Automated Vision System for Recognising Lycra Spandex Defects

Introduction

The inspection of fabric quality has a very important role in the textile industry. Srinivasan et al. [1] remarked that the price of second-quality fabric is only 45% - 65% of the first-quality fabric price. At present, however, fabric inspection still mainly relies on human inspection. The procedure of traditional human inspection is usually dull and uninteresting, which often deflects the inspector’s attention. In addition, the reliability and stability of inspectors may not be sufficient enough, which can easily cause mistaken judgments, resulting in issues such as an increase in costs, low quality, and low speed manufacturing. Therefore, using automatic inspection to improve overall quality and reliability is even more important.

In their research into fabric flaw inspection, Hu et al. [2] adopted best wavelet packet bases and the back-propagation neural network (BPNN) to inspect missing ends, missing picks as well as oily and broken fabric. In their research important design issues in the building of an artificial neural network classifier were studied to find an appropriate network topology (number of hidden layers and processing elements in each layer) and the weights between the processing elements in different layers. Tiloca et al. [3] used an artificial neural network to detect fabric defects, such as large knots, slubs, broken thread, and knots. Besides this they proved from the experimental results that the artificial neural network had a powerful learning ability.

However, the disadvantages are as follows if the BPNN is to be the classifier:

- a global minimum cannot be obtained if the number of learning cycles is not enough; to increase the learning rate, the momentum factor must be raised. However, back and forth oscillations occur if the momentum factor is too large, causing the difficulty of convergence drawback.

Therefore this paper proposes methods of improving on the issues concerning the BPNN. By using the Taguchi method within the experiment process, an effectiveness equal to the full factorial experiment can be obtained with extremely few runs of experiments, as a result of which an optimised combination of learning parameters will be achieved. This improves the overly time-consuming drawback of the BPNN, which uses the trial-and-error method to adjust the learning parameters. This enables the network to converge even faster, with an even smaller convergence error and better recognition rate. The experimental results proved that the final root-mean-square error convergence of the Taguchi-based BPNN was 0.000104, and that the recognition rate can reach 97.14%.

Key words: lycra spandex defects, automated vision recognition, Taguchi method, neural network.

Research methods

The research used a charge-coupled device (CCD) to gather a surface image of the fabric, which was used to study the features on the surface of the fabric and, by using these features, to classify unknown fabric types. The specifications of the hardware are as follows: Sony XC-711 CCD, Matroc II PCI interface image grabbing card. The seven lycra spandex defect images collected are shown in Figure 1. The image has 256 grey levels,

![Figure 1. Seven fabric defects; a) Laddering, b) End-out, c) Hole, d) Oil spot, e) Dye stain, f) Snag, g) Crease mark.](image-url)
Figure 2. Fabric defect image classification flowchart.

Figure 3. Snag image of 512×512 pixels.

the size of which is 512×512 pixels. Collecting features of the fabric image was done by GLCM to evaluate them using the Taguchi-based BPNN as a classifier. The procedure of the operation is shown in Figure 2.

- **Gray level co-occurrence matrix**

This paper uses a gray level co-occurrence matrix to define the feature of the fabric. The feature of the GLCM can be seen, by observing the gray level relation of a pixel pair, at the same texture configuration, observing the gray level relation of a pixel pair. The method is described below:

**Figure 3** is a 512×512 size snag image in a 256 gray level range (i.e. the distribution of gray level values are between 0 and 255). Two parameters, d and θ, are introduced, where d is the distance between two pixels, θ is the relative angle relation between the two pixels, of which there are a total of eight angles: horizontal level θ = 0, right opposite angle θ = 45, vertical angle θ = 90, left opposite angle θ = 135, and θ = 180, 225, 270 and 315 are the rotating angles of the previous four. To avoid complicated calculations, only the former four angles are required for calculation. A matrix is established with a size of 512×512, and then the occurrence matrix is regulated and substituted into the selected feature index to calculate the feature.

The definition of the selected texture feature index in this study is as follows:

1. **ASM:**
   \[ \text{ASM} = \sum_{i} \sum_{j} P(i,j) \log P(i,j) \]  
2. **Contrast:**
   \[ \text{Contrast} = \sum_{i} \sum_{j} |i-j| P_{ij}^2 \]  
3. **Correlation:**
   \[ \text{Correlation} = \sum_{i} \sum_{j} P_{ij} |i-j| \]

where \(P_{ij}\) is the co-occurrence matrix after normalisation. For the co-occurrence matrix, \(d = 1\), and \(θ = 0\) & 45.

The defect image was then calculated by the GLCM, and the normalised co-occurrence matrix obtained was substituted into the three defined feature indexes to calculate the texture feature of the fabric. Once we obtained the image’s feature, the BPNN was used to carry out training.

- **Taguchi method**

The characteristic of the Taguchi method lies in the use of an orthogonal array to plan the signal-to-noise ratio (SN ratio) in order to analyse experimental data. The use of an orthogonal array to design experiments and the SN ratio to analyse experimental data enables the designer to simultaneously study the effect of multiple control factors on the average of quality characteristic and variance in a fast and economical way. Thus by using extremely few experimental runs within the process of the experiment, an equally full factorial experiment is created to obtain an optimised learning parameter combination [5 - 7].

Parameter design in the Taguchi method converts the quality characteristics into an SN ratio in order to evaluate the statistical values of the performance. The object of the research was to make the root-mean-square-error of the BPNN as low as possible. Therefore the smaller the quality characteristic selected the better. The SN ratio was as shown below:

\[ η = -10 \log \left( \frac{\sum y^2}{n} \right) \]  
where \(y\) was the measured value and \(n\) - the total number of measurements.

