Fabric Defect Detection Using Sparse representation Algorithm

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***Abstract*— In fabric manufacturing technology, many types of fabric defects occur during production. These defects still detected by human inspection. But this system led to several disadvantages. To solve these drawbacks, machine vision based techniques are designed to detect the defects. In this paper, proposed fabric inspection model consists of image pre processing, feature extraction, defect detection and classification. The image pre processing improves the image contrast in order to make the details of defects more clear. Denoising techniques used to remove the noise and increase the quality of the image. Non locally centralized sparse representation algorithm is employed for defect detection and multi svm method used for defect classification. This model has high detection accuracy and low false alarm. It is suitable for identification of tiny defects, especially oil stain, ink stain, soil stain.**

***Index Terms---* Fabric detection; defect classification; Fabric Inspection module;**

I INTRODUCTION

Traditionally fabric detection based on visual inspection, which is expensive and low efficiency [1-4]. Its disadvantages are overcome by automated fabric inspection system. For automated fabric inspection system, previous authors proposed numerous approaches such as statistical, spectral, model based, learning, structural [5-7] and many techniques such as fourier transform, gabor transform, wavelet transform, GLCM, Bollinger bands. Structural approaches consider texture as composition of textural primitives. Texture analysis is performed by two steps. Obtaining the texture features is the first step, and inferring their replacement rules is the second step. By this texture analysis approach, the overall texture of the pattern can be obtained with the composition of simple texture structures. Structural texture analysis consists of two stages. First stage is fabric texture detection. Second stage is overall fabric texture pattern modeling. Disadvantage of this approach is low reliability. This method is reliable in fabric defect segmentation in which texture pattern is very regular. Statistical methods [8-15] use first order statistics and second order statistics to extricate textural features in texture classification. Methods includes in this approach are co- occurance matrix, histogram features, auto correlation function, mathematical morphology, cross correlation, statistical moments and edge detection.

Spectral approaches extract and generalize the fundamentals of image texture with the spatial layout rules. Wavelet transform [16-17], Fourier transform [18], Gabor transform [19-21] are the methods of spectral approaches. Wavelet transform discern the fabric defects of missing ends, missing picks, broken fabrics, and oil stains.

In this paper, a novel detection model, which is based on non-locally centralized sparse representation, is used for fabric defect identification. The proposed detection model includes four main parts: pre processing, dictionary learning, sparse coding [22-34] and defect segmentation. In pre processing, gray level conversion is employed to reduce noise formed by digital imaging and increase the contrast between defects and background. In the dictionary learning process, training samples are divided into K clusters by K –means clustering [35]. Compact sub dictionary will be formed for each cluster by using principal component analysis method. Defects are finally segregated from the residual image of the testing image and the corresponding restored image. Multi SVM technique used for classification of defects. [37- 42]

II RELATED WORKS

Jiancho yang et al. presented a new approach to single image super resolution, based upon sparse signal representation. Sparse representation for each patch of the low resolutions input is fixed. Then the coefficients of this representation are used to generate the high resolution output. This algorithm generates gray level relationship among s high resolution images that are competitive and superior in quality to images produced by other similar super resolution methods. Sparse modeling of this approach is robust to noise. This algorithm can be handle super resolution with noisy inputs in a more unified frame work.

Julian mairal et al. developed two different approaches for image restoration. First approach is learning a basis set (dictionary) adapted to sparse and classification tasks.

Second approach is exploiting the self similarities of natural images has led to the successful non local means approach for image restoration. For combining these two approaches in a natural manner, simultaneous sparse coding is proposed as a frame work. This is achieved by jointly decomposing groups of similar signals on subsets of the learned dictionary. This method effectively restores raw images from digital cameras at a high speed and low cost. This method applied in denoising and demosaicing tasks.

Ignacio Ramirez et al. proposed a frame work for designing sparse modeling priors was introduced. Universal coding tools formalize sparse coding and modeling from minimum description length (MDL) principle. The obtained priors lead to models both theoretical and practical advantages over the traditional one. This method used in the recovery of sparse signal, image denoising, and classification applications.

Kumar and Pang have proposed fabric inspection models based on a gabor filter bank. This gabor filter bank consists of 24 gabor filters. These gabor filters was generated at four scales and six orientations to detect the defects on the fabric. This method is based on the multi resolution analysis. Defect features were represented by fusing the outputs of all gabor filters. Parameters defined empirically, implementation of this detection model is easy. Here drawback is gabor filtering generate large amount of data, which disturbs texture discrimination.

III METHODS

A. *Image pre processing*

Fabric is synthetic material. It having fine weaving structure, made by fine raw materials. When the contrast between defect and the back ground of fabric is minimum, the discrimination of normal fabric and defects is a complicated task. Fabric material easily absorbs dust in the air and fabric images are affected by noise.

Noise appearing as bright dots or dust particles. It degrades or distorts the image quality. Noise can be fixed valued or random valued. These noises are mistakenly identified as defect pattern and therefore noise to be removed.

