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Fabric Defect Identification System Using Statistical Approach and Artificial Neural Network Techniques

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Abstract: The fabric defect identification system requires efficient and Robust Defect Detection algorithms. Due to large number of fabric defect classes, the automatic fabric inspection system is very challenging. When researchers consider reduction of labor cost and its benefits, the automatic fabric inspection system is very economical. Various techniques have been developed to detect fabric defects. Based on the features of fabric, the defect detection techniques have been characterized into three categories. They are statistical, structural and model based techniques. This study presents entropy based fabric defect detection from the images of textile industry. Textile industry needs to produce less defective textiles for minimizing production cost and time consumption. The images are acquired, preprocessed, statistical feature-entropy is extracted. The artificial neural network is used as identification model. The extracted feature is given as input to the artificial neural network, it identifies the defect. The proposed method shows a better performance when compared with the existing methods.

Key words: Artificial Neural Network (ANN), Back Propagation algorithm, entropy, fabric defect detection, image processing

INTRODUCTION

Quality control means conducting observations, tests and inspections so that making decisions which improve its performance. 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 in expensive, easy to weave and easy to finish. First quality fabric plays the main role to insure survival in a competitive market place in a weaving plant. This introduces stress on the weaving industry to work towards low cost first quality products as well as just in time delivery. Second quality fabric may contain a few major defects and/or minor several structural or surface defects (Zhu *et al*., 2008). Online system provides images from current production and is located directly on or in the production line while offline system is located after the production line. Until now the fabric inspection is still undertaken offline and manually by skilled staff with a minimum accuracy. The dream of textile manufacturers is to achieve optimum potential benefits such as quality, cost, comfort, accuracy, precision and speed. Plain-woven fabric inspection systems still a challenge due to the variable nature of the weave.

The types of weaves: The simplest of all patterns is the plain weave. Each weft yarn goes alternately over and under one warp yarn. Each warp yarn goes alternately over and under each weft yarn. The plain 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: Diagonal ridges formed by the yarns which are exposed on the surface, characterize Twill weave. 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.

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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.

The fabric defect is a change in or on the fabric construction. The weaving process may create a huge number of defects named as weaving defects. These defects appear either in the longitudinal direction of the fabric (warp direction) or in the width direction (weft direction). Presence or absence of the yarn causes defects such as miss-ends or picks end outs and broken end or picks (Zhu *et al*., 2008). Some defects are due to yarn defects and additional defects are due to machine related and appeared as structural failures.

Automatic fabric inspection systems are designed to increase the accuracy, consistency and speed of defect detection in fabric manufacturing process to reduce labor costs, improve product quality and increase manufacturing efficiency (Gururajan *et al*., 2008; Zhang *et al*., 2011). The operation of an automated fabric inspection system can be broken down into a sequence of processing stages. The stages are image acquisition, image preprocessing, feature extraction, training and decision.

MATERIALS AND METHODS

Image acquisition: The woven fabric images of without defect and with defect are acquired and then processed. The most important parameter used in the image acquisition is the resolution. The resolution can refer either 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 (Lu and Zhang, 2007). The scanning of fabric images begins from 300 dpi resolution because the human vision is approximately 300 dpi at maximum contrast. The scanned image is stored in 'jpg' format. Initially, the resolution level is set to 300 dpi and then gradually increased by step of 100 dpi till 1000 dpi as a maximum resolution (Ma, 2007). The image acquisition is performed by different types of camera like CCD (Charged Coupled Device), CMOS (Complementary Metal Oxide Semiconductor), digital camera, etc.

Image preprocessing: After acquiring the image, the image is resized and normalized using Bicubic Interpolation Method. Bicubic interpolation performs better than the other interpolation techniques. The output pixel value of bicubic is a weighted average of pixels in the nearest 4 by 4 neighborhood. It solves for the value at a new point by analyzing the 16 data points surrounding the interpolation region. This method fits a bicubic surface through existing data points. Bicubic interpolation requires more memory and execution time than either the nearest neighbor or bilinear methods but this method produces a much smoother surface than nearest neighbor or bilinear interpolation. This is the key advantage for using Bicubic Interpolation Method. The normalized image is filtered with adaptive median filtering. This median filter belongs to the class of edge preserving smoothing filters which are non-linear filters. For two images f1(x) and f2(x), Median[f1(x)+f2(x)]≠ median(f1(x))+median(f2(x)). Adaptive median filter smoothens the image by keeping the small and sharp details. The adaptive median filter performs spatial processing to determine which pixels in an image have been affected by noise. This filter classifies pixels as noise by comparing each pixel in the image to its surrounding neighbor pixels and preserves detail of the image. This approach often produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image. In median filtering, the value of an output pixel is determined by the median of the neighborhood pixels rather than the mean. The median is much less sensitive than the mean to extreme values called outliers. Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image. The preprocessed image is converted into binary image by using threshold values. From this binary image, the statistical feature entropy is extracted.

Statistical approach: 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. 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 (Chandra *et al*., 2010; Yin and Yu, 2008). 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. Higher order statistics not considered for implementation due to interpretation difficulty and calculation time. The first order statistic entropy is considered among the available statistics as texture features in this study.

