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ENHANCED WAVELET BASED APPROACH FOR DEFECT DETECTION IN FABRIC IMAGES

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ABSTRACT

Fabric defect detection is one of the indispensible units in the manufacturing industry to maintain the quality of the end product. Wavelet transform is well suited for quality inspection application due to its multi-resolution representation and to extract fabric features. This paper presents the comparison of three wavelet based models. These models include Tree structured wavelet transform, wavelet transform with vector quantized principal component analysis and Gabor wavelet network. The wavelet based models are combined with golden image subtraction to identify the fabric defect. The energy and entropy features are extracted and thresholding is performed to produce the binary image. The performance of the models is evaluated to verify the detection rate based on the segmented results. It can be concluded that the Wavelet transform with vector quantized principal component analysis provides better detection result.

Keywords: fabric, defect detection, wavelet transform, principal component analysis, vector quantization.

1. INTRODUCTION

The automated visual inspection has been increasingly popular among many industries like steel, ceramics, wood, wallpaper etc. Fabric defect detection is one of the most important phases in fabric production to improve the fabric quality. Generally fabric inspections are done by human experts and inspectors which involve high cost and low performance. While using manual inspection only 80% of fabric defects can be identified [1]. For the past decade considerable research has been carried out to automate the fabric inspection and the ultimate objective of the research is to find efficient approach to increase accuracy meanwhile to reduce complexity and cost.

A fabric defect is any abnormality in the fabric that hinders its acceptability by the consumer. The textile processing does not eliminate variability incurred during different steps in textile manufacturing. As materials flow from one stage of processing to another, components of variability are added and the final product may involve a cumulative variability that is much higher than the variability of the input fibers and thus it cause a defect in the fabric. The main factors that lead to fabric defects are failure of opening and cleaning the machines that completely eliminate contaminants and trash particles, and it may leads to spinning, weaving and knitting related defects. So the fabric inspection has to identify all types of defects with minimum effort.

Several methods have been proposed to address the problem of detecting defects in textile fabrics, including statistical, spectral and model based approaches. The wavelet transform provides a solid and unified mathematical framework for the analysis and characterization of an image at different scales [2]. It provides both time and frequency information, and can be successfully applied for textile defect detection. Fabric defect detection based on wavelet transform performs better with less computation than the traditional statistical texture analysis approaches in identifying defects. A Gabor filter has an optimal localization both in the spatial domain and in the spatial frequency domain and it is one of the most famous spectral approaches that are widely used in the field of defect detection.

In this paper the three wavelet based models are combined with golden image subtraction. And the performances of the methods are compared based on average specificity, sensitivity and detection rate. The performance of these three methods is evaluated on patterned fabric especially for dot patterned fabric. Section II of this paper gives the proposed three wavelet based models. Experimental results and discussion are presented in Section III. Finally, conclusions are presented in Section IV.

2. METHODOLOGY

The input image is preprocessed using histogram equalization to adjust the contrast of the input image. The lattice is extracted from the template image and the features such as energy and entropy are extracted using the wavelet based method, similarly the features are extracted from the input lattice. Then the difference between the template lattice and the input lattice is calculated and thresholding is applied to generate the binarized image. Enhanced switching median filter is applied for smoothening the binarized image. And from the binarized image it can be identified whether the input image is defective or non defective. The steps involved in fabric defect detection are depicted in Figure-1. The energy and entropy features are calculated from defect free lattices then it is compared with the input lattice. The performances of the wavelet based methods are evaluated using sensitivity, specificity and detection rate.

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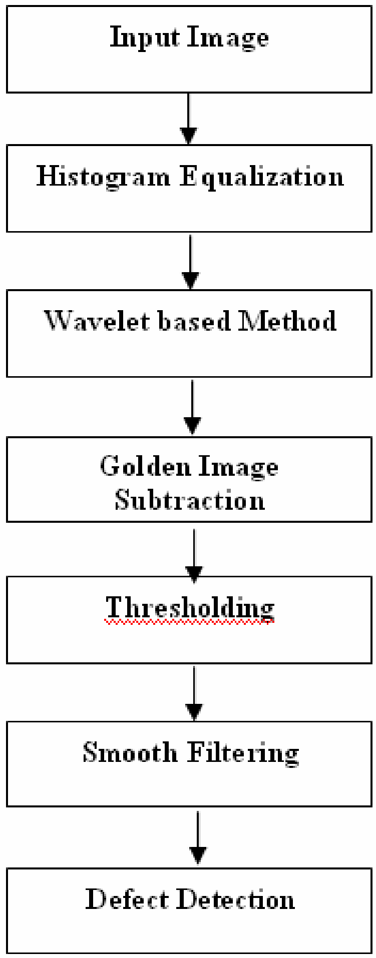

Figure-1. Process involved in the proposed method for defect detection.

