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A Back-Propagation Neural Network for Recognizing Fabric Defects

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ABSTRACT

Appearance is an important property of fabrics. Traditionally, fabric inspection is done by workers, but it is so subjective that accuracy is a problem because inspectors tire easily and suffer eyestrain. To overcome these disadvantages, an image system is used as the detecting tool in this paper. A plain white fabric is adopted as the sample, and the distinguishing defects are holes, oil stains, warp-lacking, and weft-lacking. An area scan camera with 512 × 512 resolution is used in the scheme, and a grabbed image is transmitted to a computer for filtering and thresholding. The corresponding image data are then used in the back-propagation neural network as input. There are three input units, maximum length, maximum width, and gray level of fabric defects, in the input layer of the neural network. This system is successfully employed to determine nonlinear properties and enhance recognition.

Generally, fabrics are inspected manually for defects, but problems arise, such as excessive time consumed, human subjective factors, stress on mind and body, and fatigue [2]. These problems further influence production volume and inspection accuracy. Therefore, techniques that can replace manual inspection have emerged, and the most comprehensive technique is image processing technology. Starting in the 1970s, there were already many image identification systems for inspection [2], including evaluation of cotton fabrics [12], fiber characteristics [10, 18], and nonwoven fabric characteristics [5–6, 8], as well as for evaluating carpet structures [11, 14–16] and fabric defects [13, 17, 19]. Recently, researchers have used neural networks in conjunction with image processing, such as Barret et al. [1] and others, who employed Fourier transformation and neural networks to classify sewing systems on line. Also, Chen et al. [3] and others used inverted transmission neural networks and Fourier analysis to inspect missing yarns and oil stains, etc. In addition, Rajasekaran [9] utilized neural networks with image processing technology to identify fabric defects. Park and Kang [7] and others used neural networks for objective assessments of sewing shrinkage. In this paper, we employ an interface written in VC++ to retrieve images, then use these data to calculate accumulated image values in the longitudinal and latitudinal directions, thus obtaining the length, width, and gray level of fabric defects. In the beginning, image technology development was limited by the excessive costs of the instruments, and when it was applied on line, the identification percentages were usually not more than 50% [4]. In this paper, we report on an image identification system for fabric inspection that actually makes a very large contribution.

Image Processing and Filtering

In our scheme, four defects—warp-lacking, weft-lacking, holes, and oil stains—are presented for analysis and recognition. Usually a larger pick force and tension [13] cause weft-lacking, and when the warp is too short, this causes warp-lacking. It is difficult to detect weft-lacking and warp-lacking which are not obvious on fabrics; it is easier to detect holes and oil stains, which are wider. In our scheme, the experimental model uses front lighting to enhance the gray level differences of the defects. Our fabric defects include texture structure, gray level differences, and shapes and sizes.

In terms of these three directions, we present three features—maximum length, maximum width, and gray level of the defects—as the input units of the neural network. The four defects are divided into eight samples for training, which consist of warp-lacking (I), weft-lacking (II), warp-lacking (III), weft-lacking (I), weft-lacking (II), weft-lacking (III), holes, and oil stains, where warp-lacking (i) is represented as missing i yarns. In our scheme, the visual C++ is mainly software architecture, and the hardware consists of an image grabber, an area-scan camera, and a 586 PC; the flowchart in the experimental procedure is shown in Figure 1. In order to analyze the grabbed images, filtering and thresholding are applied to the pre-process.

Noise easily occurs during image processing and influences image recognition. We have adopted a smooth-
FIGURE 1. Image processing flowchart.

From Figures 3–6, we can obviously see the oil stain, hole, weft-lacking, and warp-lacking images grabbed by the area-scan camera. This procedure can exclude pixels corresponding to yarn interlacing points, which have a brightness similar to defects.

\[
\frac{1}{9} \sum_{m=1}^{3} \sum_{n=1}^{3} f(m, n) \quad (1)
\]

From Figures 3–6, we can obviously see the oil stain, hole, weft-lacking, and warp-lacking images grabbed by the area-scan camera. This procedure can exclude pixels corresponding to yarn interlacing points, which have a brightness similar to defects.

