicating its algorithmic modules



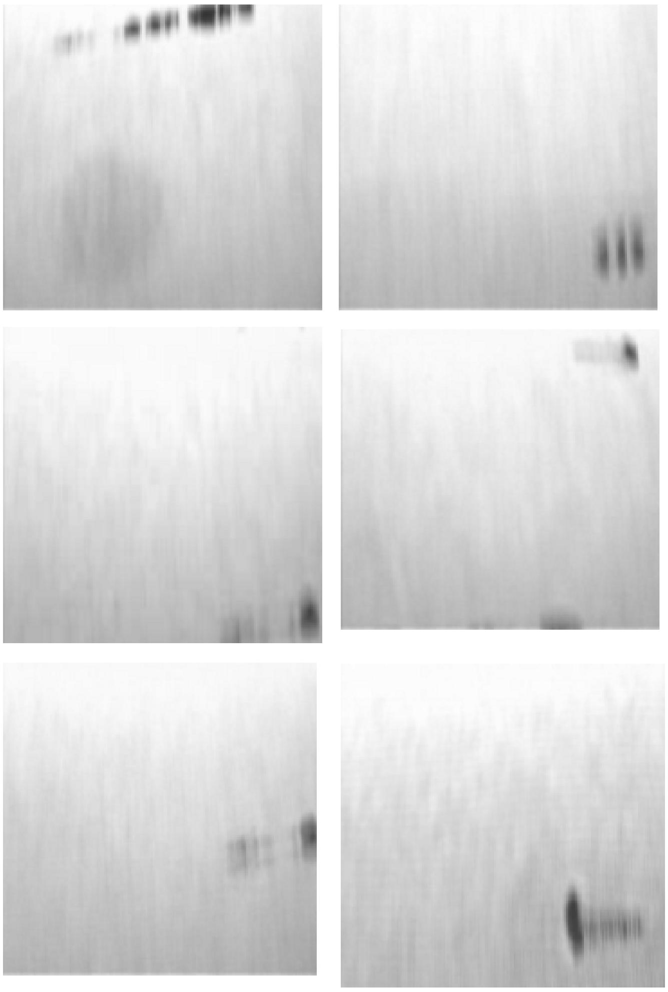


Figure 3. An image of a knitted fabric with different defects

Obtaining high-quality, high-resolution images from the fabric of an on-circular knitting machine presents several challenges. One of these is isolating the mounting components from the considerable vibration that is produced during the operation of a circular knitting machine. Another challenge is designing an inspection system whose cost-effectiveness can justify its use on many, if not all, of the circular knitting machines in the knitting mill.
As described in the following sections, each of these challenges has been addressed and met in developing our (on-circular knitting machine) image acquisition subsystem.

a) Hardware description

The image acquisition subsystem is implemented with standard components on a low-cost personal computer. These components, shown in Fig.(1), consist of an 80-elements simulated circular knitting machine, a digital camera, a source of illumination for front-lighting the fabric, an interface board, a parallel port, a personal computer (PC) and a display monitor.

These components are used to acquire high-resolution, vibration-free images of the fabric under construction and tostore them on the personal computer's memory. The software running on the interface board controls the image acquisition process, and accumulates a two-dimensional (2-

D) image suitable for the ensuing analysis (i.e., defect segmentation).

b) Image acquisition operation

During image acquisition, the camera exposure time is designed to be fixed, regardless of the simulated circular knitting machine speed. The fixed exposure time is realised by the exposure time control of the camera-encoder interface. The acquired image frame serves as an input to the image analysis or, more specifically, to the defect segmentation algorithm, which is also executed on the interface board. To maintain full coverage of the fabric, the acquisition subsystem begins capturing the next frame while the current frame is being analysed for defects. The following section presents a detailed description of the defect segmentation algorithm.

2.3. Defect segmentation algorithm

In designing the defect segmentation algorithm for our inspection system, we observed that the images of fabrics constitute ordered textures that are globally homogenous, that is, statistics measured from different patches in an image are correlated. It was further noted that images containing defects are less homogenous than those that are defect-free. Therefore, the essence of the presented segmentation algorithm is to localise those events (i.e. the defects) in the image that disrupt the global homogeneity of the background texture. We shall now describe the algorithmic modules as shown in Figure 2 that are designed to accomplish this very goal under the following conditions:

1) defects exhibit low-intensity variation within their boundary, and
2) relative to the textured background, they constitute a small portion of field of the field of view. The acquired images are transferred to the host computer and processed by the procedures in Figure 2.