During image acquisition, inhomogeneties occur due to variance in relative position of the light source, camera position, and the textile position. These inhomogeneties make some part of the image appear darker and many have uneven contrast. To solve these issues, contrast enhancement is applied. Adaptive histogram equalization is a valid method of contrast enhancement which provides adequate contrast in local areas than traditional histogram equalization methods.

B. Dictionary learning using KPCA

Clustering is a mostly used searching tool whose main task is to identify and group similar objects together. K means algorithm is one of the most used clustering algorithm which divide S observations in K clusters in which each observation belongs to the cluster with the nearest mean.

Non defective fabric images are portioned into small patches which are clustered based on their structural

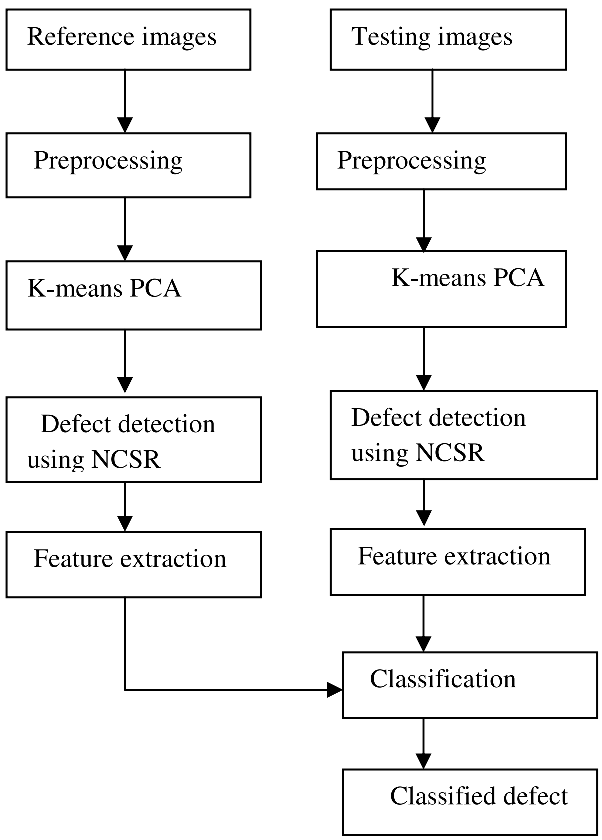

Fig.1. Flowchart of the defect detection process includes dictionary learning and detection model

fabric texture element. Sparse representation used to find a linear combination of a small number of basic atoms to restore the signal with minimum approximation error. Dataset is taken as S means, it can be divided into K clusters and, sub dictionary learned from each clusters.

PCA is a de-correlation based method which is suitable for learning sub dictionaries that finds a linear transformation W on a multi variant data X represented as X'=WX Principal component analysis is a signal de-correlation and dimensionality reduction technique. This method extracts the principal components of a set of possibly correlated data. This data revealed the internal structure of the data. In this proposed model, PCA scheme is applied on each cluster of image patches, for achieving a set of values of linearly un correlated variables. This variable composes a compact dictionary. This dictionary is sufficient for sparse representation of an image patch. This scheme reduces the computation cost. All sub dictionaries together formed an over complete dictionary that characterizes all the possible local structures of fabric images.

KPCA is a method for speeding up feature extraction and it is an improved PCA. This scheme widely used for non linear feature extraction. KPCA is applied to dimensionality reduction of the feature vectors. KPCA maps the high dimension features in the input space to new lower dimension eigen space through a non linear mapping. Principal component analysis scheme is used to find a set of eigen vectors which are non linearly related to the input data.

Algorithm proceeds as follows,

1. Pick k random points as cluster centre positions.

2. Assign each point to the nearest centre.

3. Recompute each cluster mean as the mean of the vectors assigned to that cluster.

4. If centers moved go to 2. The algorithm requires a distance measure to be defined in the data space and euclidean distance is used.

C. Defect detection using NCSR

For defect detection, Non locally Centralized Sparse Representation (NCSR) method is applied. In NCSR, each patch is coded using adaptive sparse domain selection strategy method.

D. Local binary pattern method for feature extraction

Local binary pattern is a easiest, efficient, and accurate method for detecting defects in fabric. This algorithm used to extract the feature value of fabric image. The basic idea is built on pixels. Relative gray value obtained by comparing the gray values of the center pixel with its surrounding neighborhood pixels, relative gray value can be obtained as the

E. Multi SVM classification

The features pull out from the local binary pattern method are used to train the support vector machines. Support vector machine is a binary classification method by supervised learning. It finds a classifier that separates the training data and to maximize the distance between two classes. SVM based multi class pattern recognition technique employed for inspecting frequently occurring fabric defects.

There are two types of approaches used for the extension of binary two class problem to n class problem .first approach is to qualify the design of the SVMs to unite the multi class learning in the quadratic solving algorithm.

Second approach is methods like one against all and one against one have been proposed, where multi class classifier is constructed by combining binary classifiers.