2.1. Optimal tree structured wavelet

The first method combines tree structured wavelet with golden image subtraction TSWT-GIS. The two- dimensional wavelet transform is applied on the input image and is subjected to decompose into four different frequency images as shown in Figure-2. The input image is decomposed into three layers. The number of sub images obtained is depend on the number of layers to decompose, more the number of layers may increase the number of sub images obtained. It is necessary to include criteria to optimize the decomposition level that is calculated based on minimum entropy. The two dimensional wavelet transform is applied on the input image. For each sub-image the energy is calculated. When the energy value less than the energy values obtained from all the remaining sub-image the decomposition is stopped. The other criterion is the size of the sub image. When the sub image size is less than 16 × 16 it may not contain meaningful information and the decomposition may be stopped.

$$E = \sum_{i}^{M}\sum_{j}^{N} H_{ij}^{2} \qquad (1)$$

$$H(z) = -\sum_{1=0}^{255} p(i)\log_2 p(i) \qquad (2)$$

The size of the image is m×n. The features energy and entropy are calculated using the above formula. Energy reflects the homogeneity of the sub-image and is defined as follows in equation (1) whereas entropy reflects the measuring of randomness within the sub-image as given in equation (2), where p (i) is the probability of the pixel i in an image.

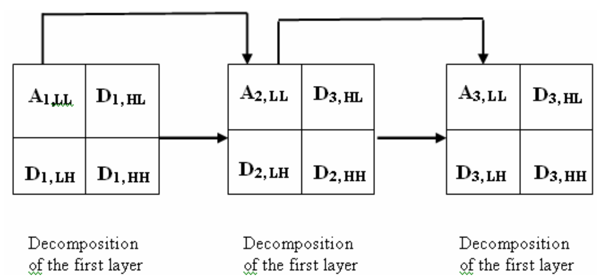

Figure-2. Schematic diagram of 2-dimensional wavelet transform.

2.2. Wavelet transform with vector quantized principal component analysis

The second method combines wavelet transform with vector quantized principal component analysis with golden image subtraction WTVP-GIS. Generally PCA is used to find a low-dimensional representation model for high dimensional data and it is used for dimensionality reduction. Principal Component Analysis is a popular technique for data compression and has been successfully used as initial step in many computer vision tasks [3, 4]. The principal components of a set of process variables 1x, 2x… px are just a particular set of linear combinations of these variables. Geometrically, the principal component variables 1y, 2y… py are the axes of a new coordinate system obtained by rotating the axes of the original system.

Because of its ability to discriminate directions with the largest variance in a data set, PCA is suitable to identify the most representative features as inputs to defect detection. Since it is difficult to identify patterns in high dimensional data, PCA is a powerful tool for analyzing data by reducing the number of dimensions, without much loss of information. PCA encodes textural information only, while geometrical information is discarded. Vector Quantization considers the low level information from the image block; hence it is suitable to produce accurate results. The VQPCA is applied to the wavelet coefficients and provides the components of feature vectors for the template image. The same process is repeated for the input image. The difference between the input image and the

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template image is compared, based on the threshold value, the input image is labeled either as defective or non defective.

Then vector quantized principal component analysis which is generally used for image representation purposes are considered the defect detection task. Generally the techniques achieve high detection accuracy but the requirement of data storage and processing time are expensive.

2.3. Gabor wavelet network

The third method combines gabor wavelet network with golden image subtraction GWN-GIS. Gabor filters have been successfully implemented in various approaches of image analysis and computer vision applications. Gabor filters can effectively combine both spatial and frequency domain textile information, hence it is suitable for defect detection application. Generally GWN is a combination of Feed Forward Neural Network (FFN), namely Multi Layer Perceptron (MLP) and the Gabor wavelet decomposition. Various experiments [1, 5, 6] show that GWN is an effective and task-specific feature extractor.

GWNs represent an object as a linear combination of Gabor wavelets and the parameters of each single Gabor functions (such as orientation, position and scale) are individually optimized to reflect the particular local image structure. Gabor Wavelet Networks have several advantages:

(1) GWN allows an efficient and sparse coding while coding is adaptive to the task at hand.

