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Grey Relational Analysis of an Automatic Identifying System for Clothing Texture

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Abstract

Abstract: Fabric quality inspection is important to the textile industry because the price of second-quality fabric is merely 45% to 65% of that of first-quality fabric. Using the wavelet transform, this paper intends to analyse fabric images and establish the different features of fabric texture, and then through grey relational analysis of grey theory, we will attempt to distinguish and classify the texture of fabrics, mainly cotton, polyester, silk, rayon, knitting and linen. The grey relational analysis approach is applied to analyse the correlation in the random factor sequence of feature indexes after some data processing and determine the texture type of the designated fabric on the basis of the highest relative degree. Experiment findings show that the automatic distinguishing system for the fabric types discussed in this paper is capable of distinguishing six different textile images.

Key words: fabric texture, automatic distinguishing system, wavelet transform, grey relational analysis.

Introduction

The quality inspection of textiles represents a highly repetitive and tedious task. In spite of its contribution to improving quality production, manual inspection is time-consuming, inefficient, uneconomical, and easily causes fatigue in the eyes. Furthermore, it follows no definite rules, only personal experience. Therefore, it is inevitable for automatic inspection to be introduced in quality management. Tak-

ing advantage of the accuracy and speed of a computer, researchers are capable of analysing fabric types accurately and objectively in a shorter time, thus assisting fabric designers, stylists, pop colour analysers, quality control personnel and yarn designers in dyeing, stamp pattern designing, graphics designing, pattern examination, colour matching, weighing, design drawing, design reviewing, etc, so that these designers and profession-

als are able to come up with competitive products which can promptly respond to international textile markets and meet shorter deadlines as a result of fierce competition [1 - 5].

In studying images of a fabric whose surface takes on a texture resulting from light reflection on the wavy yarn, the weave of the fabric can be established through analysing its texture. In general, distin-

