

Machine vision tool for real-time defect detection and classification on circular knitting machines by using statistical parameters and Radon Transform

ROCCO FURFERI

LAPO GOVERNI

Department of Mechanics and Industrial Technology

University of Florence

Via di Santa Marta, 3 50139 - Florence

ITALY

Abstract: - This work presents a new highly automated artificial vision inspection (AVI) tool for real-time defect detection and classification on circular knitting machines based on the combination of statistical analysis, Image Processing and Radon Transform. The tool (software + hardware) is directly attached to a circular knitting machine and the inspection is performed on-line. The automatic inspection allows the detection and classification of the most frequently occurring types of defects on knitted fabrics, which are significant for purposes of quality control and fabric grading. The reliability of the detection tool is about 93% (defect detected vs. effectively existing defects).

Key-Words: - real time, image processing, knitting machines, skewness, kurtosis, radon transform.

1 Introduction

In the last three decades automated visual inspection of industrial goods for quality control shows an ever-increasing role in production process as the market exhibits higher demand for quality [1]. In most cases, quality inspection by visual inspection is still carried out by specially trained workers. However, the reliability of manual inspection is limited by ensuing fatigue and inattentiveness [2, 3]. In textile industry the most highly trained inspectors can only detect about 85% of the defects. Therefore, the automation of visual inspection process is required to maintain high quality of products at high-speed production. Numerous approaches have been proposed in scientific literature; for instance, in the approach proposed by Ajay Kumar [4], the segmentation of local textile defects using feed-forward ANN is provided; Campbell et al. [5] have performed fabric defect detection using model based clustering. Fourier transform based techniques are successfully used for defects that cause a global change of fabric texture [6]. Moreover texture features based on multi-scale wavelet decomposition [7] have been used. Some industrial systems has been also developed, like the BarcoVision's Cyclops the Elbit Vision System's I-Text and Zellweger Uster's Fabriscan. However these monitoring systems involve the use of appositely developed additional

machinery so that the defect detection (or classification) process is performed off-line (not along the normal production line). Furthermore textile surfaces are highly variable, but commercially available systems require a long lasting training process on the same kind of fabric which is not always a feasible solution.

2 Objectives

This work presents a new, real-time, highly automated tool for defect detection and classification based on the combination of statistical and Image Processing approach. The tool (software + hardware) is directly attached to a circular knitting machine and the inspection is performed on-line. The specific goals of this investigation are to develop an efficient non intrusive, on-line defect detection and to perform an automatic defect classifier. These are achieved by creating a machine-vision system able to perform real time acquisition, image processing and Radon-based feature extraction and classification. The automatic inspection allows the detection and classification of the most frequently occurring types of defects on knitted fabrics, which are significant for purposes of quality control and fabric grading (see § 3.1). The knitted fabric is wrapped on a cylinder rotating with a tangential speed of 15 m/min. Each knitted

fabric unit has a 900 mm length and a 1000 mm of circumferential development i.e. a diameter of approximately 318.5 mm. In Fig. 1 is also represented the reference system of the linear camera. The classification and detection error must be, at least, comparable to that one of operating experts who inspect the knitted fabric (90% of the defects with sliding to low speed visually, that is 5-6 m/min).

Accordingly the developed tool is required to:

- Detect and classify the defect of knitted fabric in "real-time" (maximum 60s).
- Be attached to a machine performing other operations like laser cut and ironing (the defect detection is a stage of the entire operations performed by the machine).



Fig.1: knitted fabric wrapped on the horizontal rotating cylinder
 - Provide a classification and detection error less than 10%. The detection error is evaluated with equation (1):

$$\eta = \frac{N_{dd}}{N_d} \quad (1)$$

where: N_{dd} is the number of detected defects and N_d is the total number of defects on the knitted fabric.

3 Development of the classification and detection tool

The work presented in this paper was carried out by the following basic tasks (Fig.2):

1. Laboratory defect classification and image acquisition
2. Image pre-processing.
3. Dark and light area or point defects detection.
4. Dark and light horizontal and vertical defects detection (localized and diffused).

3.1 Laboratory defect classification and image acquisition

In order to develop the defect detection and classification tool we used a set of 12 knitted fabric 4 of which without defects and 8 of which with different kinds of defects. Before describing the

devised AVI system it is suitable to bring back the typical typologies of defects that could be found on a knitted fabric.

