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Automated Vision System for Recognising Lycra Spandex Defects

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Abstract
Fabric defect detection and classification plays a very important role in the automatic detection process for fabrics. This paper refers to the seven commonly seen defects of lycra spandex: laddering, end-out, hole, oil spot, dye stain, snag, and crease mark. First of all, the gray level co-occurrence matrix was used to collect the features of the fabric image texture, and then the back-propagation neural network was used to establish flaw classifications of the fabric. In addition, by using the Taguchi method combined with BPNN, the BPNN drawback was improved upon, which requires overly time consuming trial-and-error to find the learning parameters, and could therefore 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.*

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. Tilocca *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, making the network even more reliable.
Furthermore, since the appearance of fabric defects is related to the localised deformation of the regular texture pattern, the selection of the texture discrimination feature is apparently important. The gray level co-occurrence matrix (GLCM) is representative of the feature expression methods in texture analysis [4]. The method involves constructing a spatial gray level co-occurrence matrix with probability density functions of the grey level at particular adjacent positions from the pixels of the original image. It is thus suitable to describe fabric defects in the texture feature.

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,

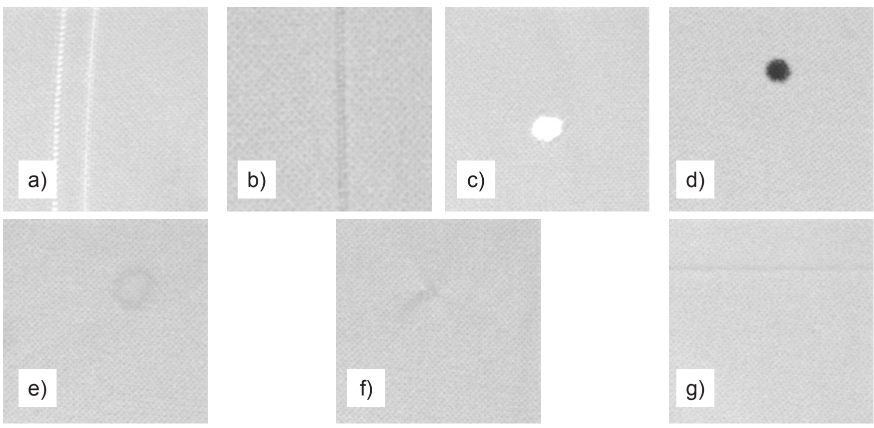

Figure 1. *Seven fabric defects; a) Laddering, b) End-out, c) Hole, d) Oil spot, e) Dye stain, f) Snag, g) Crease mark.*

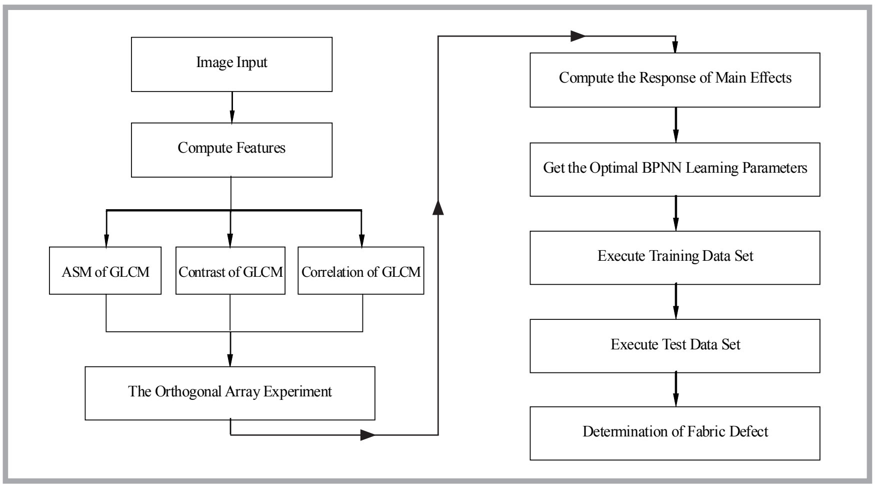

Figure 2. *Fabric defect image classification flowchart.*

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, which is done to quantitatively determine the chance of occurrence of a certain gray level appearance feature of the 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 co-occurrence matrix is regulated and substituted into the selected feature index to calculate the feature.

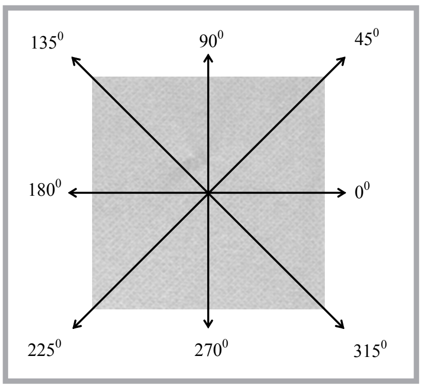

Figure 3. *Snag image of 512×512 pixels.*

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

$$\text{ASM: } \sum_i \sum_j P(i,j) \log P(i,j) \tag{1}$$

$$\text{Contrast: } \sum_i \sum_j |i-j|\, P_{ij}^2 \tag{2}$$

$$\text{Correlation: } \sum_i \sum_j P_{ij}\, |i-j| \tag{3}$$

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:

$$\eta = -10 \log\left(\sum y^2 / n\right) \tag{4}$$

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:

