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Fabric Defect Classification Based on LBP and GLCM ⋆

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Abstract

Inevitably there will be various types of fabric defect exists in textile production line. In order to distinguish and classify the types of defects more efficiently and accurately, an algorithm which combines Local Binary Patterns (LBP) and Gray-level Co-occurrence Matrix (GLCM) is proposed in this paper for fabric defect classification. The most pivotal step of the algorithm is to extract the local and global feature values of defect images. Firstly the local feature information of the image is extracted by adopting LBP algorithm. And then the overall texture information of the image is described via GLCM algorithm. In this way, the fabric image can be fully described from global and local. Finally, the two-part feature information are structured as a whole as the input of BP Neural Network. Thus the trained BP Neural Network can be used to classify the different types of defects. Experimental results show that the algorithm has higher classification accuracy.

Keywords: LBP; Gray-level Co-occurrence Matrix (GLCM); BP Neural Network; Defect Classification

1 Introduction

With the rapid development of textile industry, quality monitoring of textile manufactories is promoted more rigorous. As one of the key factors of the quality of textile, fabric defects impact the worth of textile immensely. Statistics information represents that fabric defects induce the worth of the textile falling by roughly 45%-60% [1, 2]. Thus effective classification of existing fabric defects becomes a pivotal step in textile production control, which facilitates the fabric repairing of various types of defects on production line, enhances work efficiency immensely, and improves the quality and worth of textile. And if different fabric defects can be correctly distinguished, producers can make improvements in production process which can product more superior quality fabric.

Nowadays automatic defects classification method has been replaced the traditional artificial operation, the accuracy and effective are remarkable increased because of the artificial classi-

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fication method based on subjective recognition is substituted by computer version technique based on digital image processing. The difficulty of increase the classification accuracy lies in the multiple types of fabric defects and generated new types of defects in production process. Additionally, the same kinds of defects may have thorough different appearance while different kinds of defects may have the same appearance which is caused by kinds of textile materials and fabric constructions [3].

In recent years, abundant research has been carried out by scholars domestic and overseas. In [4, 5], fabric defect classification is based on geometrical characteristic of textile image. The characteristics of defect area and the length of its boundary line is extracted and fuzzed, defect classification is then made on the basis of fuzzy logical [4]. Similarly, Stojanovic et al. process the classification of fabric defects through neural network, whose input are defect area, center coordinate, horizontal and vertical projection, and co-occurrence matrix [5]. But these kinds of classifications' accuracy cannot reach a high level. In [6], a defect detection and classification method is proposed by Chan et al. Firstly Fourier transform is processed on the textile image, and then seven characteristics values including the peak values of magnitude in spectrogram in horizon and vertical are extracted as the basis of classification. While in this method, some detailed information of the image spatial domain and local variations may be lost. In [7], Yang et al. adopt the average energy of coefficients of wavelet transformation as characteristic parameter to classify the fabric defects. Kuo et al. propose a classification method by computing the correlation of GLCM features between detected sequence and sample [8, 9]. But these two methods are not applicable for the classification of local defect.

In this paper, a defect classification method that combines LBP and GLCM is proposed. Firstly, the textile image information is depicted locally and integrally respectively. And then the feature values are extracted by LBP and GLCM from locally and globally, respectively. Through this combination of global and local information extractions, the fabric defect image can be fully described and used as input of a BP Neural Network. In this research, the training function of BP Neural Network is selected as trainlm function based on LM (Levenberg-Marquard) algorithm. Finally, the trained BP Neural Network can be used to distinguish different types of defects. Experimental results with samples from TILDA Textile Texture Database show that compared with the existing classification methods the proposed classification algorithm has higher classification accuracy.

2 Local Binary Patterns

Local Binary Patterns (LBP) is firstly proposed by Ojala in 1999, which is an effective texture operator to depict the local texture characteristic of an image.

The main idea of LBP is based on comparisons of pixel gray values, the relative grayscale between a pixel and its adjacent pixel is used as a response result. Such that LBP is invariant for monotonous gray value change. Basic LBP operator is shown in Fig. 1. In this model, a 3×3 window is used as an operating unit and gray value of the center pixel is taken as a threshold for achieving relative grayscale compared with 8 local pixels. If a local pixel gray value is bigger than that of the center pixel, it is labeled as 1. On the contrary, it is labeled as 0. After labeling all the 8 local pixels, the binary value is taken out clockwise from top left. Then a response result can be got through transforming the binary string into decimal number.