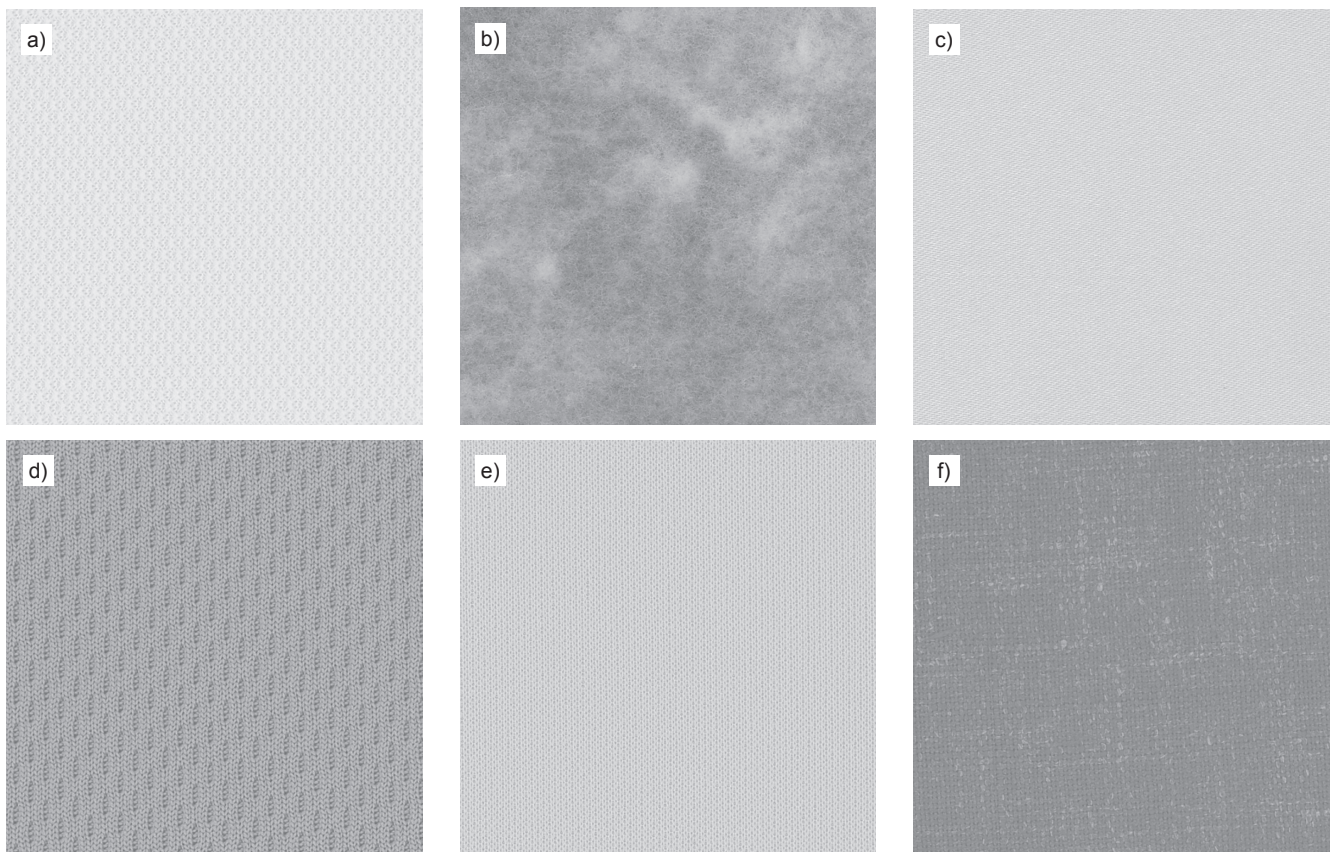


Figure 1. Six different textures of fabrics; a) woven fabric (100% cotton, plain), b) nonwoven fabric (100% polyester), c) woven fabric (100% silk, 1/2 twill), d) weft knitted fabric (100% rayon), e) weft knitted fabric (65% polyester/35% cotton), f) woven fabric (100% linen, plain).

guishing algorithms include the structural method, the statistical method and the screen spectrum method, in which the structural method is employed to gather texture features that can be represented in terms of smoothness and roughness; features of the texture can also be described by the statistical method, such as the mean, the histogram, variation, co-occurrence matrix, etc. Since the energy of the wavelet transform can better describe features of the texture image, this paper takes advantage of it to represent the features of fabric texture [6].

As regards textile inspection research undertaken in previous literature, Tsai et al. [7] used a back-propagation neural network to inspect fabric defects including missing ends, missing picks, broken fabric and oiled fabric. They proposed a statistical method to calculate nine characteristic parameters of input neurons in a neural network. However, the statistical method required more testing time. Shiau et al. [8] applied a back-propagation neural network to identify neps and trash in a web. However, the system misjudged trash and miscalculates both its area and amount when the maximum weight exceeds 32.9 g/m². Hu et al. [9] adopted best wavelet packet bases and a back-propagation neural network to inspect missing ends, missing picks, as well as oily and broken fabric. In their research, the important design issues in building an artificial neural network classifier were used to find an appropriate network topology (the number of hidden layers and processing elements in each layer) and the weights between the processing elements in different layers.

Used as a distinguishing system classifier, a back-propagation neural network has the following disadvantages: if the initial weight is not well set, the learning efficiency and precision will be affected; if the learning efficiency is to be improved, the learning rate or momentum factor has to be increased, however, a too high learning rate or momentum factor will lead to vibration; and if the learning cycles are not enough, it will be hard to achieve the global minimum. To address these problems, this paper proposes some approaches for improvement.

Experimental descriptions

The research makes use of a machine vision approach to examine the type of

fabric texture and study features of the fabric surface that will be utilised to classify the texture of unknown fabrics. The textures of six different fabrics are shown in **Figure 1**: woven fabric (100% cotton, plain), nonwoven fabric (100% polyester), woven fabric (100% silk, 1/2 twill), weft knitted fabric (100% rayon), weft knitted fabric (65% polyester/35% cotton), and woven fabric (100% linen, plain), respectively.

