DETECTION OF LOUSINESS IN SILK FABRIC USING DIGITAL IMAGE PROCESSING

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Abstract
An inspection method based on binary image processing technique has been developed in an effort to obtain lousiness profile of silk fabric. The image data are used in the mathematical morphology and the back propagation neural network (BPNN) for evaluation. Maximum length, maximum width and grey level fabric defects are considered as input units in the input layer of BPNN. The grey level values corresponding to the image pixels are used to perform recognition of three types of defects namely, lousiness (high), lousiness (moderate) and lousiness (low) successfully with frequency of each defect per unit area. The average recognition rate is found to be 98.56 % under 3-3-3 BPNN topology. The results prove that the inspection method developed is very effective not only in identifying and recognizing the defects of very small size like lousiness but also act as a tool in generating almost zero-defect finer fabric.
Keywords : Binary image processing; Lousiness; Silk fabric; Neural network; Mathematical morphology; Fourier transform; Spatial filtering

Introduction

Silk fabrics are adorded by people for their pleasing lustre and softer handle. However, the generation of oligomers at the time of silk worm spinning results in the accumulation of oligomers within the reeled yarn which ultimately reflects on the fabric surface as lousiness (tiny entangled fibrils with highly crystalline fibroin). Lousiness in silk fabric is a burning problem in sericulture industry as it lies out of focus during visual inspection at its grey stage. Mending of such defect is regarded as an impossible task which not only plays a negative role to maintain the high quality standards established for the textile industry but also results in high financial loss to sericulture industry. Keeping this long standing pending problem of sericulture industry in mind, it is therefore thought worthwhile to develop a suitable method so that it can easily be characterized and identified and mended properly in order to avoid post dyeing defects.

Presently, the technology of image processing techniques has been applied [1-9] to inspect detailed parameter of fabric structure by using a texture tuned mask method but maximum results were found to be poor. Therefore the fabric defect detection still remains a hot applied research topic as the appearance of defects influence not only the quality but also the price of the fabric. Moreover, the similarities and the diversities of different classes of defects make their segregation a uphill task for the researchers. Since, most of the defects in linear textile products have different textual features than the original fabric, so detection of fabric defects can be considered as texture analysis or segmentation and identification problem.

But, a study of the literature over the past decade revealed no information dealing with the detection of lousiness in silk fabric. The present work was undertaken with a view of studying the feasibility of digital image processing for evaluating the lousiness in silk fabric.

Materials and methods

Fabric

Commercially woven Murshidabad silk fabric (1/1 plain weave, 21^d warp, 34^d weft, 62 ends/cm, 54picks/cm, 60gsm and 15.46 cover factor) was used.

Model development

An intelligent lousiness classification and recognition system has been developed whose structure is shown in Figure 1. There are mainly five steps in the developed system: image capture, image processing, feature extraction, classification and recognition.