(2) Gabor filters are good feature detectors [1] and the optimized parameters of each of the Gabor wavelets are directly related to the underlying image structure.

(3) The wavelet coefficients (or weights) of each of the Gabor wavelets are linearly related to the filter responses and with that they are also directly related to the image structure.

(4) The precision of the representation can be varied to any desired degree ranging from a coarse representation to an almost photo-realistic one by simply varying the number of used wavelets.

(5) GWNs are invariant to affine deformations without shear and homogeneous illumination changes [3, 7].

GWN allows the tuning of filter parameters to match a particular texture feature, such as orientation and central frequency. GWN is used to extract image feature which can be used in pattern recognition. The prior information for the design of optimal Gabor filter is obtained from GWN [5, 8]. The GWN with single hidden layer can extract local features form non-defective texture pattern. However, single layer in GWN, requires the initial parameters of wavelet to be selected carefully.

The wavelet networks proposed [6] the concept of Gabor Wavelet for solving the 2D problems in pattern recognition [9], in which an imaginary Gabor wavelet function is used as a transfer function in the hidden layer of the network. The mapping form of the network can be governed by equation (3).

$$\mathbf{f(x,y)} = \sum_{\mathbf{i=1}}^{\mathbf{N}} \mathbf{w_i\, g_0^i\,(x,y)} + \bar{\mathbf{f}} \tag{3}$$

where $\mathbf{w_i}$ is a network weight from the hidden layer to the output layer and $\bar{\mathbf{f}}$ is introduced to eliminate the DC value of an objective function. The imaginary part of the Gabor function is used and it is referred as the transfer function, and is expressed in equation (4).

$$g_{o=}^{i} exp\left\{-\frac{\left[\left(x-t_x^i\right)\cos\theta^i-\left(y-t_y^i\right)\sin\theta^i\right]^2}{2(\sigma_x^i)^2} - \frac{\left[\left(x-t_x^i\right)\sin\theta^i-\left(y-t_y^i\right)\cos\theta^i\right]^2}{2(\sigma_y^i)^2}\right\} \tag{4}$$

$$\times \sin\left(2\pi\omega_{\mathbf{x}}^{\mathbf{i}}\left[(\mathbf{x}-\mathbf{t_x^i})\cos\boldsymbol{\theta}^{\mathbf{i}}-\left(\mathbf{y}-\mathbf{t_y^i}\right)\sin\boldsymbol{\theta}^{\mathbf{i}}\right]\right)$$

where $\mathbf{t_x^i}$, $\mathbf{t_y^i}$ are the translation parameters of the ith Gabor wavelet, and ($\sigma_{\mathbf{x}}^{\mathbf{i}}$, $\sigma_{\mathbf{y}}^{\mathbf{i}}$), $\theta^{\mathbf{i}}$ and $\omega_{\mathbf{x}}^{\mathbf{i}}$ are the radial frequency bandwidths, the orientation and the central frequency respectively of the ith hidden node. The network input vector [x, y] is the position of a pixel in a studied image IM, and the output is the grey level of the corresponding pixel.

In the network, the five parameters for each of the gabor wavelet should be calculated by the network learning process, such as translation parameters, orientation, radial frequency bandwidth, centre frequency, and its corresponding weight.

The objective function of the learning process is defined as given in Equation (5).

$$\text{E=min} \; \| IM \sum_i w_i\, g_i \|_2^2 \tag{5}$$

In fact, the network proposed in [5] has only two input nodes and one output node. In the network, the input vector [x y] is the position of a pixel in the template image, and the output is the grey level of the corresponding pixel. The GWN is offered with a supervised training with the non defective fabric image as the template and it is used to determine the parameters of optimal Gabor filter. Once the network is trained, the optimal filter is used to discriminate defective and non defective from the fabric images with the same texture background as in the template image.