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as:

$$\mathrm{Sum}(p \times \log2(p))$$

where, p contains the histogram counts returned from imhist. By default, entropy uses two bins for logical arrays and 256 bins for uint8, uint16 or double arrays. The image can be a multidimensional image. If the image has more than two dimensions, the entropy function treats it as a multidimensional grayscale image and not as an RGB image:

$$\mathrm{Entropy} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I(i,j) - \ln(I(i,j)) \quad (1)$$

Artificial neural networks: 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. In two aspects, it resembles the human brain. It acquired knowledge from its environment through a learning process. Synaptic weights used to store the acquired knowledge which is interneuron connection strength. There are three classes of neural networks, namely single layer, multilayer feed forward networks and recurrent 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 of the Back Propagation algorithm. In forward pass, each node in hidden layer gets input from all the nodes from input layer which are multiplied with appropriate weights and then summed. The output of the hidden node is the non-linear 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 of this node is the non-linear transformation of the resulting sum.

The output values of the output layer are compared with the target output values. The target output values are those that researchers attempt to teach the 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 of the Back Propagation algorithm. 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 Back Propagation algorithm produces best result when compare with the other algorithms. The algorithm for back propagation is as follows:

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

$$a_j = \sum w_{ij}\ z_i \quad \text{and} \quad z_j = h(a_j) \quad (2)$$

- Evaluate ∂_k for all output using:

$$\delta_k = y_k t_k \quad (3)$$

- Back propagate the ∂s using:

$$\delta_j = h'(a_j)\sum w_{kj}\delta_k \quad (4)$$

$$\mathrm{Use}\frac{\partial E_n}{\partial w_{ji}} = \delta_j z_i \quad (5)$$

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.

RESULTS AND DISCUSSION

The inspection system captures fabric images by acquisition device (digital camera) and passes the image to the computer. Initially, the inspection system normalizes the image using interpolation methods. The normalized image is filtered with adaptive median filtering. The number of connected components and their region property area with bounding box is calculated. Taking the value of area as threshold the image is converted into binary image (Table 1 and Fig. 1-4a, b).

Matlab 7.0 Software platform is use to perform the experiment. The PC for experiment is equipped with an

Table 1: Experimental result

Analysis	Defect free image	Defected image
Entropy	0	0.5295
Result		

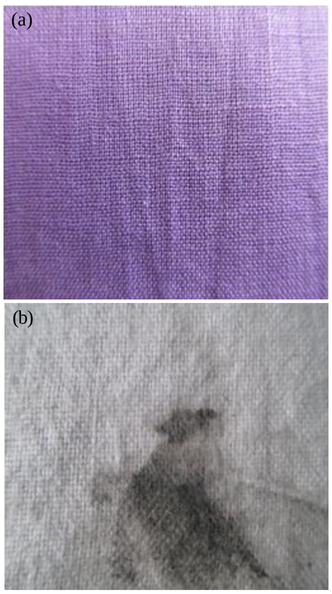

Fig. 1: Original; a) Woven defect free image and b) Stain defect image

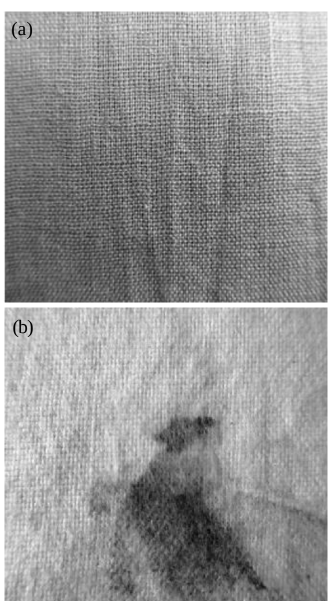

Fig. 2: Normalized; a) Woven defect free image and b) Stain defect image

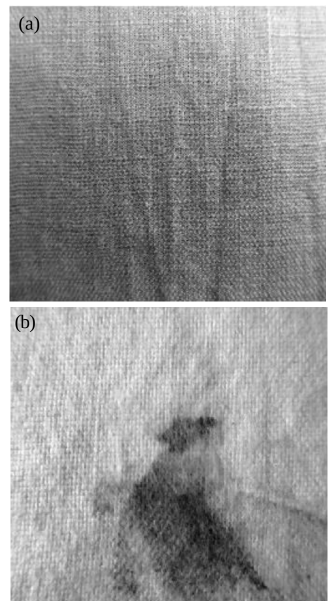

Fig. 3: Filtered; a) Woven defect free image and b) Stain defect image

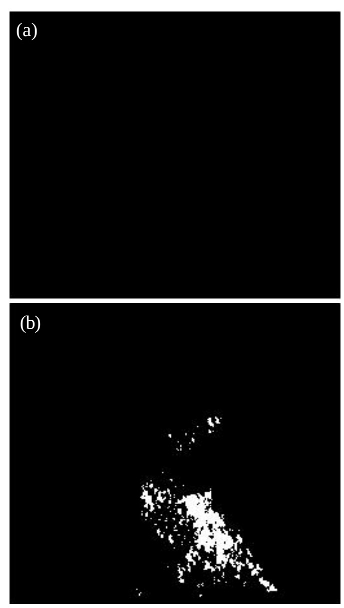

Fig. 4: Binary; a) Woven defect free image and b) Stain defect image

Intel core 2 Duo 1.6 GHz Personal laptop and 2 GB memory. The proposed scheme is tested using image processing and artificial neural networks. From the simulation of the experiment results, researchers can draw to the conclusion that instead of taking all the first order statistical features, if researchers take only one statistical feature-entropy produces high accuracy system for fabric defect identification in textile industry.

CONCLUSION

In this study, an artificial neural network based fabric defect identification system was demonstrated. Researchers achieved success rate of fabric identification is 94.6%. The results obtained by the proposed system indicate that a reliable fabric inspection system for textile industries can be created.

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