Fabric Defect Identification Using Back Propagation Neural Networks

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Abstract
Fabric defect identification plays a very important role for the automatic detection in fabrics. Fabric defect identification mainly includes three parts: The first, preprocessing with Frequency domain Butterworth Low pass Filter and Histogram Equalization. The second, extraction of texture features from fabric using Gray Level Co-occurrence Matrix (GLCM).The Co-occurrence matrix characterizes the distribution of co-occurring pixel values in an image to be at a given offset, and then the statistical features are extracted from this matrix. The Third, the extracted GLCM features are used for the classification of the texture using Back Propagation Neural Network with different learning rules for their effectiveness comparison.

Keywords: *gray level co-occurrence matrix (GLCM), back propagation neural network (BPNN)*

INTRODUCTION
Over the decades, the automation process has been of increasing interest in textile and clothing manufacturing industries. Due to the unpredictable variability in the fabric material properties, automation is still a challenging task. There is a necessity for the development of more efficient computer techniques for the automated control of the textile manufacturing process.

Quality control of textile represents a major problem in textile industry, measurement of quality is highly important for cost reduction and improvement of the final product. One among the main problems in quality control of textile is that, the testing sample is the whole production of the factory, which clarifies the need for an efficient fast quality control method. Presently, textile inspection is performed off line (after production) using a manual process. The time consumption of this process is high and it is inefficient.

Yarns are interlaced to form woven fabrics. There are two basic yarns: “warp” and “weft”. The long vertical yarns wrapped around the looms are known as Warp. The horizontal yarns woven through the warp yarns are known as Weft.

In [1], a novel scheme to solve the problem of automated defect detection for woven fabrics based on morphological filters is proposed. A Trained Gabor wavelet is used to extract important texture features of the fabric.

In [2], an approach for modelling features scale of fabric deformations and defects is

proposed. A high fidelity digital element method is used for predicting the as-woven geometry of a single unit cell. By geometric reduction, a macro-scale fabric model is obtained from the unit cell geometry. Two and three dimensional approaches with an accompanying yarn mechanical model for yarn geometry representation are proposed,.
[3] proposes a new approach for fabric defect classification using radial basis function (RBF) network improved by Gaussian mixture model (GMM).

Lucia Bissi et al [6] proposed the method in two phases namely feature extraction phase and defect identification phase. A complex symmetric Gabor filter bank and Principal Component Analysis (PCA) is employed in a feature extraction phase and the Euclidean norm of features is employed for defect identification phase.

In [7] and [25]Soft computing techniques such as fuzzy logic, Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) approaches are used.
[9] uses image processing techniques for evaluating the yarn defects. The yarn defects were identified based on their geometric shape and surface area.
In [10], an optimized elliptical Gabor filter (EGF) is proposed to detect defects in textured surface. A genetic algorithm (GA) is used to tune the proposed EGF.
[11] proposes a new cluster-based approach to extract features from the coefficients of a two-dimensional discrete wavelet transform.
[12] addresses the application of harmony search algorithms for the supervised training of feed-forward(FF) type NNs, which are frequently used for classification problems. Studies on five different variants of harmony search algorithms are done by giving special attention to Self-adaptive Global Best Harmony Search(SGHS) algorithm.
Adaptive Neuro Fuzzy Inference System (ANFIS) for the software fault prediction problem is presented in [13].
In [15], gray level co-occurrence matrix is used to extract automatic woven fabric image with 2-D wavelet transform and learning vector quantization neural network is used for classification.
Gabor filters with two scales and six orientations is proposed in [16].
[17] presents a machine vision system for detecting surface defects using basic patch statistics from raw image data combined with a two layer neural network.
In [18], gray level co-occurrence matrix (GLCM) is used to extract the textural features of fabric images. From the GLCM of the fabric image, a textural energy is computed by a sliding window technique for defect detection.
[19] provides a review of automated fabric defect detection methods developed in recent years.
[20] provides a study of motif-based patterned fabric defect detection using ellipsoidal decision regions which improves the original detection success using max–min decision region of the energy-variance values.

The proposed method consists of two steps: 1) feature extraction using GLCM and 2) the detection of defects using back propagation neural network.

PROPOSED METHOD

The proposed method flow chart for defect detection of woven fabrics is shown in Fig. 1.