The specification of the equipment unit is EPSON PERFECTION 2400 PHOTO scanner (photo resolution: 2400 dpi). The images acquired from six types of fabrics have 256 grey levels with a size of 600 × 600 pixels and resolution of 600 dpi.

While obtaining the features of fabric images, the wavelet transform approach is employed to work out features of the images, which are then sequenced with the images of six different fabrics for the study of their grey relational degree, as well as for further classification. The process is shown in **Figure 2**.

Theory

Wavelet transform

The wavelet transform approach is widely used in fields such as signal processing, image processing, video compression, etc. Wavelet analysis is a significant development of Fourier analysis because it not only retains the advantages of Fourier theory but also overcomes its deficiencies. In other words, the wavelet transform divides an image into four subimages, through which both the frequency and spatial features are revealed. In addition, these subimages contain the features of high-frequency and low-frequency filters, with the high-frequency filter extracting a high-frequency message from the original image and the subimage of the low-frequency filter gathering most of the energy of the original image [10 - 12].

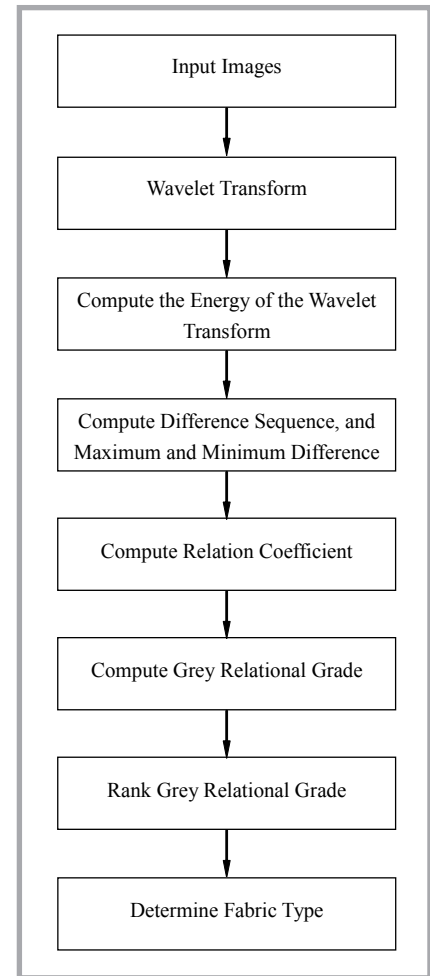


Figure 2. Experimental flowchart.

The algorithm of the wavelet transform is shown below:

$$f(t) = \sum_{j \in Z} \sum_{k \in Z} c(j, k) \psi_{j, k}(t) \quad (1)$$

where

$$\langle \psi_{j, k}(t) \psi_{m, n}(t) \rangle = 0, j \neq k, m \neq n \quad (2)$$

$$c(j, k) = \langle f(t) \psi_{j, k}(t) \rangle \quad (3)$$

where $f(t)$ is the original signal, $c(j, k)$ the coefficient matrix, and $\psi_{j, k}(t)$ is the frequency j of the wavelet transform. As for the wavelet function at location k , the inner product of any two functions with a different basis must be 0 in terms of the

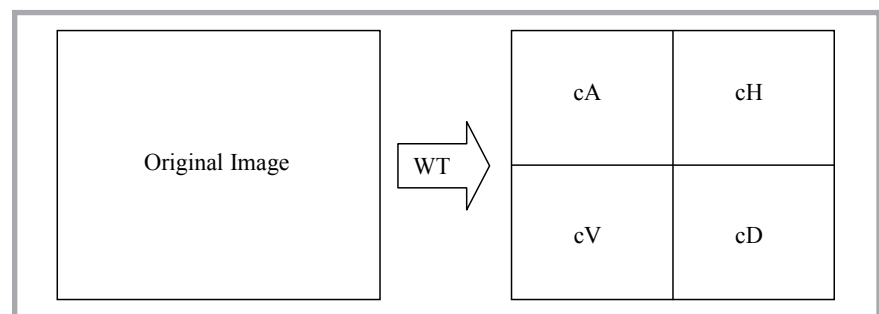


Figure 3. Signal decomposition graph of wavelet transform.

orthogonal wavelet function, as shown in equation (2). Accordingly, the coefficient $c(j,k)$ is obtained from the original signal and inner product of the basis, as shown in equation (3).