An example of the application of this algorithm of a fabric image is shown in Figure 3.

In the following sections, the modules are described in detail, and their efficacy is clearly demonstrated using the images captured by the image acquisition subsystem.

d) Feature extraction system

Having pre-processed the digitised mammograms and isolated the knitting defects from their background, the next step is to extract some features which can be used to discriminate between normal (standard) and defective fabrics. These features will be used as the input to the classifier.

This chapter introduces a detailed discussion of the feature extraction stage. Two sets of features are introduced; statistical features and texture features.

i) Statistical features

The main aim of feature extraction is to find some characteristics that distinguish between normal (standard) and defective fabrics. Figure 5 shows several pairs of histograms; in each pair, the first histogram is for a normal knitted fabric and the second is for a defective one. It is obvious from the figures that there is a discriminating difference between normal histograms and defective ones. The histograms of the normal cases are unimodal, and the grey level values are centred around the mean values with small variance, while those of defective cases are bimodal or multimodal. The grey level values are spread over a wider range of values.

Statistical features are numerically descriptive measures of the histogram. Knowledge of the parameters allows us to reduce large amounts of information into a summary form that is easy to interpret. These parameters describe the states of nature in decision problem [26]. Therefore, statistical features such as mean, standard deviation, variance, coefficient of variation, moment, skewness and kurtosis are used to characterise the histograms and to distinguish between normal and defective fabrics. The mathematical definitions of these features are:

$$f1 = Mean = \mu = \frac{1}{N}\sum_{i=1}^{N} x_i \text{.............}(1)$$

$$f2 = \text{Standard Deviation} = \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \text{.............}(2)$$

$$f3 = Variance = \sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2 \text{.............}(3)$$

$$f4 = Coefficient\ of\ Variation = C.V = (\mu/\sigma)x100 \text{...........}(4)$$

$$f5 = Moment = E(x-\mu)^k \text{.............}(5)$$

$$f6 = Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^3 \text{.............}(6)$$

$$f7 = Kurtosis = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4 \text{.............}(7)$$

ii) Texture features

We can use boundary information to describe a region, and shape can be described from the region itself. A large group of shape description techniques is represented by heuristic approaches which yield acceptable results in describing simple shapes. Region area, rectangularity, elongation, direction, compactness, etc. are examples of these methods. Unfortunately, they cannot be used for region reconstruction, and do not work for more complex shapes.