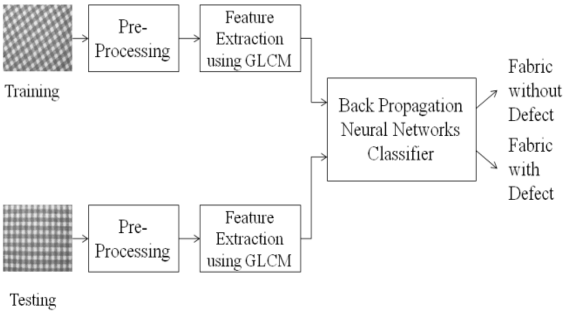

Fig. 1. *Flow chart for the proposed method*

Preprocessing

A number of computer-simulated and real woven material images are used to evaluate the proposed method. To increase the processing speed the images are resized into 256 X 256 pixels and then converted into grayscale.

For noise reduction and image enhancement, a frequency-domain Butterworth low-pass filter and histogram equalization are used respectively.

GLCM feature extraction

The texture of an image is defined with respect to its global properties or by the composition of repeating units. The feature is extracted based on the specific properties of pixels in the image or their texture. In this work the texture from a woven is extracted by gray level co-occurrence matrix.

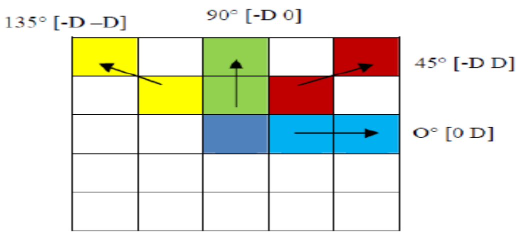

Fig. 2 *Texture of an image with offset varying in distance and orientation*

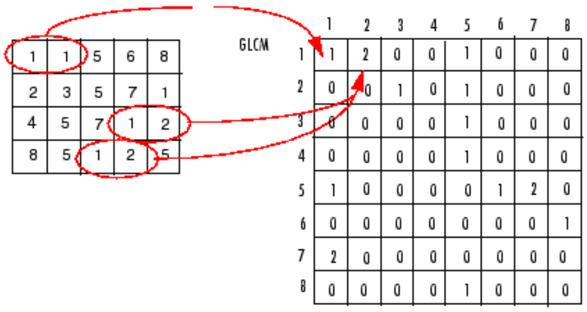

Fig. 3 *Process used to create GLCM*

The calculation of the co-occurrence matrix is affected by two parameters. These are D, the distance between two pixels, and θ, the position angle between two pixels (p,q) and (j,k).Figure 2 shows the four directions for the position angle: the horizontal position θ = 0°, the right diagonal position direction θ = 45°, the vertical direction θ = 90° and the left diagonal direction θ =135°. All the values of the co-occurrence matrices need to be normalized; After normalization, the co-occurrence matrices, can be expressed as:

$$P_{ij} = \frac{P_{ij}}{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{ij}} \qquad (1)$$

Haralick defined from these co-occurrence matrices (reference) to analyze textures. For this work GLCM parameters which are described below are used.

Contrast: Measures the local variation in the Grey level Co-occurrence matrices

$$CON = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 P_{ij} \qquad (2)$$

Correlation: Measures the joint probability occurrence of the specified pixel pair

$$COR = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{ij} \frac{(1-\mu_i)(1-\mu_j)}{\sigma_i \sigma_j} \qquad (3)$$

Entropy: Measures the randomness of the elements of the co-occurrence matrix.

$$ENT = -\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{ij} log_2(P_{ij}) \qquad (4)$$

Homogeneity: Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$HOM = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \qquad (5)$$

Angular Second Moment: Measures homogeneity of an image. A homogeneous scene will contain only a few gray levels, giving a GLCM with only a few but relatively high values of P(i, j).

$$ASM = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \{P(i,j)\}^2 \qquad (6)$$

Inverse Difference Moment: Measures local homogeneity

$$IDM = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2} \qquad (7)$$

Variance: Measures the gray level variability of the pixel pairs and is a measurement of heterogeneity.

$$VAR = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-\mu)^2 P(i,j) \qquad (8)$$

Cluster shade: Measures the skewness of the matrix and is believed to gauge the perceptual concepts of uniformity.

$$Shade = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i + j - \mu_x - \mu_y)^3 \times P(i,j) \quad (9)$$

Cluster prominence: Measures asymmetry

$$Prom = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i + j - \mu_x - \mu_y)^4 \times P(i,j) \quad (10)$$

