TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 13/20 pp447-452
Volume 12, Number 4, August 2007

Automatic Fiber Orientation Detection for Sewed Carbon Fibers*

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Abstract: Automatic production and precise positioning of carbon fiber reinforced plastics (FRP) require precise detection of the fiber orientations. This paper presents an automatic method for detecting fiber orientations of sewed carbon fibers in the production of FRP. Detection was achieved by appropriate use of regional filling, edge detection operators, autocorrelation methods, and the Hough transformation. Regional filling was used to reduce the influence of the sewed regions, autocorrelation was used to clarify the fiber directions, edge detection operators were used to extract the edge features for the fiber orientations, and the Hough transformation was used to calculate the angles. Results for two kinds of carbon fiber materials show that the method is relatively quick and precise for detecting carbon fiber orientations.

Key words: machine vision; fiber orientation; Hough transformation; edge detection; autocorrelation

Introduction

The number of different reinforced composite structures has steadily increased during the past two decades. For example, non-crimp fabrics (NCF)[1] are now commonly used in everyday life. Glass and carbon fiber reinforced plastics (FRPs)[2], because of their advanced mechanical properties (like cohesiveness) together with their relative low weight, have been identified as key technologies in several areas, including aerospace, automotive, medicine, and metrology.

Today, the so-called "preforms" from FRP are still mostly done manually. The production process requires correct placement of several cloth structures on top of each other. The accurate positioning and the characteristics of each cloth structure are crucial for the whole product quality. Particularly, special reinforcements may be required in order to properly meet the mechanical specifications of the product, and the quality and placement of these reinforcements are vital. This production method is very complex and also expensive, because of deficiencies in existing online measurement technologies, e.g., systems to inspect each cloth structure during its placement, so fully automated FRP machines are not yet available. Processing of composite materials is still a young industry and inspection systems are oriented to research purposes rather than industrial production. Increased automation level of the production of FRP is needed to significantly reduce production costs. Thus, customers can profit by the advantages of automated fiber orientation detection in many products.

Received: 2006-06-01

∗ Supported by the DAAD (German Academic Exchange Service) on Its Exchange Student Program

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1 Algorithms and Strategy

1.1 Hough transform

Historically, the Hough transform has been the main means of detecting complex shapes, particularly straight lines in optical systems. Since the fiber segments in FRP can be treated as straight lines, the Hough transform can be used to effectively locate the fibers. The basic concept involved in locating lines using the Hough transform is the point-line duality[3], with the main process being to transform the line in Cartesian space to a point in a parametric space.

Just as a point can define a set of lines, a line can define a set of points. This makes the Hough transform approach to line detection a mathematically elegant method. The form in which the method is originally applied involves parameterizing lines using the slope-intercept equation

$$y = mx + c \tag{1}$$

which can be transformed into

$$c = -xm + y \tag{2}$$

Every point (x, y) on a straight line described by Eq. (1) is then plotted as a line in (m, c) space corresponding to all the (m, c) values consistent with its coordinates. To overcome the lack of limited ranges of the values in the (m, c) space (near-vertical lines require near-infinite values of these parameters), the slope-intercept formulation is replaced with the so-called normal (ρ, θ) form of the straight line

$$\rho = x\cos\theta + y\sin\theta \tag{3}$$

With this form, the set of lines passing through each point P_i is represented as a set of sine curves in (ρ, θ) space. For example, for point $P_1(x_1, y_1)$ the sine curve has the equation

$$\rho = x_1\cos\theta + y_1\sin\theta \tag{4}$$

Multiple hits in the (ρ, θ) space then indicate, via their θ, ρ values, the presence of lines in the original image. The hits are located by seeking peaks built by the accumulation of data from various locations.

However, the Hough transform is quite slow. For a 256×256 image, each Cartesian coordinate (x, y) requires that ρ be calculated $180/\Delta\theta$ times for θ varied from 0° to 180°, which means $256\times 256\times 180\times 2$=23 592 960 calculations of the trigonometric function with additions and multiplications for $\Delta\theta = 0.5$. To reduce the number of calculations, this paper develops a method transforming the images into logical images using edge detection algorithms, so that only pixels with value 1 are analyzed.