- **Back-propagation neural network**

This research’s BPNN had three layers, as shown in Figure 4. The BPNN uses the gradient steepest descent method in order to minimise the error function and correct the network’s weight. The method used here to verify the network learning was the root-mean-square-error (RMSE), which is shown below:

\[ \text{RMSE} = \frac{1}{M \times N} \sum_{p=1}^{M} \sum_{j=1}^{N} \left( T_{pj} - Y_{pj} \right)^2 \]  
where \(M\) was the total number of training sets, \(N\) the number of neurons on the output layer, \(T_{pj}\) the jth output unit’s target output value of the pth training set, and \(Y_{pj}\) was the jth output unit’s hypothesised output value of the pth training set.

- **Results and discussion**

This paper used the BPNN as a classifier for fabric detection. However, there are several important learning parameters in need of setting in the BPNN algorithm, such as the number of learning cycles and hidden layer neurons, the learning rate and momentum factor. Table 1 lists the four control factors and their levels in the experiment. Since different settings of the neural network learning parameters will result in different convergence results, the L9(3^4) orthogonal array of the Taguchi method was used in the experiment for analysis of the four main learning parameters.
As shown in Table 2, the use of extremely few experimental runs can achieve an equally full factorial experiment to obtain an optimised learning parameter combination and improve on the overly time consuming trial-and-error drawback. Since the quality target of this experiment was ‘the lower the RMSE the better’ for the network convergence, the design of parameters was selected according to the small-the-better. Of the nine sets of experiments planned, each set collected five experimental measurements, in which an average was taken, and, according to equation (4), the SN ratios were calculated.

The BPNN in this research has six input and seven output neurons; the six input neurons of the input layer were six defined features, respectively, and the seven output neurons of the output layer were seven different fabrics, respectively. As the BPNN proceeded with learning, 105 feature images were collected (15 for each of the seven types of defect) and became the set of training data after normalisation. The target output vector (1,0,0,0,0,0) for laddering, (0,1,0,0,0,0) for an end-out, (0,0,1,0,0,0) for a hole, (0,0,0,1,0,0) for an oil spot, (0,0,0,0,1,0) for a dye stain, (0,0,0,0,0,1) for a snag and (0,0,0,0,0,1) for a crease mark.

After completion of the nine sets of orthogonal array experiments, a response graph, as shown in Figure 5 (see page 46), could be obtained by using main effect analysis. Optimised BPNN learning parameters can be obtained from the figure. Based on the main effect analysis, the combination sequence of the learning parameters, from large to small, was D1, A3, C3, and B2. Once the network had completed the learning, its RMSE converged to 0.000104. The optimised learning curve is shown in Figure 6 (see page 46).

Once the network completed the learning, recall was then proceeded to assess the BPNN’s categorised results. The set of test data was from 70 fabric feature images (10 for each of the seven kinds of fabric). Among the 70 test samples, the total amount of misjudgments was two, both of which were non-woven fabric mistakenly recognised as plain weave fabric. Thus, the recognition rate of this system’s structure is 97.14%. Moreover, because the texture variation of non-woven fabric itself has no regularity, it was easier to misjudge.

Table 1. Control factors and t.

<table>
<thead>
<tr>
<th>Code</th>
<th>Control factors</th>
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<th>2</th>
<th>3</th>
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<td>8000</td>
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<tr>
<td>B</td>
<td>Learning rate</td>
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<tr>
<td>C</td>
<td>Number of hidden neurons</td>
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<td>7</td>
<td>8</td>
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<tr>
<td>D</td>
<td>Momentum factor</td>
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Table 2. L9(3^4) orthogonal array and experimental results.

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<th>Factors/levels</th>
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<th>B</th>
<th>C</th>
<th>D</th>
<th>y</th>
<th>( \eta_y ) dB</th>
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Conclusions

Once the Taguchi-based BPNN method has gone through learning and recall, it can achieve a learning cycle of 8000, a learning rate of 0.5, a hidden neuron number of 8, a momentum factor of 0.2 for the learning parameter combination and can reach a fast convergence target and finally converge to a RMSE of 0.000104. The experiment proved that during the Taguchi-based BPNN experiment process, the use of extremely few
experimental runs can create an equally full factorial experiment and obtain an optimised learning parameter combination, which can greatly improve on the BPNN drawback with respect to the overly time consuming trial-and-error of finding the learning parameters. Finally, form the 70 test images it was proved that the Taguchi-based BPNN can efficiently classify fabric types, and the recognition rate can reach 97.14%.

References


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INSTITUTE OF BIOPOLYMERS AND CHEMICAL FIBRES

LABORATORY OF BIODEGRADATION

The Laboratory of Biodegradation operates within the structure of the Institute of Biopolymers and Chemical Fibres. It is a modern laboratory with a certificate of accreditation according to Standard PN-EN/ISO/IEC-17025: 2005 (a quality system) bestowed by the Polish Accreditation Centre (PCA). The laboratory works at a global level and can cooperate with many institutions that produce, process and investigate polymeric materials. Thanks to its modern equipment, the Laboratory of Biodegradation can maintain cooperation with Polish and foreign research centers as well as manufacturers and be helpful in assessing the biodegradability of polymeric materials and textiles.

The Laboratory of Biodegradation assesses the susceptibility of polymeric and textile materials to biological degradation caused by microorganisms occurring in the natural environment (soil, compost and water medium). The testing of biodegradation is carried out in oxygen using innovative methods like respirometric testing with the continuous reading of the CO2 delivered. The laboratory’s modern MICRO-OXYMAX RESPIROMETER is used for carrying out tests in accordance with International Standards.

The methodology of biodegradable testing has been prepared on the basis of the following standards:


The following methods are applied in the assessment of biodegradation: gel chromatography (GPC), infrared spectroscopy (IR), thermogravimetric analysis (TGA) and scanning electron microscopy (SEM).

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