Sum Average:

$$AVG = \sum_{i=0}^{2N-1} iP_{x+y}(i) \quad (11)$$

Sum Entropy:

$$SENT = -\sum_{i=0}^{2N-1} P_{x+y}(i) \log_2 \left(P_{x+y}(i)\right) \quad (12)$$

Difference Entropy:

$$DENT = -\sum_{i=0}^{N-1} P_{x-y}(i) \log_2 \left(P_{x-y}(i)\right) \quad (13)$$

Sum Variance

$$SVAR = \sum_{i=0}^{N-1} \left\{ i - \sum_{i=0}^{2N-2} P_{x+y}(i) \log_2 \left(P_{x+y}(i)\right) \right\}^2 * P_{x+y}(i) \quad (14)$$

Difference variance:

$$DVAR = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i^2) * P_{x-y}(i) \quad (15)$$

Dissimilarity:

$$Dissim = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - j) P(i,j) \quad (16)$$

Homogeneity(M):

$$Homogenity = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)}{1 + |i - j|} \quad (17)$$

Correlation:

$$Corr = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{(i \times j) \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \quad (18)$$

Maximum Probability:

$$Max\ Prob = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \max\left(\max\left(P(i,j)\right)\right) \quad (19)$$

Autocorrelation:

$$ACorr = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \{i \times j\} \times P(i,j) \qquad (20)$$

Back Propagation Neural Network

Due to their non-parametric nature and complex decision regions description ability, Neural networks are one of the fastest and most flexible classifier for detecting faults. ANN'S are networks of interconnected computational units, usually called nodes. The input of a specific node is the weighted sum of the output of all the nodes to which it is connected. The output value of a node is, in general, a non-linear function (referred to as the activation function) of its input value. The multiplicative weighing factor between the input of node j and the output of node i is called the weight w_{ij}.

Back-propagation NN's used in this study consist of one input layer, one or two hidden layers, and one output layer. With back-propagation, the input data (Extracted GLCM Features) is repeatedly presented to the Artificial Neural Network, with each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the Artificial Neural Network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as Training.

The Training of these networks consists in finding a mapping between a set of input values and a set of output values. This mapping is accomplished by adjusting the value of the weights w_{ij} using a learning algorithm, the most popular of which is the generalized delta rule. After the weights are adjusted on the training set, their value is fixed and the ANN's are used to classify unknown input images.

Back Propagation Training Algorithm

In each iteration the j^{th} layer weights W^j and biases B^j variations are calculated as

$$W^j(n) = W^j(n-1) + \Delta W^j \qquad (21)$$

$$B^j(n) = B^j(n-1) + \Delta B^j \qquad (22)$$

i. Gradient descent algorithm

$$\Delta W^j = \eta_{W^j} \frac{\partial E}{\partial W^j} \qquad (23)$$

$$\Delta B^j = \eta_{W^j} \frac{\partial E}{\partial B^j} \qquad (24)$$

ii. Gradient descent with adaptive learning rate algorithm

$$\Delta W^j = \eta_{W^j} \frac{\partial E}{\partial W^j} \qquad (25)$$

$$\Delta B^j = \eta_{W^j} \frac{\partial E}{\partial B^j} \qquad (26)$$

iii. Gradient descent with momentum algorithm

$$\Delta W^j = M * \Delta W^{j-1} + \eta * (1-M) * \frac{\partial E}{\partial W^j} \qquad (27)$$

$$\Delta B^j = M * \Delta B^{j-1} + \eta * (1-M) * \frac{\partial E}{\partial B^j} \qquad (28)$$

iv. Gradient descent with momentum and adaptive learning rate algorithm

$$\Delta W^j = M * \Delta W^{j-1} + \eta * M * \frac{\partial E}{\partial W^j} \qquad (29)$$

$$\Delta B^j = M * \Delta B^{j-1} + \eta * M * \frac{\partial E}{\partial B^j} \qquad (30)$$

v. Resilient Back propagation

Weight Updation

$$\Delta W^j = \begin{cases} +\Delta^j, if \ \frac{\partial E}{\partial w^j} > 0 \\ -\Delta^j, if \ \frac{\partial E}{\partial w^j} < 0 \\ 0 \quad , \ otherwise \end{cases} \quad (31)$$