1.2 Autocorrelation

Let $\{a_i\}_{i=0}^{N-1}$ be a periodic sequence. Then the autocorrelation of the sequence, sometimes called the periodic autocorrelation[4], is the sequence

$$p_i = \sum_{j=0}^{N-1} a_j\ a_{j+i} \tag{5}$$

where the final subscript is understood to be modulo N.

For a complex function, the autocorrelation is defined by

$$p_f(t) \equiv f * f = \overline{f}(-t) * f(t) \tag{6}$$

For discrete 2-dimensional (2-D) data, like an $M\times N$ pixel digital image $I(m, n)$ and a spacing vector (d_x, d_y), the normalized autocorrelation function of $I(m, n)$ is defined as[5]

$$\rho_{xy}(d_x, d_y) = \frac{1}{S_2}\sum_{m}^{M-1}\sum_{n}^{N-1} I(m,n)I(m+d_x, m+d_y),$$

$$S_k = \sum_{m}^{M-1}\sum_{n}^{N-1} I^k(m,n).$$

A fast calculation of ρ_{xy} is performed using the relationship between the autocorrelation and the Fourier transform. With the fast Fourier transform (FFT) and the inverse FFT (IFFT) the autocorrelation can be computed as[6]

$$\rho_{xy}(m,n) = \text{IFFT}\{\text{FFT}[I(m,n)] * \text{FFT}[I(m,n)]\} \tag{7}$$

The autocorrelation processing presented in Eq. (7) can enhance the dominant patterns in an image, as shown in Fig. 1.

1.3 Edge sharpening and extraction

Image sharpening falls into a category of image processing called spatial filtering. The method analyzes how quickly the gray-scale values or colors change from one pixel to the next.

1.3.1 Gradient operators

First order operators (using first derivative measurements) are particularly good at finding edges in images. The Sobel, Prewitt, and Roberts edge enhancement operators are examples of first order filters.

The Sobel operator is a 3 × 3 window centered at (j, k)

$$\begin{pmatrix} A_0 & A_1 & A_2 \\ A_7 & f(j,k) & A_3 \\ A_6 & A_5 & A_4 \end{pmatrix}.$$

The intensity gradient at the point (j, k) is defined as either $s = (s_x^2 + s_y^2)^{1/2}$ or $s = |s_x| + |s_y|$ where s_x and s_y are computed from the neighbors according to

$$s_x = (A_6 + 2A_5 + A_4) - (A_0 + 2A_1 + A_2),$$

$$s_y = (A_2 + 2A_3 + A_4) - (A_0 + 2A_7 + A_6).$$

So the mask for the Sobel operator are

$$\boldsymbol{W}_x = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}$$

and

$$\boldsymbol{W}_y = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}.$$

Figure 2 shows the original image and the results after Sobel operators with different parameters.

Similarly, the mask for the Roberts 2 × 2 operator is

$$\boldsymbol{R}_x = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}, \quad \boldsymbol{R}_y = \begin{pmatrix} 0 & 0 \\ 1 & -1 \end{pmatrix};$$

and the mask for the Prewitt 3 × 3 operator is

$$\boldsymbol{P}_x = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix}, \quad \boldsymbol{P}_y = \begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{pmatrix}.$$