IV RESULTS AND DISCUSSION

response of the center pixel. LBP is invariable for monotonic gray scale changes. LBP is a combination

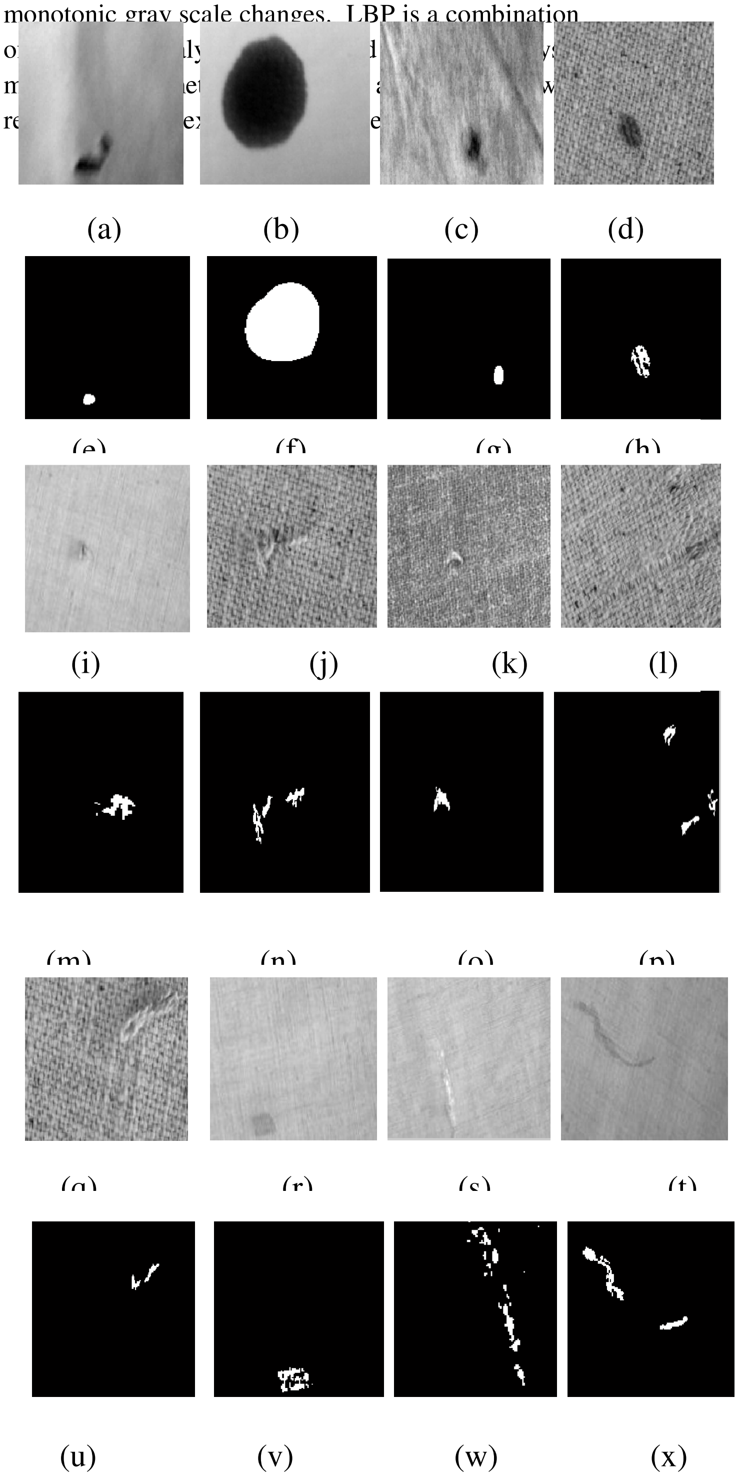

Fig.2. Detection results of fabric images

The performance of the proposed fabric detection l is done using TILDA data base which is created by a texture analysis workshop of deutsche forschungs gemeins chaft germany. [36]. This data base contains most common types of defects that always appear in the textile industry.

In this paper, the following four measurements (expressed as percentages) are used to judge the performance of defect detection models.

1) **Precision = TA / TA+FA**

2) **Sensitivity = TA / TA+FN**

3) **Specificity = TN / TN+FA**

4) **Accuracy = TA+TN / TA+TN+FA+FN**

. False abnormal means white pixels appear in the binary feature image of a defect free sample. True normal means white pixels not appeared in defect free sample. False normal means white pixels is not appeared in the binary image though it is affected by defect.

Precision defined as the percentage of correct alarm during detection, sensitivity defined as the percentage of defective samples that are correctly identified, specificity defined as the percentage of defect free images that are correctly classified as normal, accuracy defined as the percentage of correct classification of all testing images. Figure 2 shows detection results of some tiny defect samples.

VI CONCLUSION

In lassification based on non-locally centralized sparse representation has been proposed. This model is mainly based on two modules: dictionary learning (off-line) and dedefect detection through image restoration (real time). The proposed inspection module efficiently locate the defect and outlined their accurate shape even the fabric structure is slightly more complex than others. TILDA data base and some more real fabric samples are used for detection process. This inspection module achieved better performance for small fabric defects. This model achieved better detection accuracy.

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