The signal decomposition graph of the wavelet transform is shown in **Figure 3**, (see page 61) in which cA represents the wavelet coefficient of low-frequency; the digit stands for the level of decomposition, and cH, cV, cD represent horizontal, vertical and diagonal high-frequency wavelet signals, respectively.

The base utilised in the research is the Haar wavelet (dbl) developed by Daubechies [13], as shown in **Figure 4**. The Haar wavelet is a ladder-shaped discontinuous function characterised by the fastest speed of calculation, quite suitable for the inspection of products of speedy manufacture. Its function equation is as below:

$$\psi(x) = 1, \text{ if } 0 \leq x < 1/2 \quad (4)$$

$$\psi(x) = -1, \text{ if } 1/2 \leq x < 1 \quad (5)$$

$$\psi(x) = 0, \text{ if } x \notin [0, 1] \quad (6)$$

Grey relational analysis

When analysing images of fabric texture, a proper mathematical model needs to be established in order to study the texture structure of fabrics and specifically represent the features of their texture. The first task is to analyse the feature factors of various fabric textures, then understand the correlation between them and master the major features of the fabric texture.

In this paper, using grey relational analysis of grey theory, the correlation of various fabric images of certain fabric texture features will be determined through the data processing of feature indexes obtained from the wavelet transform.

Grey relational analysis of fabric images is defined in [14 - 16]:

In this paper, the calculation steps of the grey relational degree are given below:

Step 1: establish the average of every sequence

Let

$$X'_i = X_i/x_i(1) = (x'_i(1), x'_i(2), \dots, x'_i(n))$$

$$i = 0, 1, 2, \dots, m$$

Step 2: determine the difference sequence

$$\Delta_i(k) = |x'_0(k) - x'_i(k)|,$$

$$\Delta_i = (\Delta_i(1), \Delta_i(2), \dots, \Delta_i(n))$$

$$i = 0, 1, 2, \dots, m$$

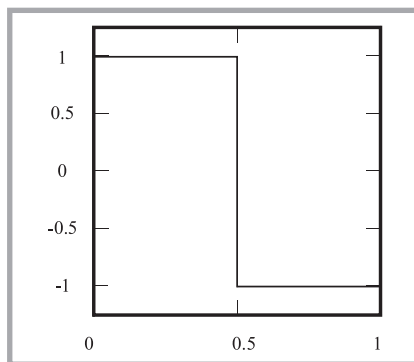


Figure 4. Haar wavelet.

Step 3: seek the maximum and minimum difference

$$M = \max_i \max_k \Delta_i(k)$$

$$m = \min_i \min_k \Delta_i(k)$$

Step 4: establish the correlation coefficient

$$\gamma_{oi}(k) = \frac{m + \zeta M}{\Delta_i(k) + \zeta}, \zeta \in (0, 1);$$

$$k = 1, 2, \dots, n; i = 1, 2, \dots, m$$

Step 5: calculate the relational degree

$$\gamma = \frac{1}{n} \sum_{k=1}^n \gamma_{oi}(k), i = 1, 2, \dots, m$$

Having processed the fabric images via the wavelet transform, the feature indexes obtained are calculated by grey relational degree analysis, and immediately their relational degree with woven fabric (100% cotton, plain), nonwoven fabric

(100% polyester), woven fabric (100% silk, 1/2 twill), weft knitted fabric (100% rayon), weft knitted fabric (65% polyester/35% cotton), and woven fabric (100% linen, plain), respectively. can be acquired; with that the texture type of fabric images inputted can be categorised.