The kind of defects analyzed for developing the present work are the followings:

- dark and light area or point defects (stains, flecks, and naps, lacerated regions and holes); these defects are caused, for instance, by contamination with substances like for instance powder, oil or rust. The defect, therefore, is considered recoverable only if the spots are localized in one limited portion of the knitted fabric. In Fig.3 the image of a knitted fabric affected by dark area defects is shown.
- dark and light localized horizontal and vertical defects (filling, double filling, weft thread, double warp thread); these are defects mainly caused by an imperfect control of the knitting operations or by variations of the diameter of the thread. The defect is recoverable if the horizontal and vertical defects are localized. In Fig. 4 an example of knitted fabric affected by a double warp thread defect is shown.
- dark and light diffused horizontal defects (diffused filling, diffused weft thread). Similar to the localized horizontal and vertical defects these are characterized by a diffusion in all the knitted fabric. So these defects are unrecoverable (Fig. 5)

In order to develop a reliable detection and classification tool, we have devised an experimental system consisting of a workbench provided with an horizontal rotating cylinder rotating with a speed varying in the range 2-20 m/min and connected to an encoder in order to send to a PC instantaneous information on the angular velocity of the cylinder (Fig.6). The encoder synchronizes the line-rate acquisition with the rotational speed of the roller. With a test speed of 15m/min, the entire circumferential distance is acquired in 4 s. With a line-rate of the camera set to 2500 lines per second, the knitted fabric is acquired as a rectangular image with resolution of 6.144x10.000 pixel. The dimension of a CCD cell is $h'=7\mu m$ those carrying out a spatial resolution $h = 0.1$ mm/pixel with a focus length $f'=43mm$ and acquiring the fabric with a distance $D = 614.3mm$, as stated in the equation (2):

$$\frac{h'}{h} = \frac{f'}{D} \quad (2)$$

The spatial resolution is 5 times lower than the minimum dimension of the defects on the knitted fabric (the maximum dimension of a dark or light spot area is about 5 mm). The camera is connected

to a PC with a frame grabber Meteor-II/Camera Link.

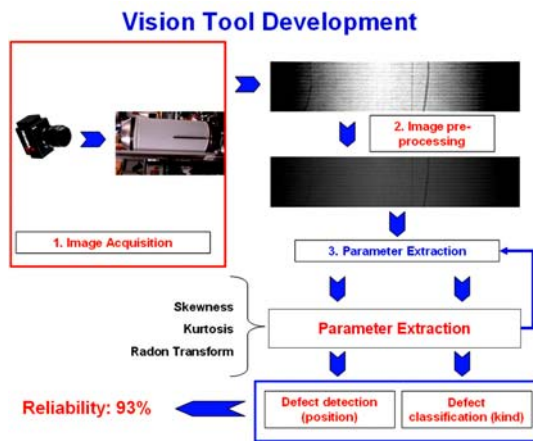


Fig.2: tasks for the vision tool development.



Fig.3 (left): an example of a knitted fabric affected by dark area defects.

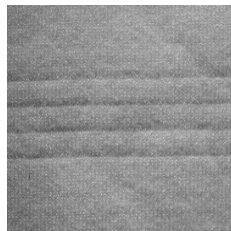


Fig.4 (right): an example of a knitted fabric affected by a double warp thread defect.



Fig.5: an example of a knitted fabric affected by a diffuse weft thread defect.

In order to reduce the computational load for the following image processing, the entire image of the knitted fabric is split in 10 sub-images with a resolution of 6144 x 1000 pixel. The light system is composed by an high frequency neon (30 kHz) able to properly illuminate the entire length of the knitted fabric. The correction of the image brightness is performed by adding to each pixel (along the Y axis in Fig.1) the distance (in grey level) between the actual brightness value of the pixel itself and the quadratic curve approximating the mean brightness of the image.

3.2 Image pre-processing

The light system described below allows an homogeneous illumination of the knitted fabric only in the central part of the fabric itself. The left and right sides of the fabric are characterized by darkest

light areas. The mean brightness of every acquired image is similar to the one showed in Fig. 7; the brightness is high in the centre of the image and low in the left and right sides, with a difference of about 20 grey level, so the image illumination has to be corrected.

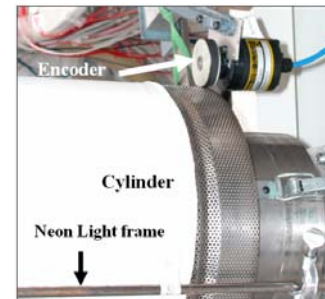


Fig.6: rotating cylinder with encoder and neon light frame.