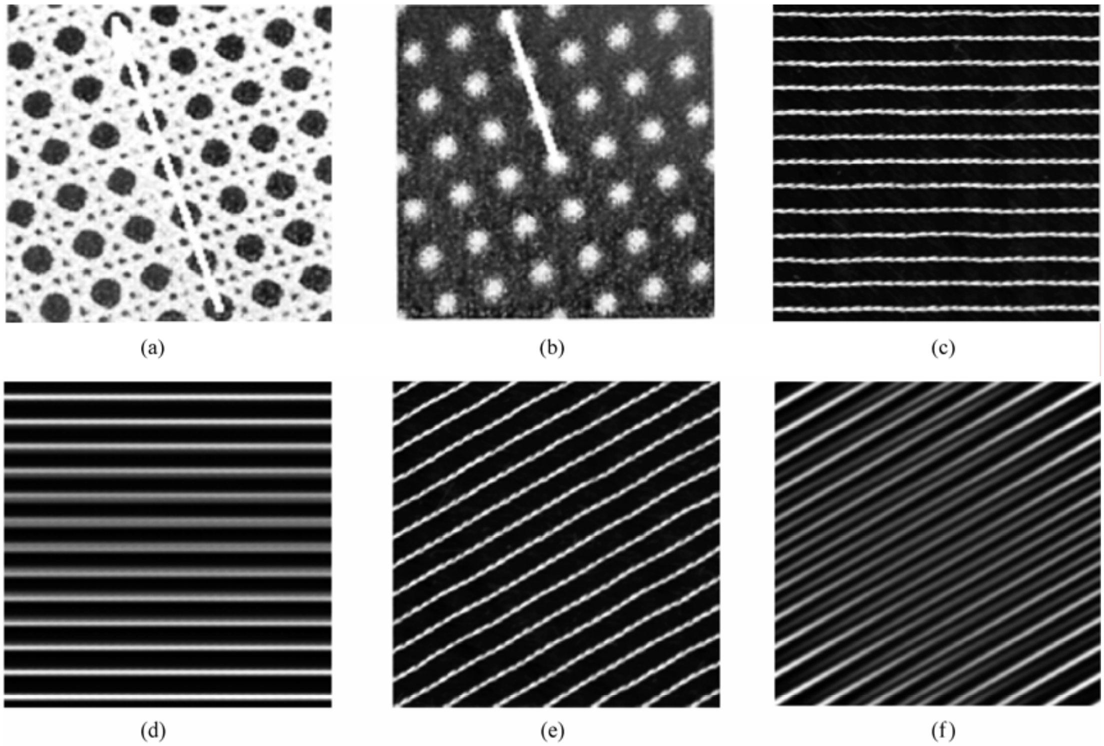


Fig. 1 Pattern enhancement following Eq. (7). (a), (c), and (e) are original images; (b), (d), and (f) are images after the autocorrelation process.

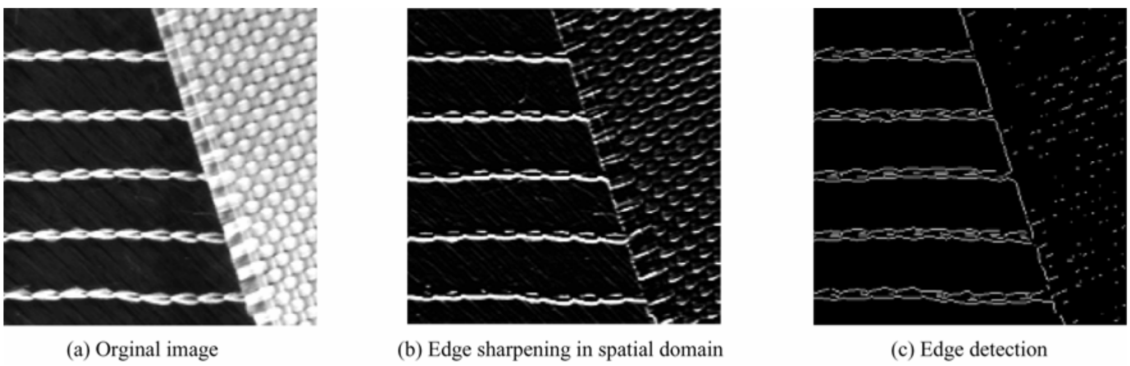


Fig. 2 Sobel operator

1.3.2 Laplacian of Gaussian (LoG) operator

The LoG operator is a typical second order or second derivative enhancement method. A Gaussian filter is applied before the Laplacian operator to eliminate the influence of noises in the images.

The mathematical approach is

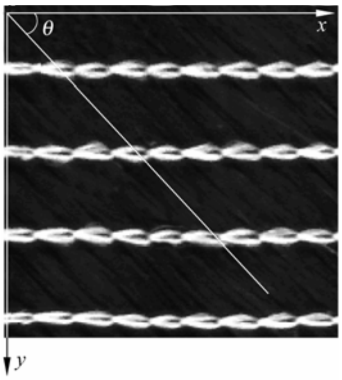
$$\mathrm{LoG} = \nabla^2 h(x,y) = \frac{\partial^2 h}{\partial x^2} + \frac{\partial^2 h}{\partial y^2} = \frac{1}{\pi\sigma^4}\left(\frac{x^2+y^2}{2\sigma^2} - 1\right)\mathrm{e}^{-\frac{x^2+y^2}{2\sigma^2}} \quad (8)$$

The 5×5 LoG operator mask is

$$\begin{pmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & -1 & -2 & -1 & 0 \\ -1 & -2 & 16 & -2 & -1 \\ 0 & -1 & -2 & -1 & 0 \\ 0 & 0 & -1 & 0 & 0 \end{pmatrix}.$$

1.4 Combined algorithm

For the sewed carbon-fiber materials shown in Fig. 3, the main disturbance comes from the sewing threads since they usually contain strong patterns. Therefore, the Hough transform cannot be applied directly to such images to extract the fiber directions. However, since the sewing threads only occupy a small space on the fabric, a regional filling process can remove the threads.