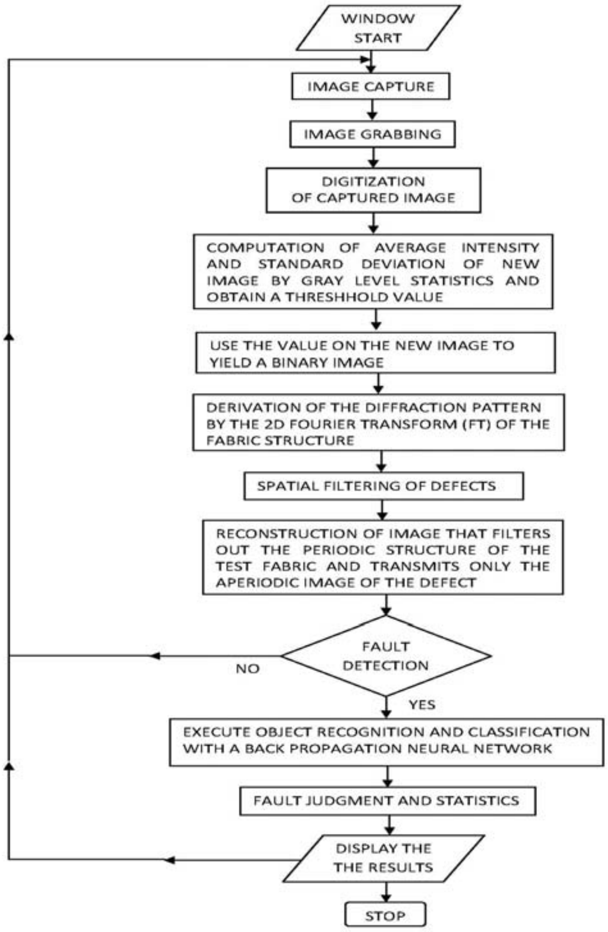


Figure 1 Flow chart of the proposed algorithm for fabric defect recognition

Image capture

The test silk fabric was illuminated with a collimated beam of light . The diffraction pattern of test fabric was produced at the focal plane of the Fourier lens having 25cm focal length. The image of the test fabric was captured by a digital camera (Olympus) and stored in a computer. The region of each image was set at 512x 512 pixels. The image was then displayed in the monitor through a frame grabber.

Digitization of captured image

The captured image as shown in Figure 2 was digitized by an image acquisition card and the digitized image is shown in Figure 3. In this study the captured area of the silk fabric sample is 1.83 × 1.83 mm at a resolution 512 × 512 pixels with grey levels. The colour image contains RGB (red, green and blue) colour co-ordinates for all pixels. From the RGB values of pixel, the grey level at that point was calculated by using the luminance function:

$$\text{Luminance}, L = 0.177R + 0.813G + 0.11B \qquad (1)$$

A colour image was converted into a grey level image using Equation 1(Alvarez et al; 1999). Each pixel was assigned a grey level from 0 (black) to 255 (white), since a grey level image is made up of a matrix of pixels with grey levels. The grey level image was stored in the file as a two dimensional array and then displayed in the colour monitor through a frame grabber.

Computation of average intensity and standard deviation values of new image

The new image is defined as 2-D functions $I(i,j)$ where *i* and *j* are special co-ordinates. The amplitude at any pair of co-ordinates is equal to the average intensity value of all pixels of the blocks. The formulation can be expressed as:

$$I(i,j)=\frac{1}{r\times c}\sum_{x=1}^{r}\sum_{y=1}^{c}f(x,y) \qquad (2)$$

where, I = 1, 2,....n ; j = 1, 2,.....n; $f(x,y)$ is the 2D function of the measured image; $r\times c$ is the size of the segmented window and $I(i,j)$ is the function of the new image.

The new image are shown in Figure 3. As the new image has the same characters of the measured image, the location of defects can easily be measured as follows:

The functional values of the new image, with the average intensity value μ and standard deviation σ are defined as:

$$\mu=\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}I(i,j) \qquad (3)$$

where, $m\times n$ is the size of the new image

$$\sigma=\sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(I(i,j)-\mu\right)^2}{m\times n}} \qquad (4)$$

The intensity threshold value (T) of the new image can be calculated as $T=\mu+c\sigma$, where , c is a control constant relating to the structure of the measured image. The value of c was found to be -1.

Generation of binary image

The grey level image $I(i,j)$ has to be operated by processing the thresholding on the new image to yield binary image $x(i,j)$. The binary image $x(i,j)$ has two values, 0 or 1 value 1 is used for pixels of lousiness defects which are called object points while 0 is used for those of normal texture, which are called background points. Thresholding processing is defined as:

$$x(i,j)\begin{matrix}=1,\ if\ \ I(i,j)\le T\\ =0,\ \text{else}\end{matrix} \qquad (6)$$

where, the size of $x(i,j)$= the size of $I(i,j)$.The binary image of silk fabric is shown in figure 5.

Derivation of the diffraction pattern by the 2D Fourier transform of the fabric structure

Silk fabric sample, when illuminated by a light source, the interlaced periodic structures of warp and weft yarns in fabrics behave like super imposed horizontal and vertical diffraction gratings. The diffraction pattern due to this periodic structure was derived by the 2-D Fourier transform of the fabric structure. So, the aperture function $f(x,y)$ and its Fourier transform $F(P,Q)$ can be written as:

$$f(x,y)=L\left[\frac{x}{2\omega_1}\right]L\left[\frac{y}{2\omega_2}\right]\times\sum_{-x}^{+x}\sum_{-x}^{+x}\delta(x-2nT_1)\,\delta(y-2mT_2) \qquad (7)$$

$$F(P,Q)=\phi 4\pi^2\frac{\omega_1\omega_2}{T_1T_2}\left[\sin c\,\frac{\omega_1 P}{\pi}\right]\left[\sin c\,\frac{\omega_2 Q}{\pi}\right]\times\sum_{-x}^{+x}\sum_{-x}^{+x}\delta\left\{P-\frac{\pi n}{T_1}\right\}\delta\left\{Q-\frac{\pi m}{T_2}\right\} \qquad (8)$$

where, $L[\ ]$ is a rectangular function of width $2\omega_1$ and $2\omega_2$ in the x and y direction; $2T_1$ is the spatial frequencies in X and Y directions and -x , -y = -α , +α.