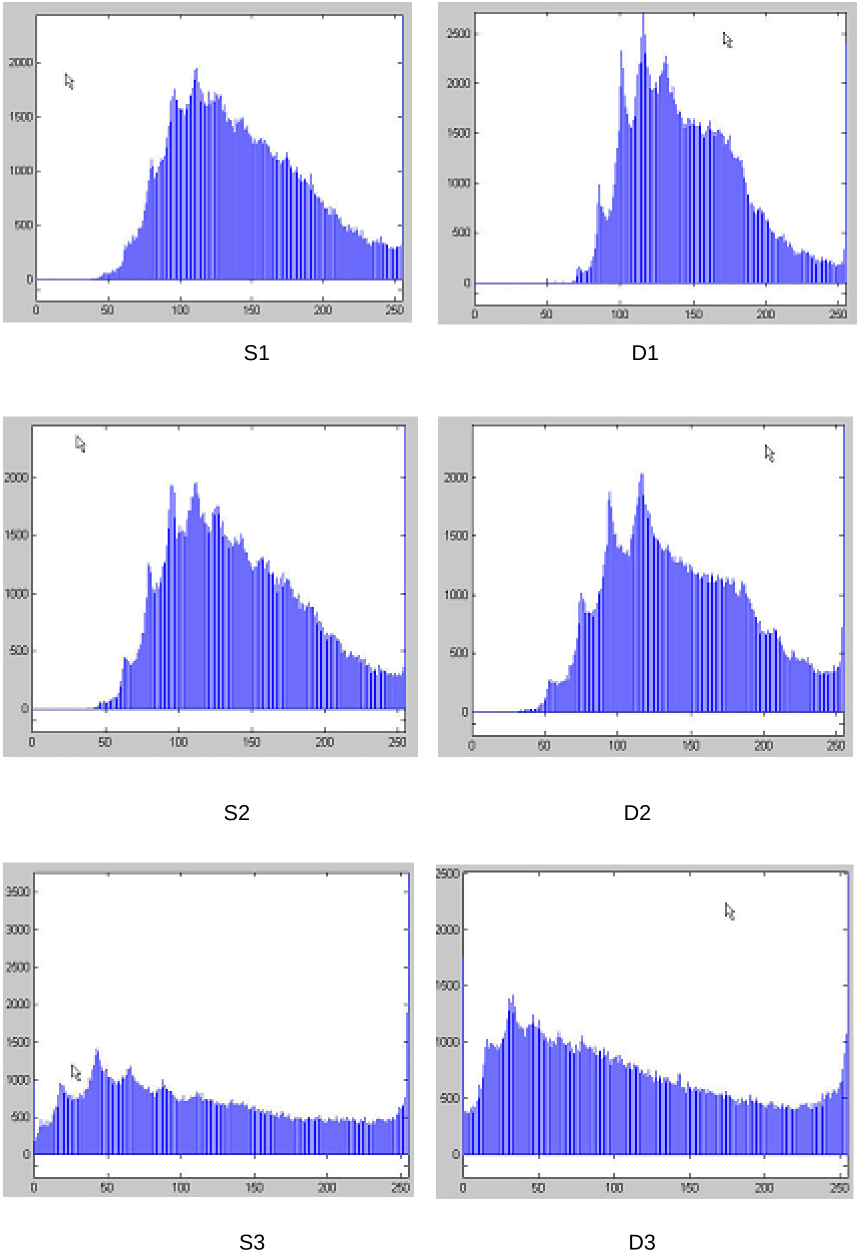


Figure 5. Histograms for standard (S) and defective (D) knitted fabrics

3. Results

The performance of the described inspection system was evaluated in seven stages using the simulated circular knitting machine. In the first stage, the camera-carrier was moved in a reciprocating motion along the height of the simulated cylinder of the circular knitting machine with a slow speed (10 mm/minute). At the same time, the simulated cylinder was rotated at the speed of 15 rpm as an operator introduced defects into the knitting process. The second stage of testing involved isolating the mounting components from the considerable vibration produced during the circular knitting machine's operation. The third stage is defect acquisition, and its rapid analysis at a rate of 10 images per second with a high-quality image analyser. The fourth stage is the identification of defect type. The fifth is stopping the simulated circular knitting machine at once as soon as the defect is acquired by the camera. The sixth stage is displaying the defect name, its image, causes and remedial method on the monitor of the computer to help the operator. The seventh stage is designing an inspection system whose cost-effectiveness can justify its use on many, if not all, of the circular knitting machines in a knitting mill. The four defect types for both plain single jersey and rib structures included almost all of the most commonly occurring knitting defects, such as needle line, dropped stitch, hole and oil spots. The image acquisition subsystem consistently produced high-quality images of the knitted fabric for both plain single jersey and rib structures. The image resolution was set at 320 pixels / 6.5 cm (125 pixels/inch). The higher resolution was necessary because the impurities that are naturally present in the knitted-yarn fabric tend to obscure the subtler defects.

Note that with a nominal circular knitting machine speed of 15 rpm and a maximum (125 pixels/inch) of 320 pixels/6.5 cm, the exposure time of the digital camera is less than the shortest time between forward motion pulses (0.25 sec), and is therefore sufficient to stop the motion of the machine. During the analysis of these images, the acquisition subsystem was directed to capture the next 320×240 image frame, so that 100 % coverage of the knitted fabric was maintained. When analysing more than 2000 images for both fabric types, the overall defection rate of the presented approach was found to be 92%, with a localisation accuracy of 3 mm and a false alarm rate of 2.5%. The false alarm rate was computed as the total number of false detections divided by the total number of processed images. Note that the detection rate of 92% represents the average over all defect types. In general, because we are dealing with an edge-based segmentation approach, defects that produce very subtle intensity transitions (e.g. mixed yarns and barre) were detected at a lower rate (i.e. 50-60%). On the other hand, for the most commonly occurring and most serious defects, such as needle line, dropped stitch, holes and oil spots, the defection rate was 92%. Because the camera sometimes captures part of the defect but not all, the defect can therefore be classified with another type; for example a dropped stitch defect can be shown as a hole. Matlab has been chosen as the programming language in which to develop the software for the purpose of this research. The intention is to use a back propagation network for the processing. Table 1 shows nominal values for the statistical features, for 30 normal and 30 defective cases for single jersey, using the radon transform.