Results and discussion

First, the images acquired must be processed via the wavelet transform. The algorithm of the Haar function discrete wavelet transform consists of two steps: one is horizontal division, the other - vertical. The former is to acquire the pixel value of images horizontally (left to right), and also save it horizontally; the latter is to acquire the pixel value of images vertically (up to down) and also save it vertically.

Step 1: horizontal division. In the horizontal direction from left to right, two adjacent pixels of the spatial image are added and subtracted, the results of which are then saved, respectively. As shown in **Figure 5**, I, II, III, IV represent four adjacent pixel values of the image, respectively. I and II are removed for an addition (I + II) and subtraction (I - II), the results of which are then saved in the array on the right. Similarly, III and IV are also removed for an addition (III + IV) and subtraction (III - IV), the results of which are then saved in the array on the right. The addition which stands for the low-frequency element of the image is

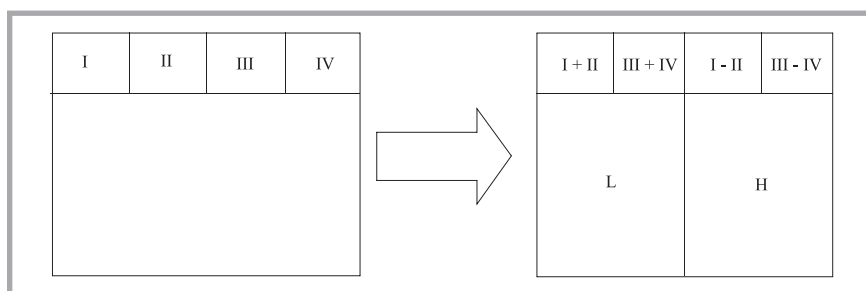


Figure 5. Horizontal division.

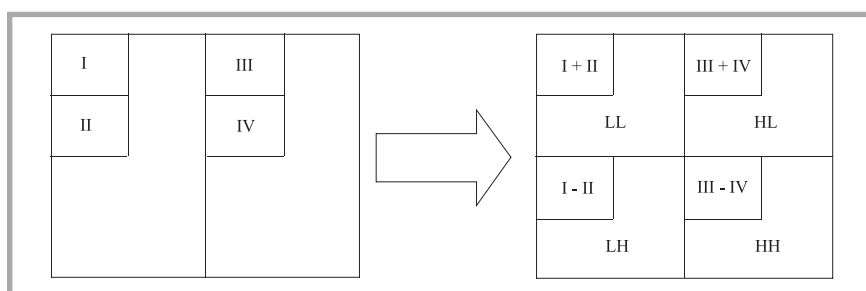


Figure 6. Vertical division.

