Binjie Xin,
Yanmei Li,
Jianxin Qiu,
***Yan Liu**

College of Fashion,
Shanghai University
of Engineering Science,
Shanghai,201620, China
E-mail: xinbj@sues.edu.cn

***Institute of Textile and Clothing,**
The Hong Kong Polytechnic University,
Hong Kong

Texture Modelling of Fabric Appearance Evaluation Based on Image Analysis

Abstract
This paper presents the development of a fairly new texture modelling method based on image analysis for the purpose of objective quality evaluation of fabric appearance. co-occurrence matrix analysis is used to give quantitative descriptions of fabric appearance properties; an expert system using a neural network is used to model the relationship between these essential features and the final rating grade of the fabric appearance. The experimental results demonstrate that a good correlation can be achieved between the actual rating grade and that predicted and reveals the possibility of the development of an artificial intelligence system to simulate the functions of the human eye and brain.

Key words: *co-occurrence matrix, fabric appearance, image analysis, artficial intelligence.*

Introduction

Fabric appearance evaluation in a laboratory usually relies on some specific machines to simulate changes in appearance during daily wearing and washing. These machines are always supplied with a standard consisting of photographs of samples with different degrees of pilling. Experienced judges assign a degree of appearance quality by comparing a sample processed by a particular machine with those standard photographs. However, a common drawback of these subjective methods, based on the estimation result made by those judges, is the inconsistency and inaccuracy of the rating grade.

With the development of digital technology, image analysis techniques have been widely used for the characterization and inspection of textile materials, instead of a human being's subjective evaluation. In an attempt to bring more objectivity and automation into the fabric rating process, many automated systems based on image analysis have been developed and described in literature. In addition, some typical applications have been established for the inspection of textile surface characteristics [1 - 5], analysis of cotton fibre maturity [6], characterisation of nonwoven structures [7, 8], and evaluation of the aesthetic appearance of carpet [9, 10].

All of these existing methods and applications either employ expensive and complicated equipment, such as laser triangulation imaging and/or employ complex image processing algorithms that involve multiple stages. More recently, approaches suitable for the objective assessment of fabric appearance using image analysis have been investigated, but these methods also employ complex hardware and software systems to complete the task. At least one system for objective fabric appearance analysis is commercially available, but no independent assessment of its performance is currently available. In general, more generic and adaptive texture modelling methods are necessary in order to develop an effective objective evaluation based on image analysis techniques.

In this paper, the co-occurrence matrix based analysis method for appearance evaluation is investigated; a preliminary neural network based expert system for the grade rating is also established as an artificial intelligent classifier.

Data acquisition

According to the comfortable feeling of visual perception when evaluating fabric wrinkle appearance, we divide fabric wrinkle appearance into five grades, as illustrated in ***Figure 1***. Grade 1 represents a deeply wrinkled appearance, while at the other end, grade 5 represents a relatively smooth surface. It is obvious that texture properties such as uniform, roughness and regularity are the most important features for quality evaluation. Investigation of this phenomenon was conducted in our previous research papers. As the co-occurrence matrix is an effective method for characterisation of a texture image, it is utilised in this paper to give a quantitative description of fabric wrinkle after the washing process.

System set-up

As illustrated in ***Figure 2***, the instrument setup consists of a digital camera to capture an image of fabric samples mounted on the sample platform, one set of lighting sources to illuminate the fabric sample at a low angle, one enclosure box containing the fixed sample platform and lighting sources, and a computer connected to the digital camera for image data collection and further data analysis. The digital camera is placed above the lighting box and mounted at a distance