Spatial filtering of defects

The spatial filter was inserted at the Fourier plane of the first Fourier lens to reconstruct an image carrying particular information on the object. If the spatial filter transmits only the orders of the diffraction pattern on the central horizontal axis, the image becomes a set of vertical lines. So, in order to observe only the warp, i.e. y directional yarn or weft i.e. x directional yarn in the image plane, an *x* directional slit of width wf_1 or a *y* directional slit of width wf_2 was placed on the Fourier plane of the first Fourier lens. Practically, superimposition of *x* directional and *y* directional slits removes the grating structure from the image. The mathematical expression for such a slit function is given by:

$$f(X,Y) = L\left(\frac{Y}{wf_1}\right) L\left(\frac{X}{wf_2}\right) \quad \text{provided, } wf_1 < \frac{\lambda F}{\omega_2} \text{ and } wf_2 < \frac{\lambda F}{\omega_1} \qquad (9)$$

where, F is the focal length of first Fourier transform lens and λ is the wavelength of the light source. Now, the diffraction pattern consists of a central zero order light spot and the related expression in given by: $F_f(P,Q) = F(P,Q)\, f(P,Q)$ (10)

where, $F_f(P,Q)$ is the Fourier transform of the image after it passes through the spatial filter.

Reconstruction of image

The reconstructed image $R_f(X,Y)$ was obtained by using another Fourier lens. Evidently, $R_f(X,Y)$ is the Fourier transform of $F_f(P,Q)$. A reconstructed image was obtained by passing of the zero-order and the diffraction pattern together with the region half way out to the next region. The resultant reconstructed image filters out the periodic structure of the silk fabric sample and transmits only the aperiodic image of the defect as shown in Figure 6.

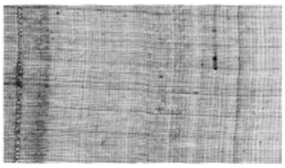


Figure 2 The Captured image of silk fabric

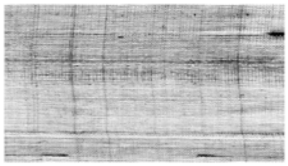


Figure 3 The digitized or new image of silk fabric

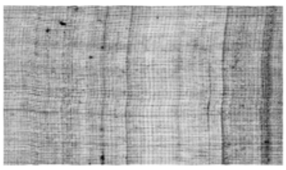


Figure 4 Fluorescent dots of silk fabric

Figure 5 The binary image of silk fabric before filtering

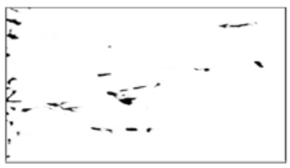


Figure 6 The binary image of silk fabric after filtering

Back propagation neural network (BPNN)

A back propagation neural network with an input layer, hidden layer and an output layer was used for classifying defects in silk fabric through nonlinear regressional algorithm as they can model highly dimentional system with extreme flexibility due to their learning ability. Three types of defects were considered for training. The initial learning rate, momentum factor and error mean square value were 0.1, 0.5 and 0.05. Three input units like, maximum length, maximum width and grey level and three output units like lousiness (high), lousiness (moderate) and lousiness(low) were considered in the present work as shown in Figure 7.The MATLAB 8.0 neural network tool was used to implement the neural network implementation in a desktop PC. The flow chart of BPNN is shown in Figure 8.