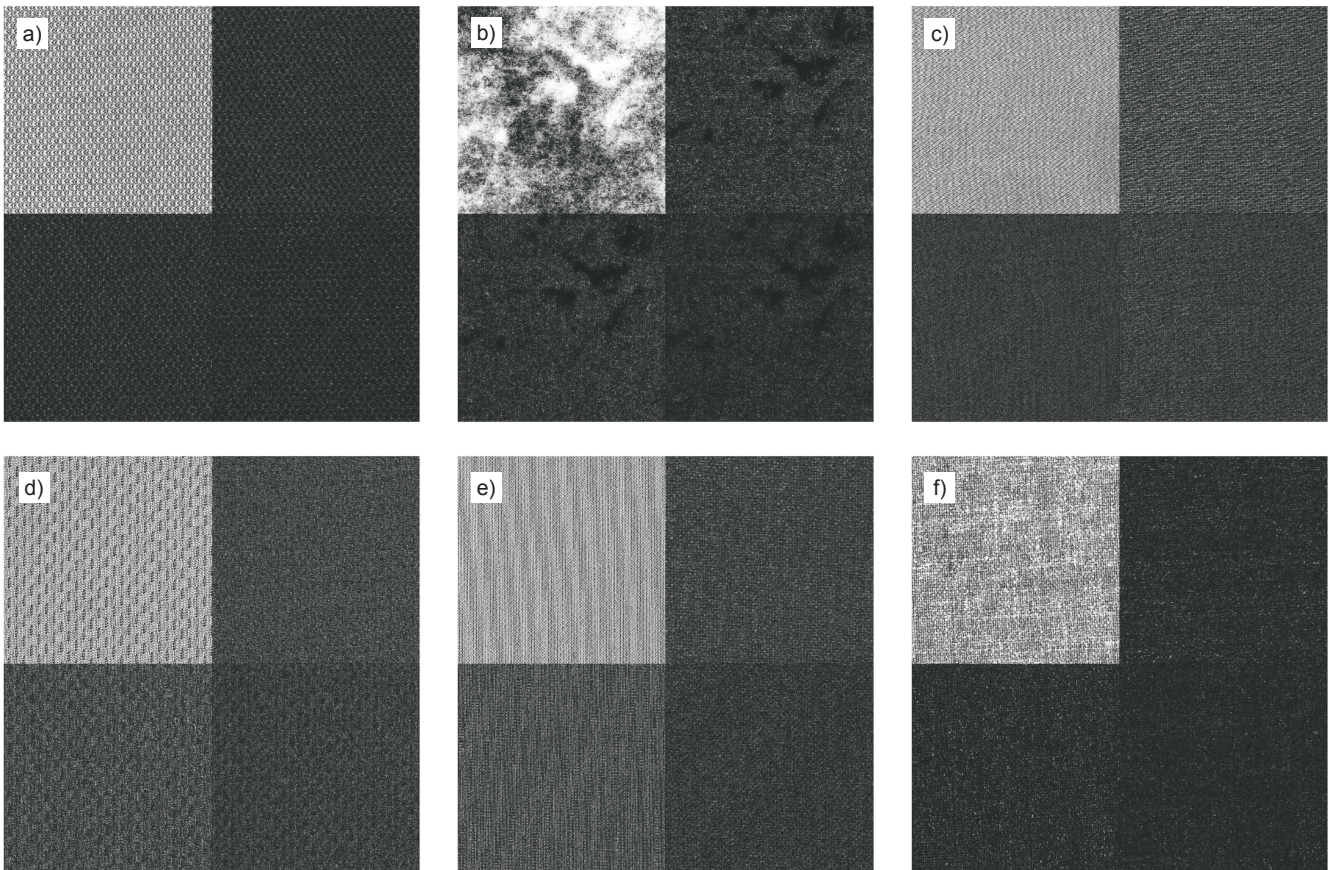


Figure 7. Wavelet transform image graphs of the six following fabrics which initial textures are presented in Figure 1: a) Woven fabric (100 % cotton, plain), b) Nonwoven fabric (100% polyester), c) Woven fabric (100% silk, 1/2 twill), d) Weft knitted fabric (100% rayon), e) Weft knitted fabric (65% polyester/35% cotton), f) Woven fabric (100% linen, plain).

represented by the symbol L, whereas the subtraction which stands for the high-frequency element of the image is represented by the symbol H.

Step 2: vertical division. In the vertical direction from up to down, and with the results obtained from the horizontal division, the pixel values of the image are added and subtracted, the results of which are then saved, respectively. As shown in **Figure 6**, I, II, III, IV represent four adjacent pixel values of the image, respectively. I and II are taken out for an addition (I + II) and subtraction (I - II), the results of which are then saved in the array on the right. Similarly, III and IV are also removed for an addition (III + IV) and subtraction (III - IV), the results of which are then saved in the array on the right. The addition set that stands for a low-frequency calculated from the low-frequencies is represented by the symbol LL, whereas the subtraction which stands for a high-frequency calculated from the high-frequencies is represented by the symbol HH.