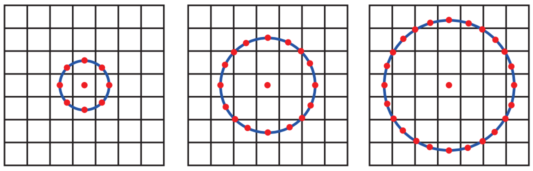
In order to extract textural feature information of different sizes, basic LBP operator is improved by substituting the square field with round field that can be extended into arbitrary size. In Fig. 2, three round models are presented with R=1, 2, 3 and local pixel number P=8, 16, 24, respectively. And in this research, these three round field LBP operators will be used in the experiments to examine the impacts of different fields on classification accuracy.

70	37	12
63	41	6
56	28	46

$\xrightarrow{\text{Threshold}}$

1	0	0
1		0
1	0	1

Fig. 1: Basic LBP operator



P=8, R=1 P=16, R=2 P=24, R=3

Fig. 2: Round field LBP operator with R=1, 2, 3 and P=8, 16, 24

Assume that an arbitrary pixel of some local region of an image is represented as $f(x_c, y_c)$, and it is seemed as the center pixel with gray value is g_c. Gray values of the local pixels of $f(x_c, y_c)$ are $g_0, g_1, \cdots, g_p$ then the texture characteristics T of this local field can be expressed as Eq. (1):

$$T \approx t(g_0 - g_c, g_1 - g_c, \cdots, g_p - g_c) \tag{1}$$

Set the gray value of center pixel as a threshold and process the other pixels of local field for binarization processing that expressed in Eq. (2):

$$\begin{aligned} &T \approx t(g_0 - g_c, g_1 - g_c, \cdots, g_p - g_c) \\ &s(x) = \begin{cases} 1 & x > 0, \\ 0 & x \leqslant 0. \end{cases} \end{aligned} \tag{2}$$

Then a p bit binary string is achieved and the LBP value of the center pixel can be got through transforming the binary string into decimal number, which is expressed as Eq. (3):

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{3}$$

In order to guarantee the LBP algorithm has an invariance property to revolution, which can eliminate the impact of image rotation, an additional definition of the basic LBP operator is as follows:

$$LBP_{P,R}^{ri} = \min\{ROR(LBP(_{P,R}, i))\}, i = 0, 1, \cdots, P-1 \tag{4}$$

LBP algorithm is now further simplified by the principle of unified form. That is to say for a local binary string in the circulating situation, if conversion times between 0 and 1 is no bigger than two, then this LBP is seemed as unified form. Contrary it is not a unified one. The principle can be expressed as the following formulation:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c), U \leqslant 2 \\ P+1, otherwise \end{cases} \tag{5}$$

where

$$U = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \tag{6}$$

3 Gray-level Co-occurrence Matrix

Gray-level Co-occurrence Matrix (GLCM) is an algorithm of depicting the texture features that is brought out by Haralick et al. in 1973 in [11]. GLCM can express the simultaneous distribution between two pixels with some spatial position relationship. It can well reflect the gray-level spatial correlation among texture pixels.

For an image with gray-level is L, the GLCM features can be expressed by a L×L matrix P_d, therein an element $P_d(i, j), (i, j = 0, 1, 2, \cdots, L-1)$ is defined as the frequency or times that two pixels whose gray-value are i and j respectively, with the spatial relationship is $d = (D_x, D_y)$. The schematic diagram is shown in Fig. 3.

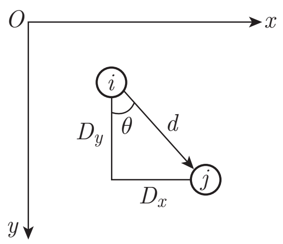


Fig. 3: Two pixels, whose gray-value are i and j respectively, with spatial position relationship d

In Fig. 3, θ is the generating direction of GLCM, its normal values are 0°, 45°, 90° and 135°. $P_d(i, j)$ is usually carried out the following normalization processing:

$$C(i, j) = \frac{P(i, j)}{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i, j)} \tag{7}$$

Initially Haralick et al. defined 14 characteristic parameters to construct GLCM. While only four characteristic parameters are found to be independent in the subsequent research. Then the classification can be completed by using these four features which are named as Energy, Contrast, Correlation and Entropy, respectively.