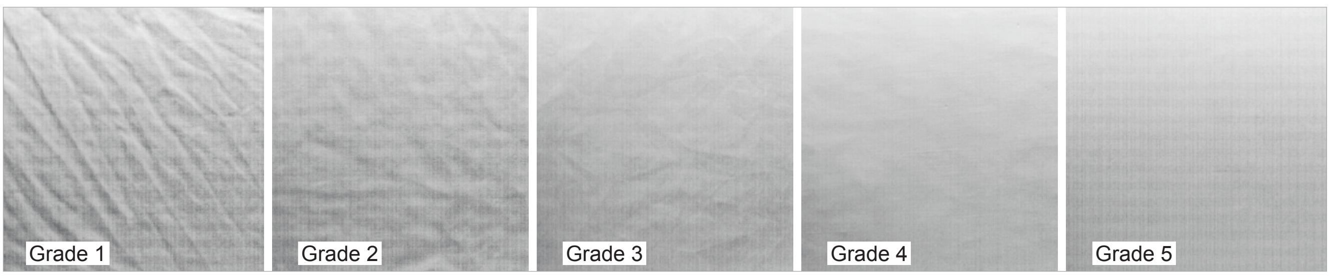

***Figure 1.** Ones set of standard fabric appearance photographs.*

sufficient to capture a well focused image of the fabric sample.

Sample Specification

In our research, 5 kinds of commercially available fabrics with solid colours and different wrinkle resistant abilities were used as samples. Each fabric sample was cut into an approximately 380 × 380 mm square and subjected to laboratory washing in a standard washing machine according to AATCC Test Method TM124..

The image resolution of the digital camera used here is 1600 by 1200 pixels. In this study, we have cropped each fabric image into a size of 512 by 512 pixels; each pixel has values of 256 gray levels, with the zero value representing black and 255 representing white. After digitalisation of the fabric appearance image, a set of algorithms for calculation of co-occurrence matrix parameters will be developed in section ‘Neural network modelling’.

Co-occurrence matrix analysis

Basic principle of co-occurrence matrix [11, 12]

The grayscale co-occurrence matrix is a widely applied method for texture analysis, whose indicators are usually used as feature parameters for such analysis. The grayscale co-occurrence matrix contains valuable spatial organisation information of the texture. A regular sharp texture is reflected by an accrete matrix concentrated around the diagonal, while a scattered co-occurrence matrix is an indication of an irregular and fuzzy texture. If the texture shows a highly uniform orientation and the displacement vector is consistent therewith, the accrete matrix will be on the main diagonal.

Assuming that the size of image $f(x,y)$ is $N_x \times N_y$ and the grayscale is Ng, the distance between two random pixels (j,k), (m,n) and the position angle θ should described by ***Equation 1***.

Times of occurrence of the grayscale pair (p,q) in the co-occurrence matrix are presented by ***Equation 2***.

Hereinto, # stands for the number of elements in the aggregation. As the co-occurrence matrix is symmetric, thus $P(i,j,d,\theta) = P(j,i,d,\theta)$.

Figure 3 (see page 50) demonstrates the co-occurrence matrix of five standard wrinkle appearance photographs by the means of 3-D chart; the vertical coordinate represents the frequency of occurrence of grayscale pair.

Feature parameters in the co-occurrence matrix

The co-occurrence matrix is normalised for the convenience of feature parameter definition before the specification of features.

- Texture uniformity (Q_1):

$$Q_1 = \sum_{i=0}^{N_g}\sum_{j=0}^{N_g} p(i,j)^2 \qquad (3)$$

Uniformity (Q_1) reflects the homogeneity of the image’s texture. A higher value of uniformity indicates a more consistent texture.

- Texture contrast (Q_2):

$$Q_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=0}^{N_g}\sum_{\substack{j=0 \\ |i-j|=n}}^{N_g} p(i,j) \right\} \qquad (4)$$

Contrast (Q_2) reflects the diversity of the image’s texture. A low value of Q_2 indicates a coarse texture.

- Texture entropy (Q_3):

$$Q_3 = -\sum_{i=0}^{N_g}\sum_{j=0}^{N_g} p(i,j)\log\{p(i,j)\} \qquad (5)$$

An ordered distribution of the co-occurrence matrix corresponds with the maximum value of entropy. A higher value of entropy indicates better regularity in texture.