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3. EXPERIMENTAL RESULTS AND DISCUSSIONS

The performance of the three methods optimal tree structured wavelet, wavelet with VQPCA and GWN are combined with GIS method are evaluated based on sensitivity, specificity, detection rate. The performance of theses proposed models are evaluated and compared with the traditional wavelet based method WBM. Totally 100 images are considered for the experimentation, 70 images are used for training and 30 images were used for testing. The sample images includes five different types of defects such as broken end, hole, netting multiple, oil stains and dirty fabric. The performances of these methods are evaluated based on sensitivity, specificity, detection rate and the formulas are given below in equation (6), (7) and (8). The measure sensitivity refers the correct detection of defective lattices; specificity refers to correct detection of defect-free lattices. And the detection rate refers to the number of correct detection of lattices over the total number of lattices expressed as a percentage.

$$\text{Sensitivity} = TP/ (TP + FN) \quad (6)$$

$$\text{Specificity} = TN/ (TN+FP) \quad (7)$$

$$\text{Detection success rate} = (TP+TN)/ (TP+FN+TN+FP) \quad (8)$$

The average performance of sensitivity, specificity, detection rate of the four methods for the five different defects is shown in the following Table-1, Table-2 and Table-3. And the binarized output of all the three proposed models with traditional wavelet based method is given in Figure-3.

Table-1. Average sensitivity.

Model	Broken	Hole	Netting multiple	Oil stains	Dirty fabric
WBM	86.39	86.18	85.64	82.77	82.10
TSWT-GIS	90.27	89.73	88.68	87.49	84.62
WTVP-GIS	91.47	90.22	89.04	88.89	86.32
GWN-GIS	91.12	89.79	88.74	88.32	85.47

Table-2. Average specificity.

Model	Broken	Hole	Netting multiple	Oil stains	Dirty fabric
WBM	87.82	87.11	84.97	81.65	81.52
TSWT-GIS	90.48	89.37	88.42	87.87	86.53
WTVP-GIS	92.04	90.54	89.64	88.68	87.54
GWN-GIS	91.29	90.05	88.99	88.47	87.31

Table-3. Average detection rate.

Model	Broken	Hole	Netting multiple	Oil stains	Dirty fabric
WBM	89.34	88.94	85.07	84.99	84.21
TSWT-GIS	92.62	90.46	90.10	89.14	88.44
WTVP-GIS	93.34	91.38	91.01	90.15	89.32
GWN-GIS	92.94	90.63	90.14	89.74	88.16

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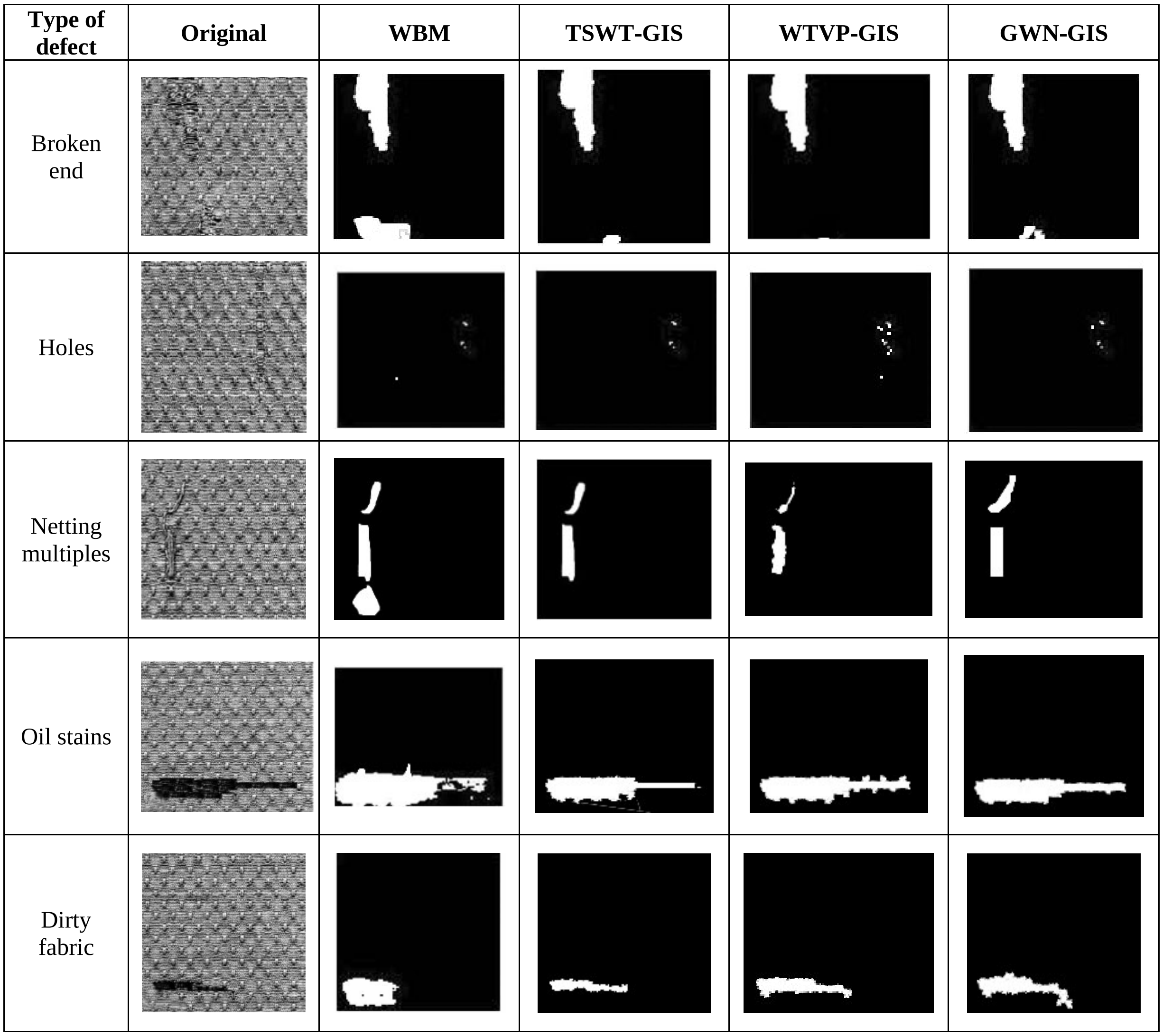