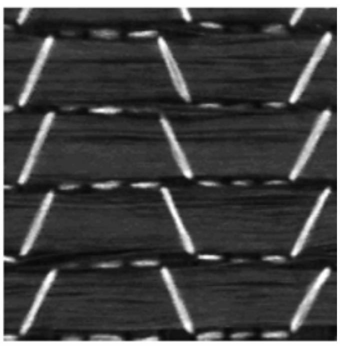


Fig. 3 Sewed carbon-fiber materials

The automatic fiber orientation detection method is then based on the following two principles:

(1) Use a regional operator to smooth the pattern in the disturbed region (sewing threads).

(2) Use autocorrelation to eliminate disturbances and extract the dominant feature (fiber direction).

The use of Principle 1 makes the fibers the major pattern in the fabric. The autocorrelation then strengthens the major pattern which is then extracted by the edge detection operations, after which the Hough transform is used to identify the lines.

The method includes the following steps: (1) Fill the sewing region; (2) 2-D-spatial filter for edge sharpening (optional); (3) Autocorrelation; (4) Edge detection; (5) Hough transform; (6) Angle extraction from the peaks in the Hough diagram.

2 Test and Results

The results of the six steps listed in Section 1.4 applied to the sewed carbon fiber material in Fig. 3a are shown in Fig. 4.

The fiber direction in Fig. 3 was then found from the data in Fig. 4h by calculating the mean value of the top 3 peaks, that is $\theta = 45.66^\circ$.

The results of the five steps in Section 1.4 (excluding Step 2) to the sewed carbon fiber material in Fig. 3b are shown in Fig. 5.

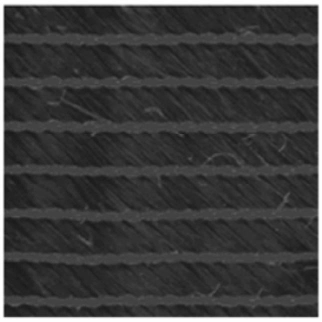
The fiber direction in Fig. 3b was extracted from the result in Fig. 5e by calculating the mean value of the top 3 peaks, that is $\theta = 0^\circ$.

3 Conclusions

The Hough transform together with autocorrelation and edge detection operators can be used to detect fiber orientations in an FRP production system by using the image processing techniques described in Section 1.4. This method gives a relatively fast and accurate approach to automatically extract the fiber orientations. The algorithm uses a regional operator to reduce patterns in disturbed regions due to the sewing threads with autocorrelation to eliminate disturbances and extract the dominant features which are the fibers. This preprocessing of the image improves the Hough transform results, which are used to calculate the fiber orientations.

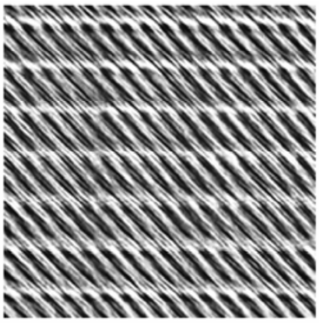
(a) Orginal image

(b) Binary mask of sewed region



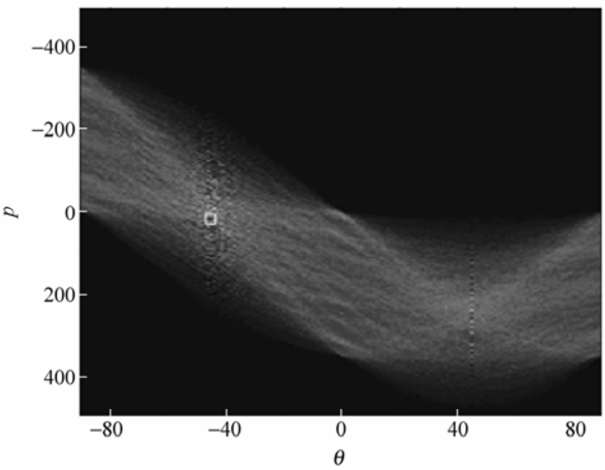
(c) Region filled according to (b)