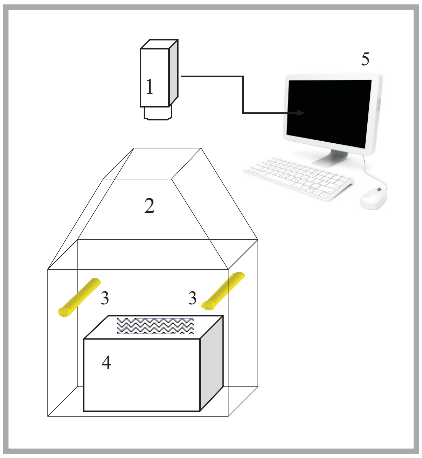

Figure 2. *Digital system for the fabric appearance evaluation; 1 - CCD camera, 2 - lighting box, 3 - lighting source, 4 - sample platform, 5 - computer.*

- Texture correlation (Q_4):

$$Q_4 = \frac{\sum_{i=0}^{N_g}\sum_{j=0}^{N_g} (ij)\,p(i,j) - u_x u_y}{\sigma_x \sigma_y} \qquad (6)$$

Hereinto, u_x, u_y, σ_x, σ_y is the mean value and variance of p_x, p_y,

$$p_x = \sum_{i=0}^{N_g} p(i,j)\,,\; p_y = \sum_{j=0}^{N_g} p(i,j)\,.$$

The correlation coefficient of texture reflects correlations between textures in different orientations. A coarse texture shows a higher correlation coefficient value than a fine one (***Table 1***, see page 51).

Neural network modelling

Artificial Neural Networks (ANN) [13-15] have been applied to different textile problems such as classifying patterns or defects in textile textures, and predicting

$$\begin{aligned}
&\theta = 0^\circ && R_H(d): |j-m| = d, k-n = 0 \\
&\theta = 45^\circ && R_{RD}(d): j-m = d, k-n = d, \\
& && \qquad j-m = -d, k-n = -d \\
&\theta = 90^\circ && R_V(d): j-m = 0, |k-n| = d \\
&\theta = 135^\circ && R_{LD}(d): j-m = -d, k-n = d, \\
& && \qquad j-m = d, k-n = -d
\end{aligned} \qquad (1)$$

$$\begin{aligned}
&P(p,q,d,0^\circ) = \#\{((j,k),(m,n)) \,||\, R_H(d), f(j,k) = p, f(m,n) = q\} \\
&P(p,q,d,45^\circ) = \#\{((j,k),(m,n)) \,||\, R_{LD}(d), f(j,k) = p, f(m,n) = q\} \\
&P(p,q,d,90^\circ) = \#\{((j,k),(m,n)) \,||\, R_V(d), f(j,k) = p, f(m,n) = q\} \\
&P(p,q,d,135^\circ) = \#\{((j,k),(m,n)) \,||\, R_{RD}(d), f(j,k) = p, f(m,n) = q\}
\end{aligned} \qquad (2)$$

Equation 2.