Table 1. Nominal value for the extracted features of both standard (s) and defective fabrics (d) for single jersey using radon transform

Sample No.	Average	Standard deviation	Variance	Skewness	Kurtosis	Moment	CV
1	218.24	26.43	698.78	-0.8	4	-14778	8.26
2	213.29	28.08	788.6	-0.8	4.24	-17719.7	7.6
3	215.77	26.46	699.98	-1.59	10.13	-29441.8	8.16
4	217.24	24	575.95	-0.75	4.94	-10366.5	9.05
5	210.57	34.86	1214.98	-1.65	6.77	-70022.9	6.04
6	208.55	32.56	1059.89	-1.25	6.18	-43289.5	6.41
7	214.46	25.18	633.92	-0.43	2.52	-6856.46	8.52
8	215.53	24.51	600.78	-0.52	3.5	-7589.85	8.79
9	206.4	30.29	917.37	-1.02	5.9	-28360.6	6.81
10	212.57	27.25	742.53	-1.22	7.69	-24632.6	7.8
11	214.87	29.22	853.86	-1.16	5.96	-28983.3	7.35
12	217.39	23.13	534.85	-0.34	2.61	-4197.85	9.4
13	209.45	33.15	1098.65	-1.27	5.61	-46421.6	6.32
14	216.28	24.21	586.34	-0.71	5.31	-10139.7	8.93
15	210.93	35.24	1241.87	-1.78	7.21	-78093.5	5.99
16	216.62	23.02	529.9	-0.29	2.6	-3542.84	9.41
17	219.73	21.32	454.75	-0.61	4.58	-5910.13	10.3
18	207.08	24.86	617.98	-1.06	6.34	-16344.7	8.33
19	215.09	28.67	822.11	-1.62	9.69	-38259.1	7.5
20	213.61	28.84	831.79	-1.37	7.34	-32974.2	7.41

Table 2 shows nominal values for the statistical features, for 24 normal cases and 24 defective ones for rib structure, using the radon transform.

Table 2. Nominal value for the extracted features of both standard (s) and defective fabrics (d) for rib structure using radon transform

Sample No.	Average	Standard deviation	Variance	Skewness	Kurtosis	Moment	CV
1	211.23	32.52	1057.58	-1.43	8.49	-49295.7	6.5
2	210.3	34.29	1175.97	-1.36	7.47	-54685.5	6.13
3	214.64	23.88	570.37	-0.98	7.2	-13338.1	8.99
4	208.67	31.72	1005.87	-1.34	8.43	-42618.9	6.58
5	213.47	26.4	696.98	-1.71	11.13	-31389.1	8.09
6	212.3	31.86	1014.8	-1.59	9.16	-51424.4	6.66
7	208.71	31.72	1006.12	-1.72	9.87	-54729.8	6.58
8	211.55	35.28	1244.76	-1.88	9.34	-82479	6
9	213.34	26.17	684.97	-0.32	2.73	-5806.94	8.15
10	212.98	25.42	646.36	-2.28	14.82	-37470.9	8.38
11	212.97	30.59	935.9	-1.4	7.48	-40033.1	6.96
12	215.41	27.96	781.51	-1.48	8.29	-32275.6	7.71
13	210.38	29.6	876.28	-1.19	7.06	-30826.4	7.11
14	216.27	21.84	476.79	-0.47	4	-4940.44	9.9
15	212.79	25.46	648.11	-1.18	8.64	-19469.4	8.36
16	208.58	31.48	991.08	-1.06	6.14	-33135.2	6.63
17	211.46	24.15	583.09	-0.23	2.63	-3186.7	8.76
18	210.55	26.3	691.92	-0.35	2.78	-6425.52	8
19	209.01	25.75	663.01	-1.75	11.21	-29842.7	8.12
20	210.62	21.88	478.81	-1.91	13.24	-19981.6	9.63

A number of simple heuristic shape descriptors (texture features) for single jersey exist in Table 3.