Accordingly by this operation the image mean brightness is scaled and becomes quite linear, preserving all information (the image does not saturate).

3.3 Dark and light area or point defects detection

Dark and light area (or point) defects are represented, in the acquired images, as areas characterized by a darker or lighter brightness with respect to the background of the image. However the environmental light conditions and the surface characteristics of the knitted fabric, even if the brightness has been corrected by software, affect the detection of the defects i.e. in some regions of the fabric the background have a brightness similar to the background. Moreover the detection algorithm has to work in different environmental light condition so it is not possible to use neither a Global Thresholding Method (GTM) or Local Thresholding Method (LTM) [8], neither an Otsu method [9] or a Maximum Entropy criteria [8] for thresholding the image. These methods allow the detection of a defect on a knitted fabric when the defect is present in it; unfortunately when the fabric is without defects the mentioned thresholding methods detect the weft and the warp of the fabric as a defect. In order to overcome these problems, in this work we decided to perform an image binarization (thresholding) by using an analogy between rough surfaces and the bi-dimensional brightness function. This analogy, showed in Fig. 9, allows the definition of some statistical parameters usually defined for analyzing rough surfaces: the skewness (Sk) and the kurtosis (Ku).

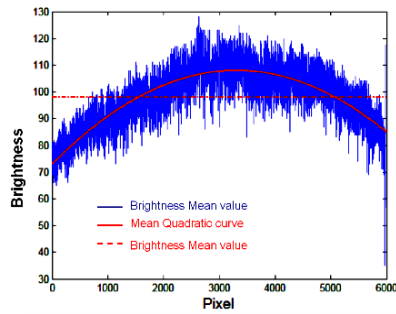


Fig. 7 mean brightness of an acquired image of the knitted fabric.

Skewness is a measure of the degree of asymmetry of a distribution. If the left tail (tail at small end of the distribution) is more pronounced than the right tail (tail at the large end of the distribution), the function is said to have negative skewness. If the reverse is true, it has positive skewness. If the two are equal, it has zero skewness.

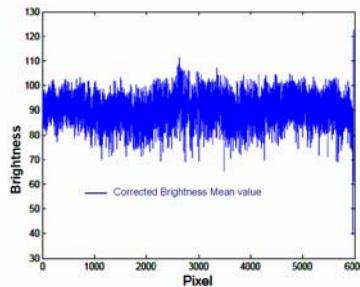


Fig. 8 corrected mean brightness of an acquired image of the knitted fabric.

Kurtosis is the degree of pitch of a distribution, defined as a normalized form of the fourth central moment of a distribution [10]. Accordingly, being an image described by a matrix I of grey levels (or brightness values) in the range 0-255, it is possible to evaluate the skewness and the kurtosis for each row and column of I (i.e. through directions x and y). In Figure 10 the values for Sk and Ku referred to a dark area defected fabric, along x and y axes are showed. The punctual value of both the curves Sk and Ku , in proximity of the dark area defect, is considerably turned out regarding the mean value. This condition allows the detection of a dark area defect as the zone (in cartesian coordinates) where both the Sk and the Ku curve present a peak (i.e. it is significantly different from the mean value of the curve itself). Moreover the Ku curve has a stronger peak for a spot defect rather than the area defect. A method to determine if a peak of one of the two curves previously mentioned is a defect or not, consists in deciding a threshold value. For example, the peaks marked with a circle in Figure 10 (for both the Sk and the Ku curves) do not correspond to a real defect of the knitted fabric even if the Skewness value is greater than the mean value of

the curve; therefore the threshold value must be properly chosen in order to detect as a defect only the one corresponding to peaks considerably greater to the mean value of the Sk curve. By using experimental values $Sk = \pm 1.5$ and $Ku = 6$ it is possible to detect correctly the 83% of the dark and light areas affecting the knitted fabric. However the experimental selection of numerical values for thresholding Sk and Ku curves leads to an unreliable defect detection in case of an environmental variation of light conditions (these leading to increase or decrease of mean brightness level of the acquired image). In order to improve the reliability of the classification tool it is possible to normalize the two curves in the range [0-1] and to perform the following considerations.