Figure 2. Schematic of smoothing filter.

\[
f(2,2) = \frac{1}{9} \sum_{m=1}^{3} \sum_{n=1}^{3} f(m, n)
\]

From Figures 3–6, we can obviously see the oil stain, hole, weft-lacking, and warp-lacking images grabbed by the area-scan camera. This procedure can exclude pixels corresponding to yarn interlacing points, which have a brightness similar to defects.

Figure 3. Image diagram of an oil stain.

Figure 4. Image diagram of a hole.

Figure 5. Image diagram of weft-lacking.

Figure 6. Image diagram of warp-lacking.
Thresholding

Thresholding plays an important role in image processing and relates the accuracy of image recognition. It can be obtained by an optimal value if the relationship of the object and background is known. A histogram with Gaussian noise is shown by

\[ P(x_o) = P_1 \frac{1}{\sqrt{2\pi} \sigma_1} \exp \left[ -\frac{(x_{ij} - \mu_1)^2}{2\sigma_1^2} \right] 
+ P_2 \frac{1}{\sqrt{2\pi} \sigma_2} \exp \left[ -\frac{(x_{ij} - \mu_2)^2}{2\sigma_2^2} \right] \] (2)

where \( \mu_1 \) is the mean gray level value of the object, \( \mu_2 \) is the mean gray level value of the background, \( P_1 \) is the proportion of the object, \( P_2 \) is the proportion of the background, \( \sigma_1 \) is the gray level standard deviation for the object, \( \sigma_2 \) is the gray level standard deviation for the background, and \( x_{ij} \) is the \( i \)th column and \( j \)th row of the pixel.

In Equation 2, if \( P_1 \) is equal to \( P_2 \), the intersection of the distributions of the object and background are \((\mu_1 + \mu_2)/2\); if \( P_1 \) is larger than \( P_2 \), the intersection closes to \( \mu_2 \). But the intersection closes to \( \mu_1 \) if we take \( T \) as the thresholding. The pixels of the object can then be classified as the background, and the probability can be written as

\[ E_1(T) = \int_{-\infty}^{\infty} P_2(x)dx \] (3)

It is possible to classify the pixels of the background as the object, and the probability can be written as

\[ E_2(T) = \int_{T}^{\infty} P_1(x)dx \] (4)

The total error is

\[ E(T) = E_1(T) + E_2(T) \] (5)

When the Equation 2 is differentiated and allowed to be zero, an optimal value \( T \) can be obtained by

\[ T = \frac{\mu_1 + \mu_2}{2} + \frac{\sigma^2}{\mu_1 - \mu_2} \ln \left( \frac{P_2}{P_1} \right) \] (6)

Oil stains and holes simultaneously exist in the fabric sample. The gray level of an oil stain is lower than its total mean value, and the gray level of the holes with back lighting is higher than the total mean value. Thresholding cannot distinguish oil stains, holes, and background. It needs to be modified [9] to

\[ T_{upper} = \mu + k\sigma \] (7)

and

\[ T_{lower} = \mu - k\sigma \] (8)

where \( \mu \) is the mean gray level value, \( \sigma \) is the signal standard deviation, and \( k \) is the constant within 3 and 5.

We choose \( \mu \) by employing a fifty-line defect-free portion of the image of the bottom section, and we calculate \( \sigma \) using these data for each pixel:

\[ \sigma = \sqrt{\frac{\sum_{i=0}^{51} \sum_{j=50}^{127} (x_{ij} - \mu)^2}{512 \times 50}} \] (9)