Table 3. Heuristic shape descriptors (texture features) for single jersey

Sample No.	Area	Major Axis Length	Minor Axis Length	Eccentricity	Direction	Filled Area	Elongation
1	2.43	24.91	13.44	0.84	89.77	2.43	1.93
2	1.06	15.46	9.25	0.8	5.04	1.06	0.6
3	0.12	4.62	3.46	0.66	90	0.12	1.33
4	1.03	13.46	10.85	0.59	81.34	1.03	1.36
5	2.25	25.02	11.76	0.88	3.31	2.25	0.48
6	0.91	14.01	8.37	0.8	100.29	0.91	1.63
7	0.07	4.31	2.23	0.86	98.35	0.07	2
8	1.32	14.97	11.72	0.62	24.29	1.32	0.86
9	3.31	26.49	16.11	0.79	1.15	3.31	0.62
10	0.2	6.83	4.27	0.78	75.91	0.2	1.75
11	1.97	20.47	12.92	0.78	84.79	1.97	1.54
12	2.02	16.89	16.06	0.31	114.64	2.02	1
13	1.3	13.76	12.28	0.45	12.9	1.3	1
14	1.18	18.02	8.99	0.87	17.27	1.18	0.63
15	1.29	15.54	10.84	0.72	96.78	1.29	1.36
16	0.7	12.02	7.85	0.76	7.9	0.7	0.67
17	1.48	16.52	11.92	0.69	103.8	1.48	1.33
18	0.64	11.34	7.5	0.75	5.85	0.64	0.58
19	0.36	7.53	6.38	0.53	121.14	0.36	1

A number of simple heuristic shape descriptors (texture features) for rib structure exist in Table 4.

Table 4. Heuristic shape descriptors (texture features) for rib structure

Sample No.	Area	Major Axis Length	Minor Axis Length	Eccentricity	Direction	Filled Area	Elongation
1	0.79	16.92	6.25	0.93	99.23	0.81	2.29
2	2.58	24.67	13.59	0.83	98.1	2.6	1.79
3	2.46	23.47	13.67	0.81	95.76	2.48	1.71
4	0.6	14.47	5.67	0.92	95.17	0.62	2.14
5	2.69	25.42	13.8	0.84	93.46	2.71	1.93
6	1.52	25.84	7.7	0.95	96.17	1.54	3.25
7	1.48	16.72	11.63	0.72	92.94	1.5	1.42
8	1.29	22.83	7.34	0.95	94.35	1.31	3.14
9	1.47	15.37	13.01	0.53	-6.5	1.49	0.8
10	2.91	27.39	13.88	0.86	88.8	2.93	2.07
11	1.32	15.63	11.02	0.71	82.39	1.34	1.45
12	1.1	16.16	8.79	0.84	102.3	1.12	1.67
13	2.31	20.03	16.66	0.56	25.18	2.33	1.05
14	1	14.98	8.75	0.81	104.99	1.02	1.67
15	1.22	16.2	9.84	0.79	123.79	1.24	1.25
16	2.01	19.38	14.89	0.64	22.45	2.03	1
17	1.35	15.14	11.9	0.62	89.88	1.37	1.38
18	3.22	22.53	19.86	0.47	55.16	3.24	1.2
19	1.82	17.79	13.52	0.65	87.85	1.84	1.43

Figures 8 & 9 and Tables 5 & 6 show the training pattern of the used network using 60 normal and 48 defected samples for both single jersey and rib structures.