$$\text{RMSE} = \sqrt{\frac{\sum_p^M \sum_j^N \left(T_j^p - Y_j^p\right)^2}{M \times N}} \tag{5}$$

where M was the total number of training sets, N the number of neurons on the output layer; T_j^p the jth output unit's target output value of the p^{th} training set, and Y_j^p was the j^{th} output unit's hypothesised output value of the p^{th} 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 (1,0,0,0,0,0,0) was defined to represent laddering, (0,1,0,0,0,0,0) for an end-out, (0,0,1,0,0,0,0) for a hole, (0,0,0,1,0,0,0) for an oil spot, (0,0,0,0,1,0,0) for a dye stain, (0,0,0,0,0,1,0) for a snag and (0,0,0,0,0,0,1) 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.

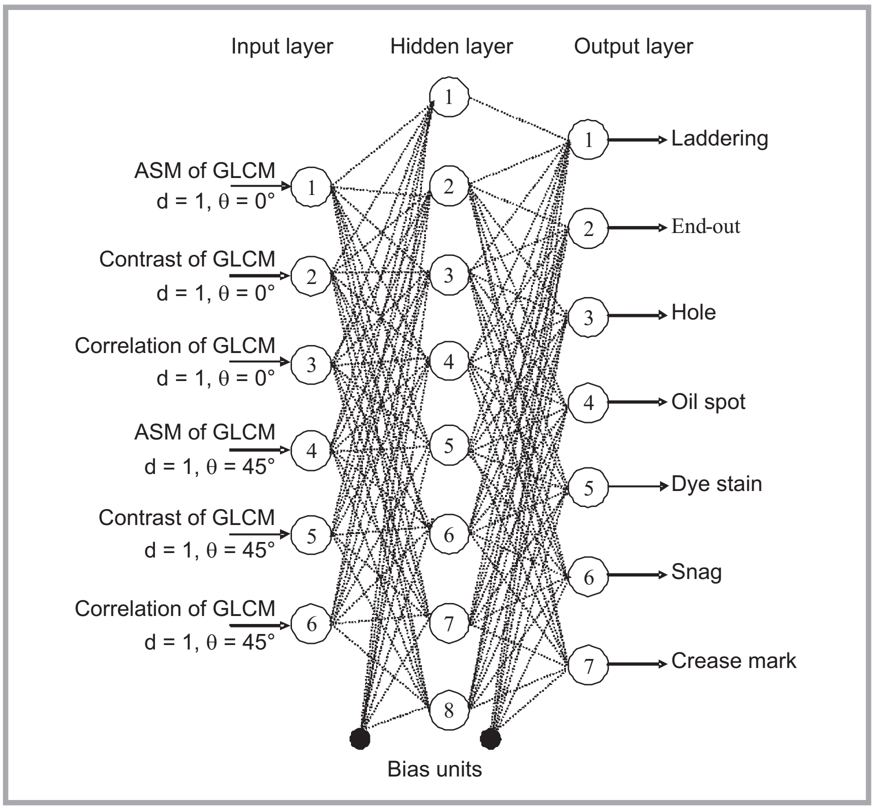

Figure 4. *Three-layer BPNN architecture.*

Table 1. *Control factors and t.*

Control factors		Levels		
Code	Source	1	2	3
A	Learning cycle	5000	6500	8000
B	Learning rate	0.3	0.5	0.7
C	Number of hidden neurons	6	7	8
D	Momentum factor	0.2	0.4	0.6

Table 2. *L9(3^4) orthogonal array and experimental results.*

Experiment no.	L_9				Experimental results	
	Factors/levels				y	η, dB
	A	B	C	D		
1	5000	0.3	6	0.2	0.000758	62.295
2	5000	0.5	7	0.4	0.000219	73.129
3	5000	0.7	8	0.6	0.001836	47.853
4	6500	0.3	7	0.6	0.001836	47.868
5	6500	0.5	8	0.2	0.000141	76.899
6	6500	0.7	6	0.4	0.003765	44.731
7	8000	0.3	8	0.4	0.000165	75.621
8	8000	0.5	6	0.6	0.000834	54.865
9	8000	0.7	7	0.2	0.000125	78.043
Optimum	8000	0.5	8	0.2	0.000104	79.615

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

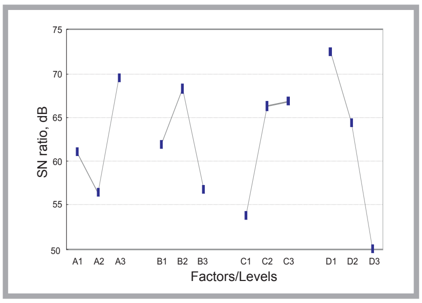

Figure 5.*Response graph of the SN ratio.*

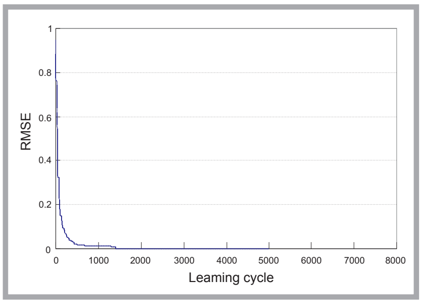

Figure 6. *Optimised learning curve.*

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%.

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