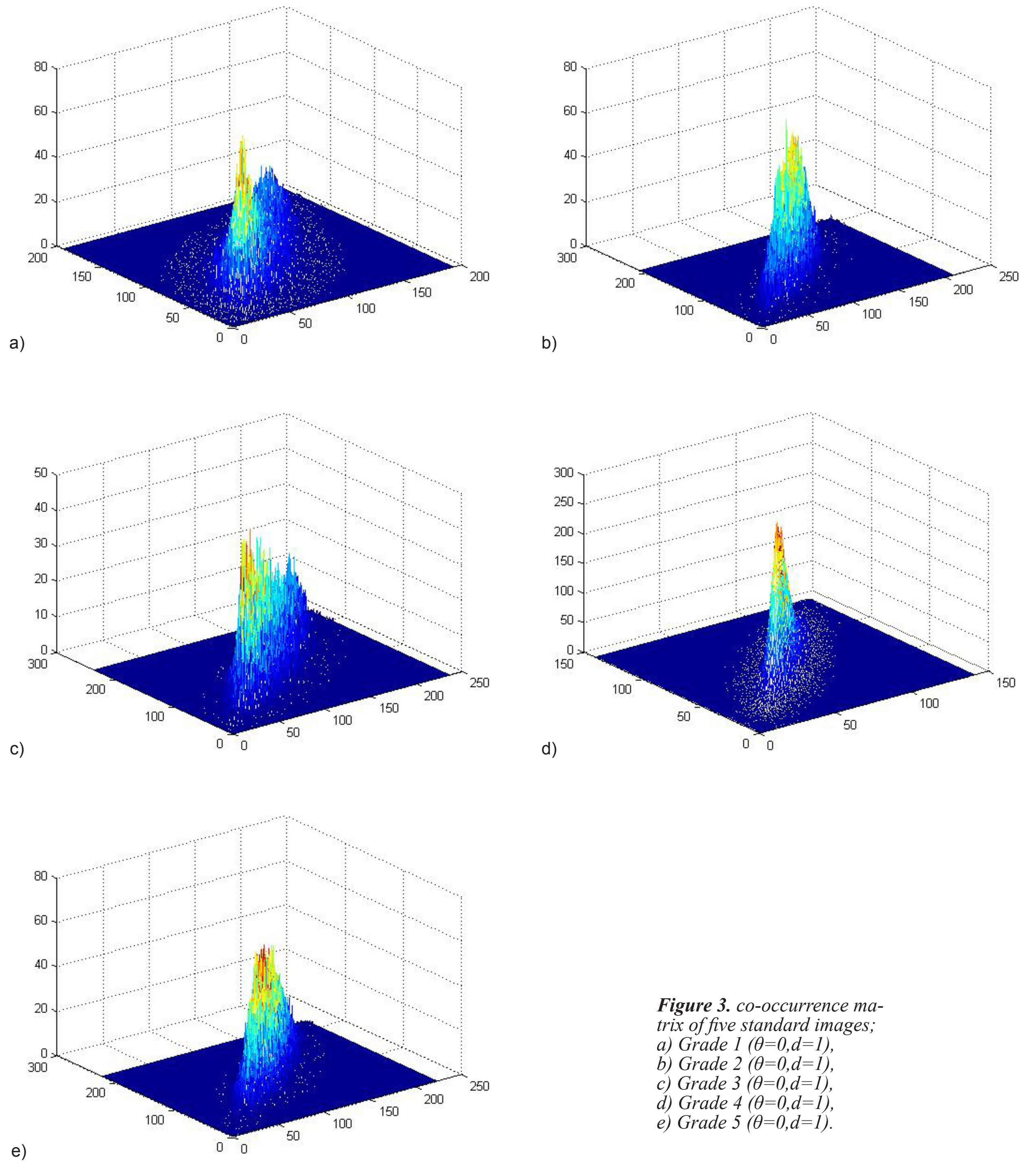

***Figure 3.** co-occurrence matrix of five standard images; a) Grade 1 (θ=0,d=1), b) Grade 2 (θ=0,d=1), c) Grade 3 (θ=0,d=1), d) Grade 4 (θ=0,d=1), e) Grade 5 (θ=0,d=1).*

fabric parameters [16, 17]. Among the many Artificial Neural Network schemes, feed-forward neural networks with back-propagation learning algorithms based on gradient descent have been widely used since they offer unlimited approximation power for non-linear mappings. Therefore, we have established an ANN model based on the feed-forward back propagation network and investigated the performance of its neuron function to simulate human judging behaviour,

According to essential texture features based on co-occurrence matrix analysis, a two-layer ANN system with 4 inputs and 1 output, as shown in ***Figure 4***, four input variables include Q_1, Q_2, Q_3 and Q_4, one output variable is the final rating grade. To be more explicit, a two-layer feed forward NN model consists of a stream of input vector X of 4 neurons, i.e. $\{x_1, x_2, x_3, x_4\}$ to the input layer, and an output layer with a single neuron. The network has the general form:

$$Y = f(X, \Theta) = f\left\{b_0 + f_1\left(\sum_{i=0}^{n} w_i x_i + b_i\right)\right\} \quad (7)$$

where Y represents the generated output response variable; Θ denotes the overall parameter space; w_i - the connecting weight of the i^{th} input neuron; b_0 and b_i are the bias nodes; and f_1 and f are the activation functions of the first layer and second layer, respectively (***Figure 4***).