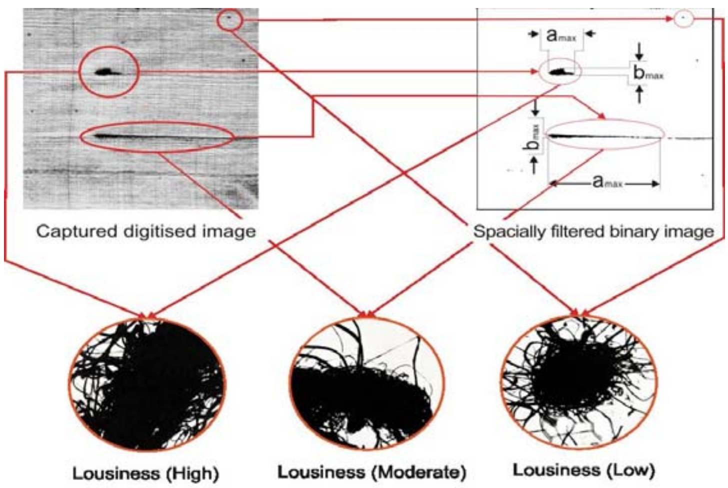
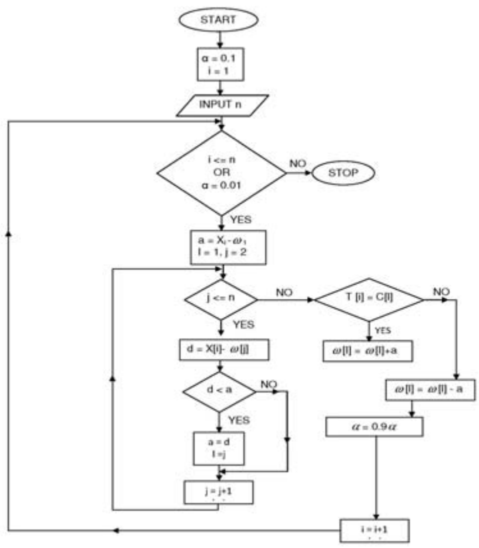


Figure 7 Representation of fabric defects



Where, X[n]= nth input unit, ω[n] = weight of nth output unit., T= class of jth output unit, a = minimum value

Figure 8 Flow chart of the BPNN algorithm

Results and discussion

Image analysis of defects

While analyzing the images of the defects, it was observed that the image of the cloth surface was scattered with many tiny dots as shown in Figure 4, because the cloth surface is lit from the back face and light comes through gaps formed by the intersections of warps and wefts. The existence of these fluorescent dots greatly affected the test results. To remove them, spatial filtering was done by placing a pinhole of 0.75mm diameter at the Fourier plane. The diameter of the pinhole was selected by satisfying the conditions of Equation 9. The results of the mathematical morphology operation on binary and spatially filtered binary images are shown in Figures 5 and 6. It reveals from the results that spatial filtering of images shows better detection of defects as it removes the basic grating structure i.e interlacement of warps and wefts of the tested silk fabric.

Identification of defective image

The method of image identification involves the accumulation of grey level values. The grey level values are accumulated and two curves are obtained by means of the difference in the grey level values of each pixel. Since the image grey level value of each defect is different, the system can identify the difference between defects and can judge their maximum length and maximum width. But sometimes when the interfering messages come in the way of acquired image, the system uses spatial filtering to eliminate such messages before recording different characteristics of the defects. The results are shown in Figure 7.

Back propagation neural network (BPNN)

The back propagation neural network (BPNN) is a nonlinear regressional algorithm which was used for learning and classifying defects in silk fabrics. In the BPNN, three input units i.e the maximum length of the defect, maximum width of the defect and grey level value of the defect were taken. For the out put layer three training output vectors, like (0,1,1), (1,1,1) and (1,1,0) were used with a three axis coordinate to show the relative position of the three target output values. After training, the BPNN system with 3-3-3 topology was used for identification and recognition of the lousiness defects. Table 2 shows the frequency and recognition % of the lousiness defects. The average recognition rate is found to be 98.56 % under 3-3-3 BPNN topology. It appears from Table 2 that the developed system not only produces excellent results but also proves to be very effective in classifying the lousiness defects in silk fabric successfully.

Conclusion

Detecting lousiness defects morphologically on spatially filtered images of silk fabric produces better results and is proved to be an efficient system especially when the fabric is fine and contains defects of small size.During image processing, placing of a spatial filter at the Fourier plane is found to be very effective in eliminating the periodic grating structure of silk fabric from the image.The three layer BPNN used as a classifier has shown excellent classification accuracy. After training for 30 times, the performance of the network is found to be satisfactory and the sum time of training is about 2 minutes.The developed technique and algorithm and the grey level values corresponding to the image pixels are used to perform classification and recognition of three types of lousiness defects in silk fabric namely lousiness (high), lousiness (moderate) and lousiness (low). The average recognition rate is found to be 98.56 % under 3-3-3 BPNN topology. The classification results demonstrate that the inspection method developed is found not only very effective in classifying and recognizing the lousiness defects but also their frequency per unit area as a whole.

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