(d) After Sobel edge sharpening

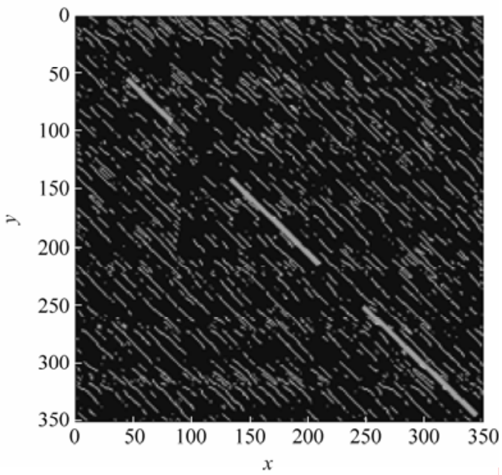


(e) Autocorrelation result

(f) LoG operator edge detection result

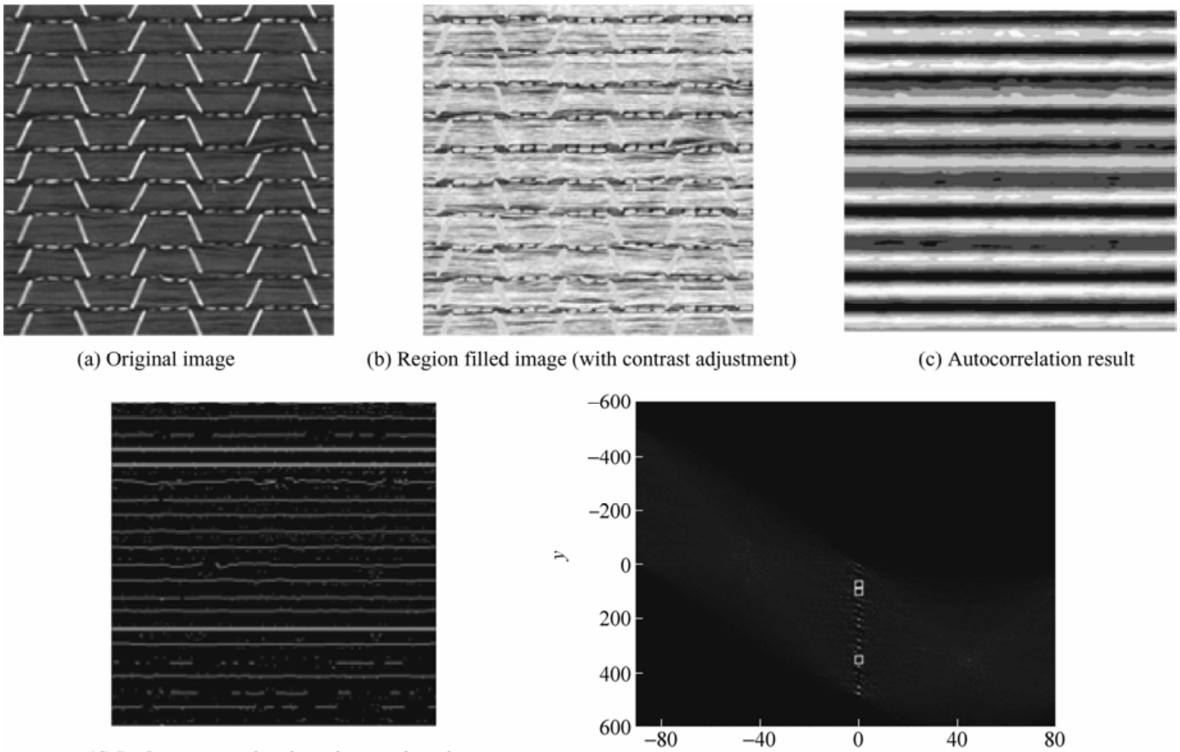


(g) Haugh transform result with marked peak



(h) Direction determined from peaks in past (g)

Fig. 4 Tests using the image in Fig. 3a



(a) Original image (b) Region filled image (with contrast adjustment) (c) Autocorrelation result

(d) LoG operator edge detection result and direction found using peaks in past (e) (e) Hough transform with marked peaks

Fig. 5 Tests using the image in Fig. 3b

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