Using \( T_{upper} \) and \( T_{lower} \), holes, oil stains, warp-lacking, and weft-lacking of the image \( g(x, y) \) can be segmented from the background. The faults are holes, warp-lacking, and weft-lacking if the gray level is larger than \( T_{upper} \). The defect is an oil stain if the gray level is smaller than \( T_{lower} \), and the other is background if the gray level is within \( T_{upper} \) and \( T_{lower} \). By segmentation, the image \( g(x, y) \) can be written as

\[ g(x, y) = \begin{cases} 
\text{gray level 1} & \text{if } g(x, y) > T_{upper} \\
\text{gray level 2} & \text{if } T_{lower} < g(x, y) < T_{upper} \\
\text{gray level 3} & \text{if } g(x, y) < T_{lower}
\end{cases} \] (10)

An oil stain, hole, weft-lacking, and warp-lacking with smooth filtering and thresholding are shown as in Figures 7–10. Here we see that the defects are separated from the background successfully.
Results

In our scheme, we use a back-propagation neural network with an input layer, a hidden layer, and an output layer. The basic concept of the back-propagation (BP) neural network is to transmit the error from the output layer to the hidden layer by a weight and update the weight in the hidden layer. The main feature of the BP is excellent learning and a tolerant ability. It is a nonlinear regresional algorithm and can be used for learning and classifying distinct defects in fabrics. In our research, the input layer includes three input units, maximum length, maximum width, and gray level, and three output units in the output layer, the grabbed images of the oil stain, hole, weft-lacking, and warp-lacking, as shown in Figures 11–14.

Furthermore, we can define the defect type. In our scheme, we have adopted eight defect samples for off-line training. The initial learning rate is 0.1; it keeps reducing to 0.01, and the momentum factor is 0.5. After 45,000 iterations, the error mean square value converges to 0.05.

Eight values of the target output are represented as (0, 0, 0), (0, 0, 1), (0, 1, 0), (0, 1, 1), (1, 0, 0), (1, 0, 1), (1, 1, 0), (1, 1, 1) in BP, and we present a three-axis coordinate to show the relative position of the eight target output values.

After off-line training, we use the BP system for on-line recognition and the recognizable rate shown in Table I.
TABLE I. The recognizable rate of each fabric defect.

<table>
<thead>
<tr>
<th></th>
<th>Warp lacking (I)</th>
<th>Warp lacking (II)</th>
<th>Warp lacking (III)</th>
<th>Weft lacking (I)</th>
<th>Weft lacking (II)</th>
<th>Weft lacking (III)</th>
<th>Hole</th>
<th>Oil stain</th>
<th>Sample</th>
<th>Recognition rate, %</th>
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<tr>
<td>Warp lacking</td>
<td>27</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>(I)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Warp lacking</td>
<td>2</td>
<td>27</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>90</td>
<td></td>
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<tr>
<td>(II)</td>
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<tr>
<td>Warp lacking</td>
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<td>0</td>
<td>29</td>
<td>0</td>
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<td>0</td>
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<td>(III)</td>
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<tr>
<td>Weft lacking</td>
<td>0</td>
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<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>28</td>
<td>30</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>(I)</td>
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<td></td>
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<tr>
<td>Weft lackin</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>30</td>
<td>93</td>
<td></td>
</tr>
<tr>
<td>(II)</td>
<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Weft lacking</td>
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<td>1</td>
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<td>(III)</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
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<td>100</td>
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</tr>
<tr>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>30</td>
<td>100</td>
<td></td>
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</tbody>
</table>

Very good reliable results are produced, and we can also prove that because of the similarities of the missing yarns in the classification, the nonlinear regressional property of the BP is very effective at classifying fabric defects.

Conclusions

In our scheme, fabric defects are inspected by image technology with a back-propagation neural network. Images of fabric defects can be grabbed by the area scanner and the noise successfully filtered with a smoothing filter. In this research, the neural network can establish its own database after it has learned different defects with different sizes and shapes. It has a superior learning ability so that tolerance can be reduced progressively due to multiple calculations. It also has an excellent ability to allow for errors, so this research can be more human-like as well.

According to our test results, the recognizable rate of warp-lacking and weft-lacking is up to 95%, and it is up to 100% for holes and oil stains. Remember, in our scheme the recognition rate is related to light source conditions.

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Literature Cited


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