(1) Angular second moment (Energy)

Angular second moment is quadratic sum of all the elements of GLCM, it is also named Energy. This feature reflects uniformity coefficient of gray-value of the whole image and texture roughness. Its definition can be expressed as:

$$Q_1 = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} [C(i,j)]^2 \tag{8}$$

(2) Contrast

Contrast is inertia moment close by the leading diagonal of GLCM. This parameter reflects sharpness of an image. It can be computed by the following formulation:

$$Q_2 = \sum_{\mathrm{i}=0}^{N-1} \sum_{j=0}^{N-1} k^2 \left\{C(i,j)^2\right\} \tag{9}$$

(3) Correlation

Correlation presents the degree of similarity among the elements of GLCM in the direction of row or column. Its value can be computed by:

$$Q3 = \frac{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} ijC(\mathrm{i},j) - \mu_x \mu_y}{{\sigma_{\mathrm{x}}}^2 {\sigma_y}^2} \tag{10}$$

where

$$\mu_x = \sum_{i=0}^{N-1} i \sum_{j=0}^{N-1} C(i,j) \tag{11}$$

$$\mu_y = \sum_{j=0}^{N-1} j \sum_{i=0}^{N-1} C(i,j) \tag{12}$$

$${\sigma_x}^2 = \sum_{i=0}^{N-1} (i - \mu_x)^2 \sum_{j=0}^{N-1} C(i,j) \tag{13}$$

$${\sigma_y}^2 = \sum_{j=0}^{N-1} (j - \mu_y)^2 \sum_{i=0}^{N-1} C(i,j) \tag{14}$$

(4) Entropy

The value of Entropy can indicate the complexity and inhomogeneity of the image texture. Its definition is as follows:

$$Q_4 = -\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} C(i,j) \log_2 C(i,j) \tag{15}$$

4 BP Neural Network

Artificial Neural Networks (NN for short) is a kind of artificial intelligence technology that simulates human brain biological processing. In the whole network, plenty of simple nerve cells are interrelated with each other and formulate a complex nonlinear system. Therefore NN is a powerful tool of nonlinear mapping to deal with ratiocination, judgment, recognition and classification and so on. BP Neural Network, which was proposed by Rumelhart and McCelland et al. in 1986, is one of the most commonly used and successful model. This model is a multilayer feedforward network that based on the algorithm of error back propagation. A typical BP Neural Network includes input layer, hidden layer and output layer. Hidden layer can be single layer or multilayer. The topology of a typical BP Neural Network that has two hidden layers is shown in Fig. 4.

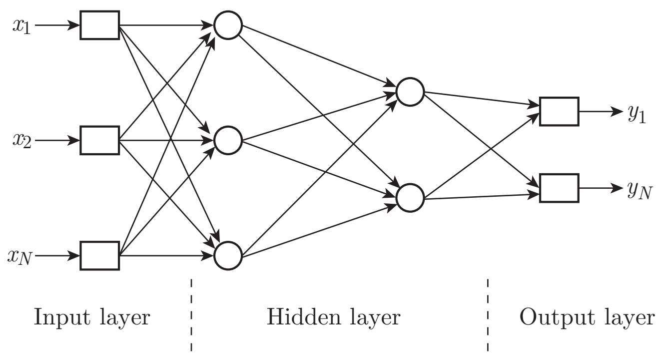


Fig. 4: Topology of a BP Neural Network

Through plenty of experimental research, a three layered BP Neural Network can realize arbitrary nonlinear mapping from input to output. So in this research we use a three layered BP Neural Network, in which the training function is selected as trainlm function based on LM (Levenberg-Marquard) algorithm. When the error performance function is in the form of quadratic sum error, this algorithm can avoid computing Hessian matrix [12, 13]. This can be approximately expressed as follows:

$$H = J^T J \tag{16}$$

where gradient can be expressed as:

