Research Article
Artificial Neural Network Techniques in Identifying Plain Woven Fabric Defects

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Abstract: Textile industry is one of the main sources of revenue generating industry. The price of fabrics is severely affected by the defects of fabrics that represent a major threat to the textile industry. In manual inspection a very small percentage of defects are detected with highly trained, experienced inspectors. An automatic defect detection system can increase the defect detection percentage. It reduces the fabrication cost and economically profitable when we consider the labor cost and associated benefits. In this study we have proposed a method to detect the defects in woven fabric based on the changes in the intensity of fabric. The images are acquired; preprocessed, statistical features based on the gray level co-occurrence matrix are extracted. The Artificial Neural Network is used as classification model. The extracted features are given as input to the artificial neural network, it identifies the defect. The result of proposed method shows that a better performance achieved with less time when compared with the existing methods.

Keywords: Artificial neural networks, defect detection, gray level co-occurrence matrix, image processing, statistical approach

INTRODUCTION

Textile industry plays an important role in Indian economy. Textile manufacturing is a process of converting various types of fibers into yarn, then into woven fabric. A fabric is a flat structure. Woven fabrics are produced by weaving, which is the textile art in which two distinct sets of yarns or threads called the warp and weft are interlaced with each other at right angles to form a fabric or cloth. The warp represents the threads placed in the fabric longitudinal direction, while the weft represents the threads placed in the width-wise direction. The weave pattern is periodically repeated throughout the whole fabric area with the exception of edges. The plain weave is the most made weave in the world, it is relatively inexpensive, easy to weave and easy to finish.

In textile industry, defect identification has always been a challenging task. Defective garments are rejected in inspection due to impact of the defect; it reduces the industry revenue automatically. Textile industries are working just in time delivery, inspection of defects can take place at several stages and the cost impact of a defect can be reduced by detecting defects early. Accurate and early detection of defects in fabrics is an important aspect of quality improvement. Defect identification is normally depends upon identification of regions that differs from the uniform background. The dream of textile manufacturers is to achieve optimum potential benefits such as quality, cost, comfort, accuracy, precision and speed. The weave may also have variations including the following:

Rib weave: the filling yarns are larger in diameter than the warp yarns. A rib weave produces fabrics in which fewer yarns per square centimeter are visible on the surface.

Matt weave or basket weave: Here, two or more yarns are used in both the warp and filling direction. These groups of yarns are woven as one, producing a basket effect.

Twill weave: Twill weave is characterized by diagonal ridges formed by the yarns, which are exposed on the surface. These may vary in angle from a low slope to a very steep slope. Twill weaves are more closely woven, heavier and stronger than weaves of comparable fiber and yarn size.

Satin: Floats one warp yarn over four or more weft yarns, then tied down with one thread, resulting in a smooth face. These are Smooth, soft luster, Excellent durability and Floats snag easily.

Jacquard: Jacquard patterns, when carefully analyzed, may be seen to contain combinations of plain, twill and satin weaves, even in the same crosswise yarn.

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Plain-woven fabric inspection systems still a challenge due to the variable nature of the weave. The accuracy of manual inspection is not good enough due to fatigue and tiredness. The automated defect identification system is the only solution to the problem of manual inspection system, which is a quality control process that aims at identifying and locating defects of fabric. The automated system increases the quality and production of the fabric. The automated defect identification system is economically profitable when we consider the associated personnel cost and benefits.

Statistical approaches compute different properties. Based on the number of pixels defining the local features the statistical approach can be classifying as first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. Srinivasan and Shobha (2008), used statistical features in their study to identify the defects.

The Artificial Neural Networks (ANN) is inspired by the way biological nervous system works, such as brain processes an information. ANN mimics models of biological system, which uses numeric and associative processing. There are three classes of neural networks, namely single layer, multilayer feed forward networks and recurrent networks. Chandra *et al.* (2010) briefed how the morphological processing used in identifying defect. Zhang and Wong (2011), explained the usage of genetic algorithm and elman network to identify the defects in fabric.

Image processing pays a vital role in defect detection. The resolution of an image can be referred either by the size of one pixel or the number of pixels per inch. The lower the image resolution, the less information is saved and higher resolution means more information is saved but larger memory size is required to store. Three main approaches were used to identify the defects. They are statistical, structural and spectral approach. Nagrale and Bagde (2013), were discussed about the various image processing techniques available in identifying the defects. Li *et al.* (2013) explained defect detection based on image layered model. Javed *et al.* (2013), do the comparative analysis of various defect detection techniques. Haralick *et al.* (1973) briefly discussed the various statistical features available for identifying the defects.

The main objective of this study is to build a system based on ANN techniques for identifying plain woven fabric defects in textile industry to overcome the drawback of manual inspection system. The proposed system increases the accuracy, speed and consistency and reduces the labor cost and time consumption for defect identification.