Table 5. Classification results for the training patterns for single jersey

Sample No.	Network Output						Average	Desired	Error	NET Classification	Human Classification
	O1	O2	O3	O4	O5	O6					
1	-0.01	-4.99	-2.02	0.21	4.27	-3.93	-1.08	0.00	1.08	Hole	Hole
2	37.28	37.24	46.14	43.02	37.60	46.49	41.29	40.00	1.29	Needle Line	Needle Line
3	61.77	61.21	59.66	61.07	61.55	61.08	61.06	0.00	61.06	Oil Spot	Hole
4	62.21	58.80	60.00	58.09	58.58	60.10	59.63	60.00	0.37	Oil Spot	Oil Spot
5	45.40	39.65	43.15	43.08	42.47	43.62	42.89	40.00	2.89	Needle Line	Needle Line
6	24.37	23.59	23.93	21.05	17.81	18.39	21.52	20.00	1.52	Droped Stitch	Droped Stitch
7	1.93	3.17	1.52	-0.74	1.58	3.92	1.90	0.00	1.90	Hole	Hole
8	41.38	36.67	41.09	35.73	44.98	37.50	39.56	40.00	0.44	Needle Line	Needle Line
9	61.61	58.05	59.23	62.60	62.48	61.30	60.88	60.00	0.88	Oil Spot	Oil Spot
10	18.80	24.71	18.67	19.52	17.13	19.49	19.72	20.00	0.28	Droped Stitch	Droped Stitch
11	37.91	46.09	35.93	46.89	45.45	36.88	41.53	40.00	1.53	Needle Line	Needle Line
12	62.23	61.93	60.46	59.41	61.65	61.93	61.27	60.00	1.27	Oil Spot	Oil Spot
13	60.32	58.80	58.56	60.13	62.85	59.23	59.98	60.00	0.02	Oil Spot	Oil Spot
14	0.26	3.76	1.48	-4.65	-0.85	-0.13	-0.02	0.00	0.02	Hole	Hole
15	-1.45	2.68	-2.74	4.13	-4.19	-4.52	-1.02	60.00	61.02	Hole	Oil Spot
16	59.72	59.62	59.72	58.87	59.01	58.42	59.23	60.00	0.77	Oil Spot	Oil Spot
17	21.82	20.92	21.35	17.33	19.02	19.88	20.05	20.00	0.05	Droped Stitch	Droped Stitch
18	60.74	59.54	60.58	59.38	59.70	60.41	60.06	60.00	0.06	Oil Spot	Oil Spot
19	1.42	-4.16	2.00	-2.52	-3.02	-3.43	-1.62	0.00	1.62	Hole	Hole

Table 6. Classification results for the training patterns for rib structure

Sample No.	Network Output						Average	Desired	Error	NET Classification	Human Classification
	O1	O2	O3	O4	O5	O6					
1	4.13	0.29	1.76	4.67	-0.09	-4.04	1.12	0.00	1.12	Hole	Hole
2	19.09	18.13	19.97	20.87	19.44	18.35	19.31	20.00	0.69	Droped Stitch	Droped Stitch
3	3.03	-2.05	4.61	2.31	3.11	0.12	1.85	60.00	58.15	Hole	Oil Spot
4	20.40	19.16	22.99	22.90	19.48	21.34	21.05	20.00	1.05	Droped Stitch	Droped Stitch
5	61.52	58.21	58.47	60.77	59.25	59.86	59.68	60.00	0.32	Oil Spot	Oil Spot
6	3.34	3.98	4.16	0.00	-4.11	2.04	1.57	0.00	1.57	Hole	Hole
7	21.84	18.28	22.13	19.48	21.27	22.57	20.93	20.00	0.93	Droped Stitch	Droped Stitch
8	61.94	61.43	58.57	61.17	60.70	62.96	61.13	60.00	1.13	Oil Spot	Oil Spot
9	18.99	18.86	21.64	19.20	21.44	19.55	19.95	40.00	20.05	Droped Stitch	Needle Line
10	20.21	18.05	19.83	21.47	20.49	19.77	19.97	20.00	0.03	Droped Stitch	Droped Stitch
11	4.82	-0.41	2.60	1.27	1.94	1.86	2.01	0.00	2.01	Hole	Hole
12	-0.30	0.94	-4.74	1.12	-2.26	-1.41	-1.11	0.00	1.11	Hole	Hole
13	61.71	62.14	60.48	59.99	62.01	58.28	60.77	60.00	0.77	Oil Spot	Oil Spot
14	22.20	19.02	20.19	19.57	20.27	20.24	20.25	20.00	0.25	Droped Stitch	Droped Stitch
15	58.13	60.81	62.67	58.33	62.58	58.42	60.16	60.00	0.16	Oil Spot	Oil Spot
16	22.50	22.41	20.76	18.52	21.40	22.11	21.29	20.00	1.29	Droped Stitch	Droped Stitch
17	1.71	4.06	2.09	-1.89	3.14	2.62	1.96	0.00	1.96	Hole	Hole
18	41.69	41.63	40.19	40.12	36.66	37.87	39.69	40.00	0.31	Needle Line	Needle Line
19	1.79	-3.58	-3.03	2.57	3.03	2.06	0.47	0.00	0.47	Hole	Hole