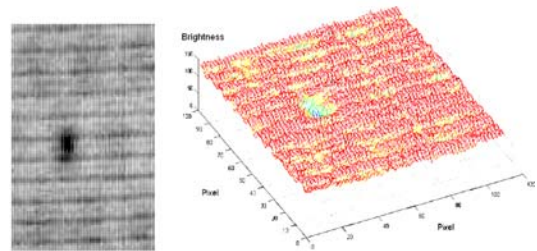


Fig. 9 bi-dimensional brightness function for a dark area defected fabric.

So let:

- I be the image of a knitted fabric;
- $Sk_x(I)$ and $Sk_y(I)$ be the normalized Skewness along x and y axes respectively;
- $Ku_x(I)$ and $Ku_y(I)$ be the normalized Skewness along x and y axes respectively.

Accordingly only two cases are possible:

1. The knitted fabric is affected by a dark or light area or spot defect: in this case the defect is detected in correspondence of the coordinates x and y where the $Sk_x(I)$, $Sk_y(I)$, $Ku_x(I)$ and $Ku_y(I)$ curves have a value 0 (dark area defect) or 1 (light area defect).
2. The knitted fabric is not affected by a dark or light area or point defect: in this case the $Sk_x(I)$, $Sk_y(I)$, $Ku_x(I)$ and $Ku_y(I)$ curves assume a value that oscillates around to the normalised mean value (0.5).

In Figure 11 the $Sk_x(I)$ curves for a defected knitted fabric (left image) and for a non defected one (right image) are shown. To select one of the previously stated possible cases and referring for instance only to the Skewness curves, it is useful to define the "Total Skewness Value through X ($TSWX$) and Y ($TSWY$) directions" as follows:

$$TSWX = Sk(Sk_x(I)) \quad (3)$$

$$TSWY = Sk(Sk_y(I)) \quad (4)$$

In case of a knitted fabric affected by a dark or light area defect, the $TSWX$ and the $TSWY$ values are approximately zero this corresponding to an oscillating distribution close to the mean value (for a distribution of infinitesimal accidental numbers would have exactly null value). In the case of presence of one or more dark (or light) area (or spots) the $TSWX$ and the $TSWY$ values assumes values strongly different from zero, positive or negative depending on the dark or light defect presence, this indicating the occurrence of one or more peaks in the distribution. In Figure 11 the $TSWX$ value for the two $Sk_x(I)$ curves relating a defected knitted fabric (left image) and a non defected one (right image) are shown. The value $TSWX = -2.77$ is due to the presence, on the left curve, of the peak in the distribution i.e. of a dark area defect. The position of the defect is detected as the area where the Skewness curve has the peak. The value $TSWX = 0.05$ is related to the right curve where the distribution has not any considerable peak.

Generalizing, the developed algorithm is able to detect:

- a dark area or point defect when the following relationships are satisfied:

$$\begin{cases} TSWX \leq -1 \\ TSWY \leq -1 \end{cases} \quad (5)$$

- a light area or point defect when the following relationships are satisfied:

$$\begin{cases} TSWX \geq 1 \\ TSWY \geq 1 \end{cases} \quad (6)$$

The knitted fabric is not affected by a dark or light area or point defect wherever the following relations are satisfied:

$$\begin{cases} -1 < TSWX < 1 \\ -1 < TSWY < 1 \end{cases} \quad (7)$$

Once detected, the defect can be classified on the basis of the Kurtosis values. By experimental observations it can be stated that if $Ku_x(I)$ and $Ku_y(I)$ curves have a peak greater than 10 the defect may be assimilated to a point defect while if $Ku_x(I)$ and $Ku_y(I)$ curves have a peak smaller than 10 the defect may be assimilated to a point defect. The reliability of the algorithm, according to equation (1) is 94%.

3.4 Dark and light horizontal and vertical defects detection

The Dark and light defects are represented in an acquired image as lines with an inclination in the range $[0^\circ \pm 5^\circ]$ in case of vertical defects and $[90^\circ \pm 5^\circ]$ in case of horizontal ones. The angle is measured with respect to a reference system $X'-Y'$ centred in the centre pixel of the image (Fig.12). These defects are detected by means of a bi-dimensional Radon Transform. Let M be an image of a fabric affected by an horizontal defect; as widely known the Radon Transform allows the evaluation of a matrix $R(\theta, X')$ where each column represents the integral line of the image, projected along the line with inclination θ . In Fig. 12 the image of a knitted fabric with horizontal defect and its Radon Transform are showed; higher frequencies are probably due to the presence of a vertical or horizontal defect. In order to decide if this high frequency on the $R(\theta, X')$ image correspond to a defect (and it is not due to acquisition noise or to the weft and warp of the knitted fabric), it is possible to develop a method similar to the one devised for detecting the dark and light area or point defects.