$$\mathrm{g} = J^T e \tag{17}$$

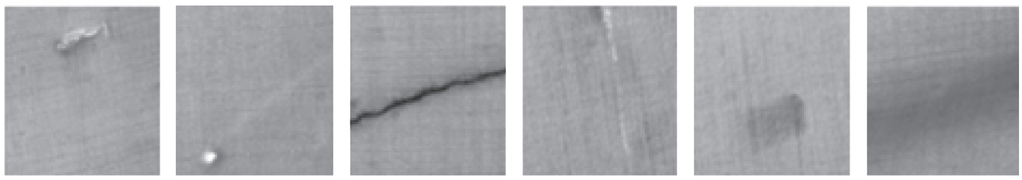
where J is Jacobian matrix in which the first-order derivatives of error performance function to network weights are included. And LM algorithm corrects the network weights based on the following iterative formula:

$$\omega(\mathrm{n}+1) = \omega(n) - [J^{\mathrm{T}} J + \mu I]^{-1} J^T e \tag{18}$$

5 Experiment Results and Discussion

In this research we use six different types of defects from the TILDA Textile Texture Database as experimental samples which are showed in Fig. 5. Every type of defect includes 100 sample images. Each image size is 256 × 256 pixels. We extract the features from GLCM and LBP features of 3 local fields from the 600 samples respectively.

Fig. 6 and Table 1 show the $LBP_{8,1}$ neighborhood feature histograms and GLCM features of 0° direction that extracted from the 600 sample pictures, respectively. Fig. 6 shows that the feature distributions of defect (a)-(d) are similar, and the feature distributions of defect (e) and (f) are similar. These two types of textile defect can be easily classified. Combined with the different GLCM features in Table 1, defect (a)-(d) and defect (e)-(f) can be classified once more.



Defect (a) Defect (b) Defect (c) Defect (d) Defect (e) Defect (f)