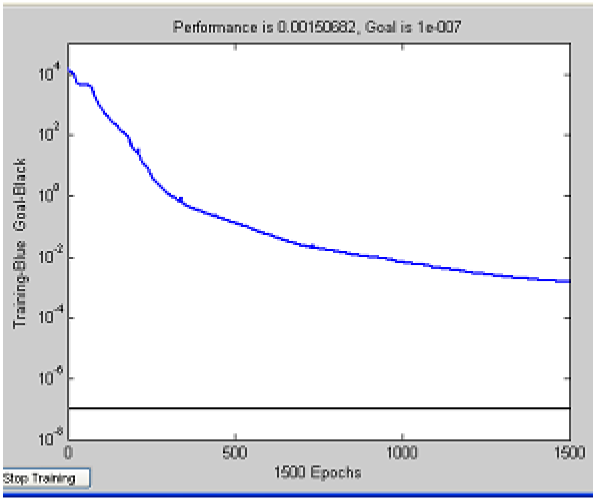


Figure 8. RMS error versus learning count of the used network for single jersey

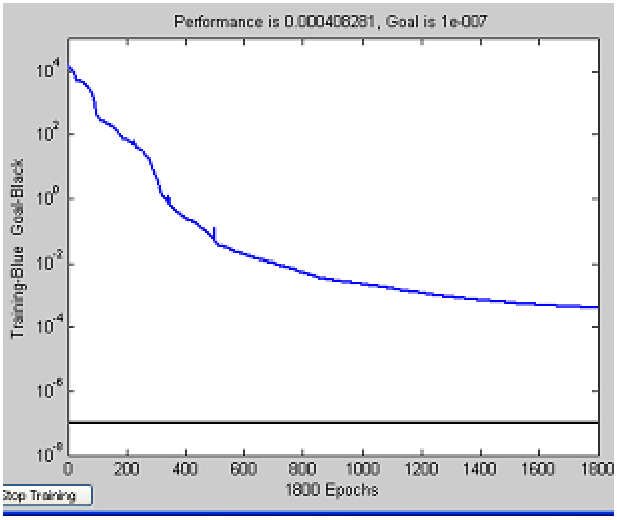


Figure 9. RMS error versus learning count of the used network for rib structure

4. Conclusion

We have described a computer vision-aided fabric inspection system to detect and classify circular knitted fabric defects using common different texture recognition methods, including thresholding analysis. radon transform, a discrete Fourier transform and neural network. It was found that the application of the discrete Fourier transform method in this work is highly promising for the identification of knitted fabric defects; with an overall success rate of 92%, it has the highest efficiency value of all the methods tested.

The results gained from these experiments show that discrete Fourier transforms act precisely and rapidly for defecting faults and specifying their area, as well as being useful as an on-line detection tool in knitting machines during the production of knitted fabrics. Finally, the usage of such a process can eliminate a further stage of human inspection. In addition, the circular knitting machine can be controlled and stopped at once, as soon as the defect is captured by the camera.

We have described a vision-based fabric inspection system that accomplishes on-circular knitting machine inspection of the knitted fabric with 100% coverage. The inspection system is scalable, and can be manufactured at relatively low cost using off-the-shelf components. This system differs from those reported in the literature in two crucial ways. First, it concerns an on-circular knitting machine; and second, it is equipped with a novel defect segmentation technique, which has been thoroughly tested under realistic conditions and was found to have a high detection rate & accuracy, and a low rate of false alarms. The fabric inspection system texture was described in terms of its image acquisition subsystem and its defect segmentation algorithm. The image acquisition subsystem is used to capture high-resolution, vibration-free images of the knitted fabric under construction. The essence of the presented segmentation algorithm is the localisation of those defects in the input images that disrupt the global homogeneity of the background texture. Novel texture features are utilised to measure the global homogeneity of the output images. A prototype system was used to acquire and to analyse more than 2000 images of fabrics that were constructed with two different types of knitted structure. In each case, the performance of the system was evaluated as an operator introduced defects from 14 categories into the knitting process. The overall defection rate of the presented approach was found to be 92%, with a localisation accuracy of 3 mm and a false alarm rate of 2.5%.

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