Exception:

$$\Delta W^j = -\Delta W^{j-1}, if \ \frac{\partial E}{\partial w^{j-1}} . \frac{\partial E}{\partial w^j} < 0 \quad (32)$$

Learning Rule:

$$\Delta^j = \begin{cases} \eta^+ . \Delta^{j-1}, if \ S > 0 \\ \eta^- . \Delta^{j-1}, if \ S < 0 \\ \Delta^{j-1}, otherwise \end{cases} \quad (33)$$

Where, $S = \frac{\partial E}{\partial w^{j-1}} \frac{\partial E}{\partial w^j}$

vi. Scaled Conjugate Gradient algorithm

Steepest descent direction on the first iteration

$$p_0 = g_0 \quad (34)$$

Optimal distance along the current search direction

$$x_{k+1} = x_k + \alpha_k g_k \quad (35)$$

Next Search direction

$$p_k = -g_k + \beta_k \quad (36)$$

$$\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}} \quad (37)$$

vii. Levenberg Marquardt algorithm

$$\text{Gradiant,} \quad g = J^T \quad (38)$$

Where J is the Jacobian Matrix

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (39)$$

The generalized delta rule involves minimizing an error term defined as

$$E_p = \frac{1}{2} \sum_j (t_{pj} - o_{pj})^2 \quad (40)$$

In this work Back Propagation Neural Network includes an input layer of four input nodes, a hidden layer of twenty neurons, and an output layer of one neuron. The nonlinear transfer function is the hyperbolic tangent function with a learning speed of 0.07, momentum coefficient of 0.7. The operational process can be divided into the learning and the recalling stage, and there are 210 training examples and 100 testing examples. The 22 texture features extracted from the grey level co-occurrence matrix are used as the input parameters of the Back-Propagation Neural Network.

RESULTS AND DISCUSSION

Fabrics with three different texture constituting nearly 310 images are taken for analysis of proposed work. Here 210 images are used for training and 100 images are used for testing the classifier and algorithm is implemented in Matlab R2013a.

Figure 3 shows some of the training and testing images. Twenty two GLCM features are taken for this work for the better results than the other parameters.

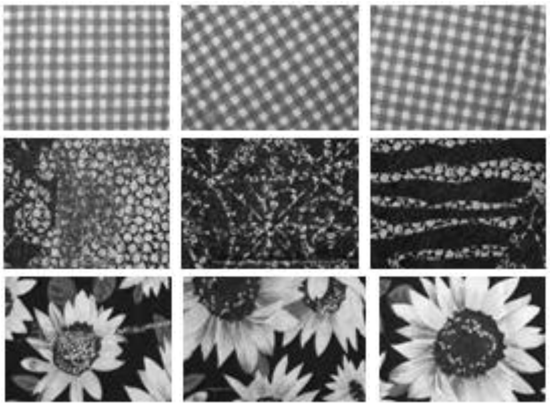

Fig. 4 *Some of the training and testing Samples*

Accuracy: Accuracy is a statistical measure of how well a classifier correctly identifies or excludes a condition. The accuracy is the proportion of true results (both true positive and true negative) in the population.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad (41)$$

Table I shows the Comparison of Minimum and maximum value of GLCM features for the defected and non-defected fabrics

Table I *Comparison of GLCM Features*

Sl. No.	GLCM Features	Non Defected Fabric		Defected Fabric	
		Max value	***Min value***	***Max value***	***Min value***
1	Contrast(M)	1.3039	0.3367	1.3479	0.3264
2	Correlation (M)	0.9676	0.8760	0.9690	0.8723
3	Correlation	0.9676	0.8760	0.9690	0.8723
4	Cluster prominence	762.65	683.49	759.52	691.40
5	Cluster Shade	4.7376	-3.770	3.3116	-3.2354
6	Dissimilarity	0.8164	0.3124	0.8404	0.2926
7	Energy(M)	0.0696	0.0395	0.0717	0.0378
8	Entropy	3.4409	2.8919	3.4705	2.8681
9	Homogeneity(M)	0.8506	0.6462	0.8592	0.6567
10	Homogeneity	0.8472	0.6253	0.8570	0.6303
11	Max Probability	0.1229	0.0864	0.1173	0.0867
12	Sum of Squares: Variance	25.574	25.175	25.611	25.082
13	Sum average	9.0490	8.9579	9.0752	8.9428
14	Sum variance	61.705	59.221	62.104	59.073
15	Sum Entropy	2.7002	2.6080	2.7018	2.6069
16	Difference Variance	1.3039	0.3367	1.3479	0.3264
17	Difference Entropy	1.1361	0.6620	1.1348	0.6525
18	Infn. Measure of Correlation 1	-0.3450	-0.6085	-0.3301	-0.6206
19	Infn. Measure of Correlation 2	0.9593	0.8728	0.9614	0.8640
20	Inverse Difference normalized	0.9655	0.9130	0.9678	0.9120
21	Inverse Difference Moment normalized	0.9948	0.9809	0.9950	0.9801
22	Autocorrelation	25.44	24.744	25.523	24.7400