The method consists in:

i. Evaluating the $R(\theta, X')$ image along the directions $\theta_0 = 90^\circ \pm 5^\circ$ and $\theta_0 = 0^\circ \pm 5^\circ$;

ii. Normalizing the $R(\theta_0, X')$ curves; for instance, evaluating the Radon Transform along $\theta_0 = 90^\circ$, as showed in Fig.13, it can be noted that the higher values for $R(\theta_0, X')$ is in correspondence with the two values $X1 = 490, X2 = -490$.

iii. Evaluating the mean value $\mu(R(\theta_0, X'))$ of each curve $R(\theta_0, X')$.

iv. Evaluating the Skewness value (scalar) $Sk(R(\theta, X'))$.

Now, only two cases are possible:

(1) $Sk(R(\theta_0, X')) \leq -1 \cap Sk(R(\theta_0, X')) \geq 1$; in this case a horizontal or vertical defect is detected; the defect has an inclination θ_0 and is localized in the position X_0 that satisfy the following relationship:

$$R(\theta_0, X_0) < \mu(R(\theta, X')) - \alpha, \quad (8)$$

(2) $0 < Sk(R(\theta)) < 1$; in this case the fabric is not affected by an horizontal or vertical defect. The value α is stated by experimental tests and is placed equal to $\alpha = 0.25$. By this, the reliability of the detection of horizontal and vertical defects, according to equation (1) is about 94%.

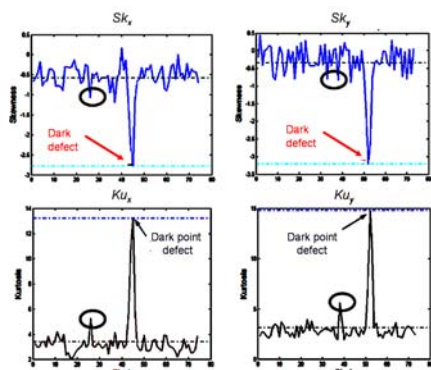


Fig. 10 the values for Sk and Ku referring to a dark area defected fabric along x and y axes.

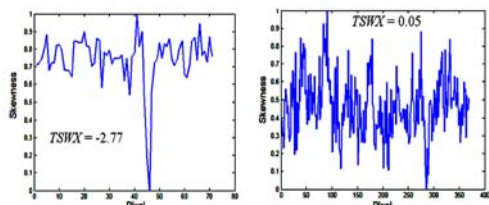


Fig. 11 the $Sk_x(I)$ curves for a defected fabric (left) and for a non defected one (right).

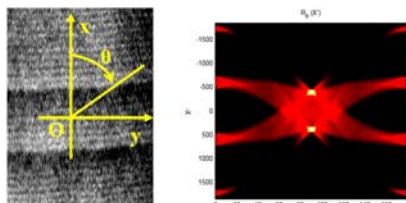


Fig. 12: Radon Transform for a fabric affected by two horizontal defects.

Referring to Fig. 13 the Skewness value is higher than 1 and for both the peaks the normalized frequency satisfy the equation (8). So the two peaks of the $R(\theta_0 = 90^\circ, X')$ correspond to the two horizontal defects showed in Fig.12.

4 Conclusion

The algorithm we developed has been tested on more than 40 circular knitted fabrics exhibiting the different kinds of defects described in §3.1. The system performance, according to the equation (1), is about 93% with a computation time (acquisition + detection and classification) lower than 60 s for a heavily defected unit of circular knitted fabric (as previously stated a unit is a cylinder with a length of 900 mm diameter of approximately 318.5 mm). It is authors' opinion that the proposed methodology can be extended to deal with a wider number of defect typologies. Moreover in literature some techniques based on the application of neural networks are used for developing classification systems. Nowadays the authors are working in order to increase the

performance of the classification system by means of neural network based systems and tools.

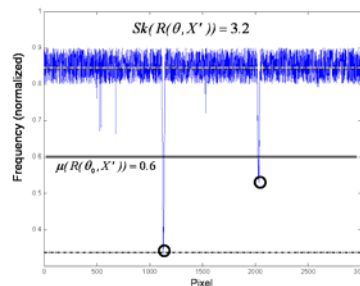


Fig. 13: Radon Transform along $\theta_0 = 90^\circ$.

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