Fig. 5: Image of fabrics with six different types of defect samples

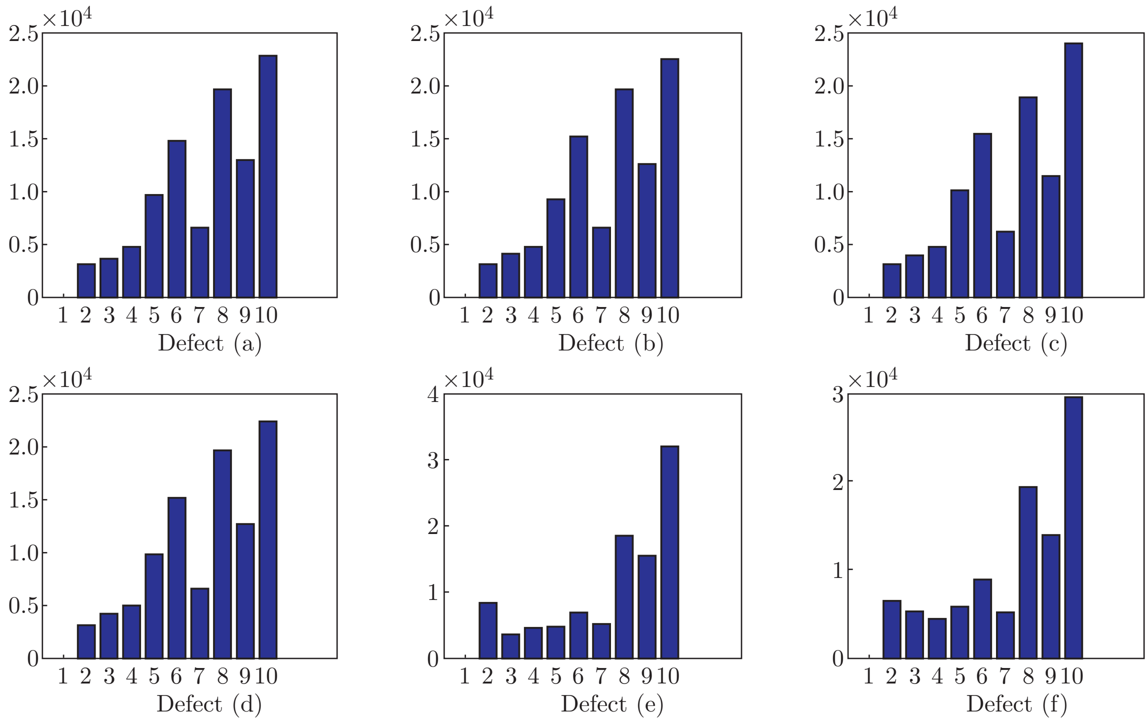


Fig. 6: Histograms of $LBP_{8,1}$ features of six type of defect samples

Table 1: The GLCM features in 0° direction of six type of defect samples

Defect type	Energy	Contrast	Correlation	Entropy
Defect a	0.24368	0.21187	−43435.86431	2.67456
Defect b	0.34630	0.18751	−119771.69014	2.12558
Defect c	0.24785	0.22368	−9031.45179	2.73130
Defect d	0.37984	0.20763	−254320.42903	1.92264
Defect e	0.20280	0.25204	−39071.64286	2.83909
Defect f	0.16996	0.22946	−14104.98792	2.96406

In our experiments 85 pictures of every type of defect sample are selected as training sample and are inputted into BP Neural Network, the remained 15 pictures are used as testing ones. Consider of the instability of BP Neural Network, we operate the classification 10 times, in each time the training sample and the testing sample are selected random. The average accuracy of these ten classifications is computed as the final result. In order to estimate the impact of different parameters and feature values, we use $LBP_{8,1}$, $LBP_{16,2}$, $LBP_{24,3}$ operators which described in Fig. 2 of Section 2, GLCM, and different combinations of the three different local fields LBP operators values and GLCM features as the combined input of BP Neural Network. The classification results of these features are shown in Table 2.

Table 2: The GLCM features in 0°direction of six type of defect samples

Defect type	$LBP_{8,1}$	$LBP_{16,2}$	$LBP_{24,3}$	GLCM	$LBP_{8,1}$ $+GLCM$	$LBP_{16,2}$ $+GLCM$	$LBP_{24,3}$ $+GLCM$
Defect a	5.3	80	86.7	81.2	92.7	93.3	94
Defect b	82.7	82	96.7	87.8	96.7	96	97.3
Defect c	13.3	68	87.8	94.5	95.3	97.3	99.3
Defect d	100	78.7	91.1	75.8	97.3	93.3	94.7
Defect e	68	78.7	92.8	98.8	99.3	98	100
Defect f	70.7	87.3	92.2	99.4	99.3	99.3	100
Average	56.7	79.12	91.2	89.58	96.8	96.2	97.6
Dimension of feature	10	18	26	16	26	34	42

It can be observed from Table 2 that the classification accuracy of 8 local fields LBP feature is lowest, up to only 56.7%. While 24 local fields LBP feature is adopt, the classification accuracy can achieve 90%. The classification accuracy of GLCM feature is just behind that of $LBP_{24,3}$. The experiment result in Table 2 also shows that the accuracy is significantly increased through combining GLCM feature and LBP feature. The accuracy of the combination of $LBP_{24,3}$ feature and GLCM is highest, it can reach to 97.6%. But in this situation the dimension of features is 42 dimensions which are highest in the experiments. The corresponding computing time is most with the increasing data size.

In [5], the classification accuracy is 86.2% by adopting geometrical characteristic; in [7], 93.1% accuracy can be achieved based on average energy of wavelet transformation coefficients. [8] indicated that the classification accuracy can be raised to 94% through computing the correlation of the GLSM features. In [9], researchers extracted 9 parameters from the Fourier power spectrum of a textile image and put them as the input of BP Neural Network, experiment results show that the accuracy of this method was 88%. Compared with these previous researches, the proposed classification method in this paper can effectively classify various types of fabric defects.

6 Conclusion

In this paper a hybrid fabric defect classification method that combines LBP and GLCM is proposed. In the experiments, six different types of defects which types include 100 images are selected from the TILDA Textile Texture Database and are used as standard test samples. The experimental data shows that with the dimension of feature values increase the classification result will be improved furthermore. The accuracy of combination of $LBP_{24,3}$ feature and GLCM can reach to 97.6%, which has significant advantage compared with existing classification methods. The disadvantage is the computing data will be increased which result in increasing computing time. Whatever compared with LBP only, GLCM only, geometrical characteristic, Fourier transform and wavelet transformation, the proposed algorithm has obvious superiority in classification accuracy which means the proposed method can effectively classify the fabric defects.

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