MATERIALS AND METHODS

In this study we focus on 100% cotton plain woven fabric with defect free and defected image. The images are taken by using digital camera begins from 300 dpi resolution and will increase by a step of 100 dpi because human vision is approximately 300 dpi at maximum contrast. The suitable resolution which provides higher detection rate is 1000 dpi. The optimal size, which produce high classification rate with minimum time, is 512×512 which is noticed from Table 1.

Figure 1 shows the captured input images of plain woven fabric taken from industry.

Method: The texture of an image looks by fine, smooth, coarse etc. The texture of an image region is described by the way the gray levels are distributed over the pixels in that region. The features are described the properties of an image region by exploiting space relations underlying the gray level distribution of a given image. The difference between first-order and higher-order statistics is that first-order statistics estimate properties of individual pixels and do not consider pixel neighborhood relationships, whereas second and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other.

First order statistics: First order statistics texture measures are calculated from the original image intensity values. They do not consider the relationship
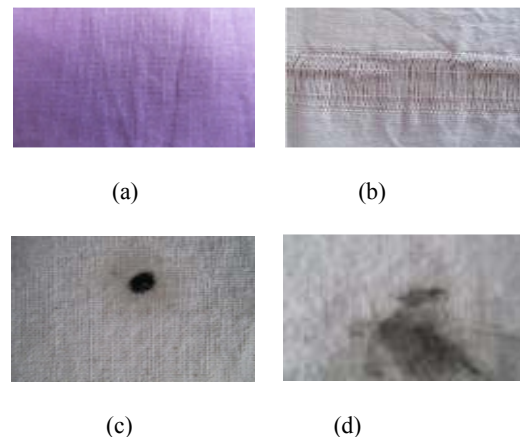

Fig. 1: Plain woven fabric image with; (a): No defect; (b): Weft float; (c): Hole defect; (d): Stain defect

Table 1: Plain woven fabric image size with classification rate and CPU time

S.No	Size of the image	Degree	Percentage of classification	CPU time
1	512×512	0	98	623.2656
2	512×512	45	92	633.2500
3	512×512	90	90	658.7813
4	512×512	135	90	635.5781

with neighborhood pixel. Features derived from this approach include moments such as mean, standard deviation, entropy, energy, skewness and kurtosis:

$$mean\ (\mu_1) = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I(i,j)}{M\ x\ N} \tag{1}$$

$$(\sigma_1) = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j)-\mu)^2}{M\ x\ N}} \tag{2}$$

$$entropy = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I(i,j) - \ln\big(I(i,j)\big) \tag{3}$$

$$energy(e_1) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I^2(i,j) \tag{4}$$

$$skewness = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j)-\mu)^3}{M\ x\ N\ x\ \sigma^2} \tag{5}$$

$$kurtosis = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I(i,j)-\mu)^4}{M\ x\ N\ x\ \sigma^4} \tag{6}$$

Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting second order textural feature from images. Co-occurrence matrix is describing the shape by sampling certain grey-levels in relation to other grey-levels. It is a function of two parameters namely relative distance measured in pixel numbers (d) and their relative orientation θ. This matrix is square in dimension N, where N is the total number of grey levels in the image. The [i, j]th element of the matrix is produced by counting the total occasions a pixel with value i is adjacent to a pixel with value j (Chandra *et al*., 2010). Each entry in the resulting matrix is the probability that a pixel with value i is to be found that is adjacent to a pixel of value j:

$$G = \begin{bmatrix} p(1,1)\ p(1,2)\ .....p(1,N) \\ p(2,1)\ p(2,2)\ .....p(2,N) \\ . \\ . \\ . \\ p(N,1)\ p(N,2)\ .....p(N,N) \end{bmatrix}$$

For example, if there are three distinct grey-levels 0, 1 and 2 and a position operator p is lower right, the resulting matrix G of the image:

$$\begin{bmatrix} 0\ 1\ 0\ 1\ 2 \\ 2\ 2\ 1\ 0\ 0 \\ 1\ 1\ 0\ 1\ 1 \\ 0\ 0\ 0\ 1\ 2 \\ 1\ 1\ 0\ 2\ 0 \end{bmatrix} G = \begin{bmatrix} 1\ 4\ 1 \\ 4\ 3\ 2 \\ 1\ 1\ 1 \end{bmatrix}$$

From our study, we find that gray level co-occurrence matrix with 0 degree and six statistical features are optimal to produce high classification rate with minimum processing time.

ARTIFICIAL NEURAL NETWORKS

In this study, multilayer feed forward network is used in which the processing elements are arranged in three layers called input layer, hidden layer and output layer. During the training phase, the training data is fed into to the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the forward pass. In forward pass, each node in hidden layer gets input from all the nodes from input layer, which are multiplied with appropriate weights then summed. The output of the hidden node is the nonlinear transformation of the resulting sum. Similarly each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights and then summed.