Here, we use LOGSIG as the activation function of four neurons of the first layer and PURELIN as the activation function of the second layer.

$$f(x) = x;$$
$$f_1(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}; \tag{8}$$

System training

The neural network model for fabric appearance evaluation was trained using a training set that included 50 samples ranging from grade 1 to grade 5. The training process was terminated at a point where all the samples in this training set were correctly identified. We first input training data to the network and perform a gradient descent using the Levenberg-Marquardt Algorithm. Parameters are adjusted iteratively until the global error function converges to some specified minimum so that satisfactory generalisation is achieved. Some important considerations are the number of training iterations, the learning rate and the momentum coefficient.

Supposing the estimated grade y is governed by the underlying function $f(x;\theta^*)$, where x is the set of input variables and θ^* represents true values of the parameter vector θ from the parameter space Θ for the function which models the process. With n observations, the simulation process is represented by:

$$y_i = f(x_i;\theta^*) + \varepsilon_i, i = 1 \sim n, \theta^* \in \Theta \tag{9}$$

The least-square estimate of θ^* is the $\hat{\theta}$, which is obtained by minimising the error function:

$$S(\theta) = \sum_{i=1}^{n} [y_i - f(x_i;\theta]^2 \tag{10}$$

The Levenberg-Marquardt algorithm uses this approximation in a Hessian matrix in the following Newton-like update:

$$\theta_{k+1} = \theta_k - [J^T J + \mu I]^{-1} J^T e \tag{11}$$

Where, J is a Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of the network errors. When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes a gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, therefore the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm. For this study, we used the mean square error (MSE) between the output of the model predicted and the actual target value as the following equation:

$$MSE = \frac{\sum_{i=1}^{n} (Y_i - T_i)^2}{n} \tag{12}$$

Where n is the number of training data sets. We trained the neural network model using parameters extracted using the co-occurrence matrix, the performance of the model on the training data set is illustrated through ***Figure 5***, the MSE between the predicted output of the model and the target actual value is 0.004635. The residual value of each training data using the neural network model is shown in ***Figure 6*** (see page 52), ranging from -0.4 to 0.4.

Table 1. *Parameters of the co-occurrence matrix.*

Grade	Q1 (θ=0,d=1)	Q2 (θ=0,d=1)	Q3 (θ=0,d=1)	Q4 (θ=0,d=1)
1	172.85	8071.9	0.076099	10.461
2	166.24	5535.7	0.022552	-1.4825
3	110.14	1634.9	0.015557	-1.5456
4	70.051	1762.8	0.058068	9.8895
5	50.391	419.04	0.016888	-1.8574