Table II. *Comaprison of Accuracy % of Differenent BPNN Learning Algorithm*

Sl. No.	GLCM Features	Back Propagation Learning Rule						
		gd	**gda**	**gdm**	**gdx**	**lm**	**rp**	**scg**
1	Contrast (M)	65.7	68.5	64.7	64.7	70.4	70.4	61.9
2	Correlation(M)	59.0	60.9	59.0	58.0	60	60	56.1
3	Correlation	59.0	60.9	59.0	58.0	60	60	56.1
4	Cluster prominence	51.4	47.6	60	50.4	47.6	47.6	52.3
5	Cluster Shade	49.5	49.5	48.5	48.5	46.6	45.7	47.6
6	Dissimilarity	53.3	60	53.3	53.3	61.9	55.2	53.3
7	Energy(M)	49.5	48.5	49.5	46.6	44.7	47.6	43.8
8	Entropy	62.8	71.4	60	61.9	67.6	68.5	61.9
9	Homogeneity(M)	40.9	40.9	40	39.0	42.8	40	39.0
10	Homogeneity	44.7	40.6	49.5	45.7	43.8	40	45.7
11	Max Probability	45.7	45.7	44.7	45.7	45.7	40	44.7
12	Sum of Squares: Variance	54.2	48.5	54.2	43.8	49.5	50.4	48.5
13	Sum average	50.4	47.6	50.4	49.5	45.7	46.6	49.5
14	Sum variance	42.8	38.0	40.9	40.9	36.1	34.2	42.8
15	Sum Entropy	48.5	47.6	40.9	39.0	44.7	40.9	38.0
16	Difference Variance	65.7	70.4	64.7	64.7	70.4	70.4	61.9
17	Difference Entropy	61.9	67.6	61.9	60.9	63.8	68.5	63.8
18	Infn. Measure of Correlation 1	62.8	73.3	62.8	65.7	68.5	72.3	65.7
19	Infn. Measure of Correlation 2	60.9	57.1	60.9	57.1	57.1	43.8	60.9
20	Inverse Difference normalized	48.5	44.7	48.5	48.5	47.6	46.6	51.4
21	Inverse Difference Moment normalized	62.8	60	62.8	59.0	55.2	56.1	58.0
22	Autocorrelation	60.9	56.1	54.2	51.4	57.1	44.7	52.3

The Table II shows the accuracy expressed in percentage for different back propagation training networks with 20 hidden layer neurons. In *Gradient descent algorithm, GLCM* feature Contrast gives better performance in terms of accuracy. In *Gradient descent with adaptive learning rate algorithm, GLCM* feature Infn. Measure of Correlation 1 gives better performance in terms of accuracy. In *Gradient descent with momentum algorithm, GLCM* feature Contrast gives better performance in terms of accuracy. In *Gradient descent with momentum and adaptive learning rate algorithm, GLCM* feature Infn. Measure of Correlation 1 gives better performance in terms of accuracy.

In *Levenberg Marquardt algorithm, GLCM* feature Contrast gives better performance in terms of accuracy. In *Resilient Backpropagation algorithm, GLCM* feature Contrast gives better performance in terms of accuracy. In *Scaled Conjugate Gradient algorithm, GLCM* feature Infn. Measure of Correlation 1 gives better performance in terms of accuracy.

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CONCLUSION

Back-Propagation Neural Network with different Learning rule is used for the texture classification for recognizing fabric defects. Twenty two GLCM features like contrast, correlation, entropy, homogeneity …are used for calculating the fabric textures. Comparing different combination of GLCM features with different back propagation Learning rule GLCM feature Contrast and Infn. Measure of Correlation 1 exhibits better performance for the fabrics having different textures in terms of accuracy.

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