The output values of the output layer are compared with the target output values. The target output values are those that we attempt to teach our network. The error between actual output values and target output values is calculated and propagated back toward hidden layer. This is called the backward pass. The error is used to update the connection strengths between nodes, i.e., weight matrices between input-hidden layers and hidden-output layers are updated. During the testing phase, no learning takes place i.e., weight matrices are not changed. Each test vector is fed into the input layer. The feed forward of the testing data is similar to the feed forward of the training data. The back propagation algorithm is used to calculate the gradient error function using chain rule of differentiation. After the initial computation, the error is propagated backward from the output units, so it is called as back propagation. The algorithm for back propagation is as follows:

- Apply feature vector x_n to artificial neural network and forward propagate through network using:

$$a_j = \sum w_{ij}\ z_i\ and\ z_j = h(a_j) \tag{7}$$

- Evaluate ∂_k for all output using:

$$\delta_k = y_k t_k \tag{8}$$

- Back propagate the ∂s using:

$$\delta_j = h'(a_j) \sum w_{kj}\ \delta_k \tag{9}$$

$$use\ \frac{\partial E_n}{\partial w_{ji}} = \delta_j z_i \tag{10}$$

To evaluate required derivative: The back propagation algorithm has higher learning accuracy and faster. Its aim is adapting the weights to minimize the mean square error. We found from our paper that 20 neurons in the hidden layer produce better performance of the network.

Table 2: Plain woven fabric image network architecture

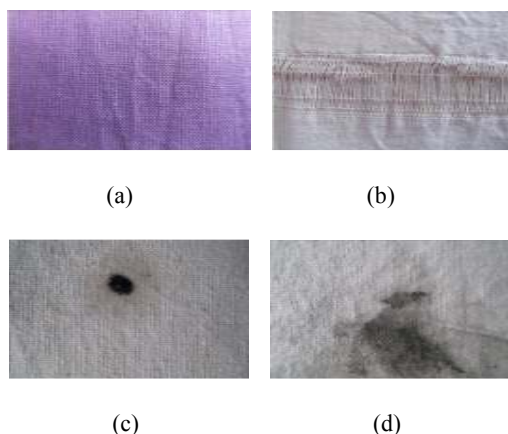| Sl. No	No. of features	NN Architecture	Percentage of classification	CPU time
1	5	5:18:1	97.3	642.0625
2	6	6:20:1	98.8	617.4219
3	7	7:22:1	98.6	625.4063
4	8	8:24:1	97.0	636.7031
5	9	9:26:1	96.2	615.2813

(a)　　　　　　　(b)

(c)　　　　　　　(d)

Fig. 2: Plain woven fabric filtered images; (a): Defect free (b): Weft float; (c): Hole; (d): Stain defect
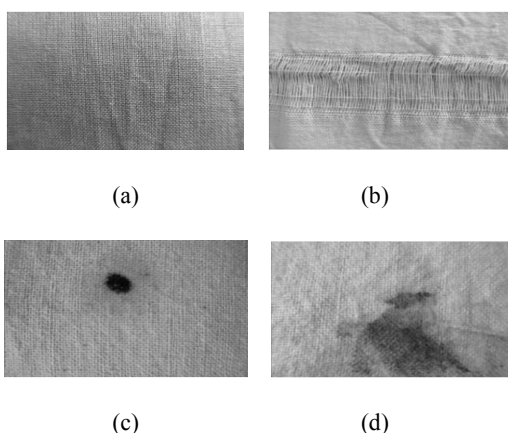

(a)　　　　　　　(b)

(c)　　　　　　　(d)

Fig. 3: Plain woven fabric gray images; (a): Defect free; (b): Weft float; (c): Hole; (d): Stain defect

RESULTS AND DISCUSSION

Four different defect types, stain, hole, warp float and weft float were analyzed on plain woven fabric images. Both defect free and defected images were taken, after preprocessing the co-occurrence matrix at 0 degree is formed. From the matrix six statistical features were extracted and these features were used an input to the neural networks. Six statistical features with 20 hidden neurons in the hidden layer produces high classification rate with minimum CPU time. From Table 2 we understood that 6 neurons of input layer, 20 neurons of hidden layer and one neuron of output layer produces high accuracy with less time.

This study proposes a multi layer artificial neural network consists of an input layer, hidden layer and output layer. The network is trained with gradient descent back propagation with adaptive learning algorithm. The network is trained by more than 75 defect and defect free images. Mean of sum of squares of the network weights and biases is used for performance function. The fabric has whole type fault, the target output of fault pattern is 1 and remaining patterns are 0. Our system is successful 98.8% in identifying whole fault accurately, 98.6% in identifying stain fault accurately, 98% in identifying warp float fault accurately and 98% in identifying weft float fault accurately. The total performance of the system is 98.35% accurately in identifying all four types of faults. The captured woven fabric images filtered using adaptive median filtering technique and then converted into gray scale image. The filtered and gray scale image are shown in Fig. 2 and 3.

CONCLUSION

In this study an automated plain woven fabric defect identification system with artificial neural network techniques was demonstrated. We achieved total success rate of fabric identification is 98.35% with CPU time 615.777. The results obtained by our proposed system indicate that a reliable fabric inspection system with better performance can be created for textile industries.

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