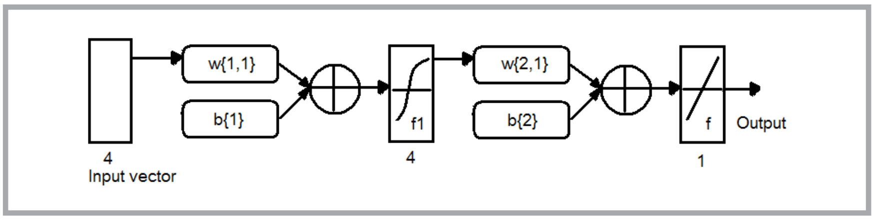

Figure 4. *Design of neural network.*

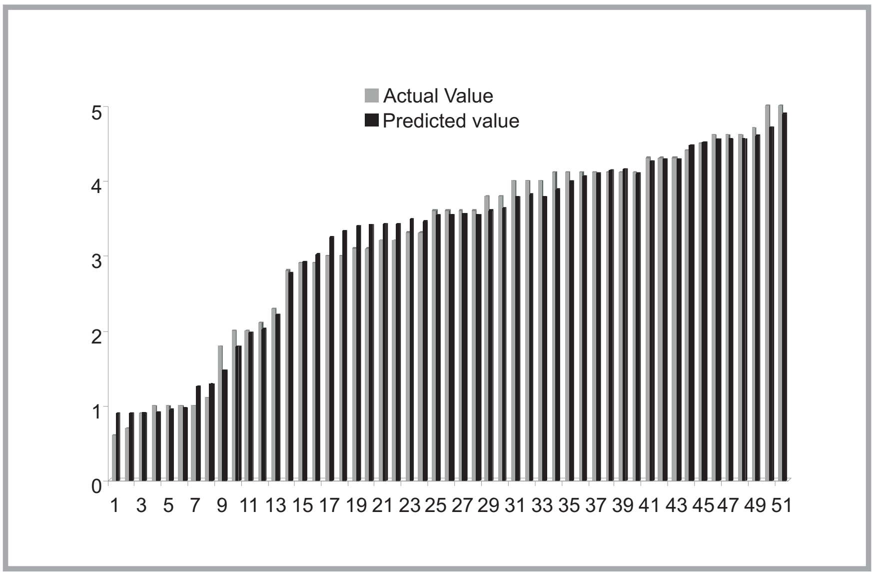

Figure 5. *Performance of the model on the training data set.*

Validation

After we trained the neural network models, the neural network system was tested using a validation data set of 50 samples. The experimental results show that the artificial intelligence system developed in this project could achieve good results consistent with those of human evaluation; the predicted rating grade tracked the actual rating grades very well, as the correlation coefficient was sufficiently high ($R^2 = 0.9798$) as illustrated in ***Figure 7*** (see page 52).

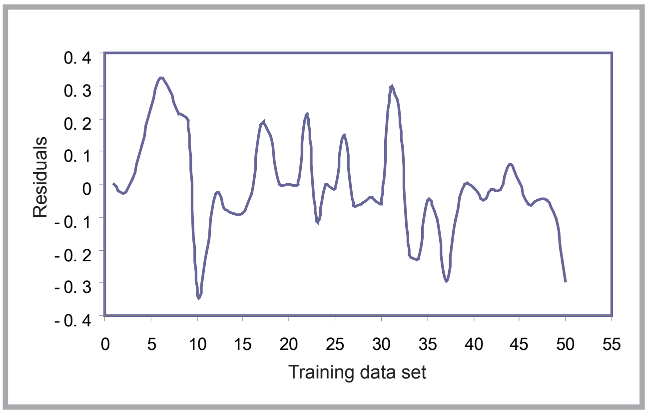

Figure 6. Training performance of neural network model.

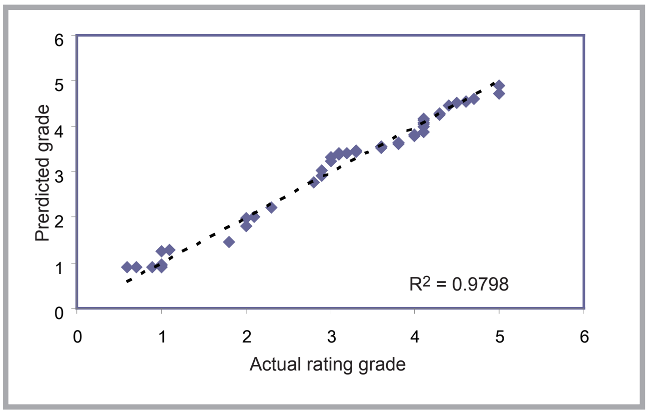

Figure 7. Validation of neural network model.

Conclusion

An expert artificial intelligence system based on image analysis and the neural network method was developed for objective evaluation of fabric wrinkle appearance. The co-occurrence matrix was used to characterize the fabric appearance and one set of two-layer feed-forward back propagation network model was established for rating of the degree of fabric wrinkle appearance. The test results for validation show that the artificial intelligent system developed in this research is consistent with the behaviour of human beings, proving that it is workable to replace the traditional subjective evaluation method based on the human eye and brain with using the modern artificial intelligence method developed herein.

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