Figure-3. Binarized output of wavelet based methods with GIS.

Similarly the performance comparison of all the wavelet based methods is given in Figures 4, 5 and 6. These Figures clearly depict that the WTVP-GIS method performs better than the other methods.

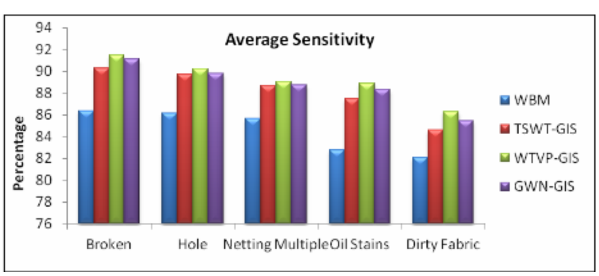

Figure-4. Performance comparison of average sensitivity.

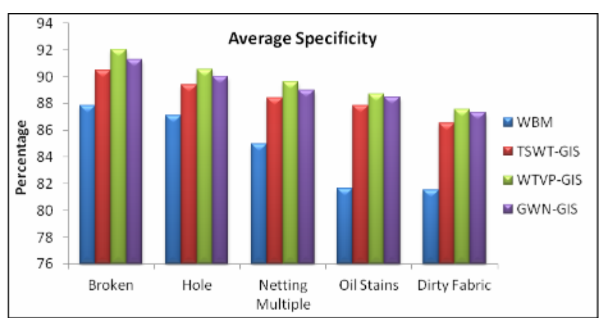

Figure-5. Performance comparison of average specificity.

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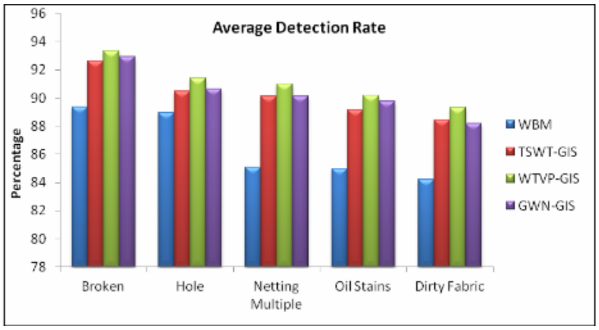

Figure-6. Performance comparison of average detection rate.

4. CONCLUSIONS

In this paper wavelet based methods are used to identify the defect in patterned textile images. The wavelet based methods are suitable for feature extraction because of its multi-resolution and multi-orientation property. The optimal tree structured wavelet, wavelet with vector quantized principal component analysis and Gabor wavelet network are combined with global image subtraction to identify the defects. The performance of the theses three models are evaluated based on sensitivity, specificity, detection rate. The functionality of the approaches is evaluated based on the segmented results of the input image and the performance metrics. Based on the experimental results, it is evident that the WTVP-GIS method out performs the other two methods. So wavelet combined with vector quantized principal component analysis is well suited in identifying the defect from the dot patterned fabric.

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