The completion of horizontal and vertical division means the completion of the wavelet transform. Here we obtain four symbols: LL, LH, HL and HH, which stand for different frequencies, respectively. **Figure 7** represent wavelet transform image graphs of woven fabric (100% cotton, plain), nonwoven fabric (100% polyester), woven fabric (100% silk, 1/2 twill), weft knitted fabric (100% rayon), weft knitted fabric (65% polyester/35% cotton), and woven fabric (100% linen, plain), respectively. In addition, the size of each part of **Figure 7** are a fourth of the original figures. As in **Figure 3**, pixels changes in the cA are the same as the original figure; the cH emphasises the change in horizontal pixels; the cV emphasises the change in vertical pixels; the cD emphasises the change in diagonal pixels. Therefore, from the figures of cA, cH, cV, and cD, different texture features could be obtained.

Then the feature values of the four are calculated, respectively, to obtain messages representing the features of the image. The equation of the energy of the wavelet transform is shown below:

$$e = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N |C_{ij}| |C_{ij}|$$

where C_{ij} represents the coefficient of the sub-image at Points i Point j after the wavelet transform, and M and N represent the size of the sub-image.

In this research, a total of 300 images, 50 for each type of fabric texture, are tested. Using grey relational analysis, the textures of cotton, polyester, silk, rayon, knitting and linen fabrics can be distinguished with an accuracy rate of 100%. The finding shows that the energy of the wavelet transform utilised in the research can describe the features of all fabric textures. In addition, grey relational analysis of intelligence theory is suitable in situations when there are few feature messages available for effectively and precisely distinguishing the texture types of various fabrics.

Conclusions

In the algorithm of grey relational analysis, the function of the distinguishing coefficient is mainly to compare the


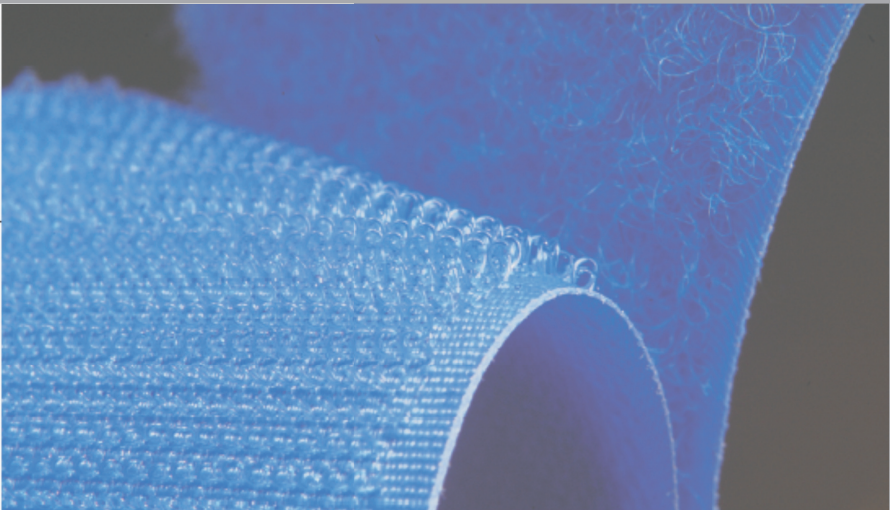
background value with 300 test images. In setting the distinguishing coefficient, an optimal one has to be found so as to improve the distinguishing rate. In this research, an optimal distinguishing coefficient ζ of 0.3 to 0.7 is found from 100 fabric image samples, and the coefficient ζ is set at 0.5. In addition, if there is uneven illumination, the grey levels of the image will be distributed unevenly, which will lead to some errors in the pre-treatment of imaging and in the calculation of feature values, possibly resulting in the misjudgement of the system. However, the problems above are avoided in the research because even lighting is ensured in acquiring images. To conclude, making full use of grey relational analysis, which requires few feature messages, the research has successfully established an intelligent fabric texture distinguishing system which can also be applied in other fields related to improving overall distinguishing efficiency and speed by avoiding misjudgment as a result of manual inspection.



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