Segmentation of Defects in Textile Images Based on Adaptive Sparse Domain Selection Method

***M Fathu Nisha*[1*], *L Ganesh Babu*[1], *P Vasuki*[2], *S Mohamed Mansoor Roomi*[2]**
[1]Assistant Professor, [2]Professor, Department of Electronics and Communication Engineering, Sethu Institute of Technology, Kariapatti, Tamil Nadu, India
***Email:** *nishahameed2016@gmail.com*
DOI: http://doi.org/10.5281/zenodo.3573570

Abstract
Generalized fabric inspection system needs perfect and efficient pattern recognition to detect and identify different types of defects in various kinds of fabrics. The inspection system needs on good environment for managing the fabric manufacturing unit and inspection unit with better results. In real time production environment, it is difficult to detect defects automatically for whole fabrics, although fabrics may be characterized by color, pattern, texture, and material quality. Human visual system is labor prone, costly, less accuracy and time consuming system. These drawbacks are overcome by automated fabric inspection system which provides warning to manufacturing unit to stop and recover the production, if it detects abnormalities in the process.

***Keywords:** Defects, inspection, pattern recognition*

INTRODUCTION

Textile industry is one of the fastest growing industries in worldwide markets, which cause for the major part of production, manufacturing, employment and business [1, 2]. Manufacturers are implementing various production techniques to increase production efficiency, which based on fabric materials and process. Defective fabric materials affect its quality and reduce profits. To avoid these difficulties, fabric inspection is needed. Traditionally fabric inspection is done by well-trained experts. When the inspector notices a defect in the moving fabric, he stops the machine, marks the defect and its location. Then starts the machine again. For each fabric roll, the number of defects per meter length is educated and the defect is classified. In this process, time consumption is more and accuracy is less. Automatic inspection system is introduced to increase the accuracy.

Methods include in this approach are co-occurrence matrix, histogram features, auto correlation function, mathematical morphology, cross correlation, statistical moments and edge detection. By analyzing the gray level relationship between image pixels, GLCM method used to detect the fabric defects. Classification accuracy can be increased by computing the correlation of the GLCM features. This method is not applicable to local defect classification. Computing time increases with the increasing data size. This approach is affected by noise and efficient filtering methods are needed. Fabric images that contain knot, thick yarn, were detected by morphological erosion operations, which are widely used in the detection of boundaries in a binary image [3, 4]. Spectral approaches remove the basics of image texture; generalize the basics of this texture with the spatial layout rules. Wavelet transform [5, 6], Fourier transform [7], Gabor transform [8, 9] are the methods of spectral approaches. Wavelet transform detect the fabric defects such as missing ends, missing picks, broken fabrics, and oil stains. Gabor wavelet features are suitable for twill fabric defect detection. Gabor filtering detects blob shaped fabric defects like knot, and odd symmetric Gabor filter was adapt at detecting edge shaped fabric defects like misspick. Even this method reduced the data size and restricts the defects they are computationally rigorous. This method achieved good adaptability and defect recognition results. Main limitation needs a large data base of fault free and faulty samples for training. Spectral domain approaches identify defects by extracting the features of normal and abnormal fabric texture. Even defects are very small and low contrast, this method influenced sensitivity. With the use of denoising techniques [10, 11] some defect detection model implemented. In sparse representation with a dictionary method, normal fabric texture estimated from the input defective samples [12−17].

In this paper, a novel detection model, which is based on non-locally centralized sparse representation, is developed for fabric inspection. The proposed detection model includes four main parts: preprocessing, dictionary learning, and sparse coding and defect segmentation. [18−20].

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 lower resolution input is fixed. Then the coefficients of this representation are used to generate the high resolution output. This algorithm generates gray level relationship between 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 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 to 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.

METHODS

Image Pre Processing

Fabric is synthetic material. It having fine weaving structure, made of fine raw materials. When the contrast between the 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, in homogeneities occur due to variations of the relative position of the light source, camera position, and the textile position. These in homogeneities make some part of the image appear darker and many have uneven contrast. To solve these issues, image enhancement is applied. Contrast stretching transformation is adopted for preprocessing. Its function is S =T(r) = 1\1+(m\r)ϵ

Where, r represents the intensities of the input image: s represents the corresponding intensities of the output: ϵ control the slope: m control center of gravity of the transformation function. The value of m set as the median value of the input gray level intensities. This value selected based on different image samples, which increases the degree of preprocessing.

Dictionary Learning Using KPCA
Non defective fabric images are divided into small patches which are clustered based on their structural features. In patches, each cluster represents a kind of 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 clustered into K clusters, from each cluster, a sub dictionary learned.

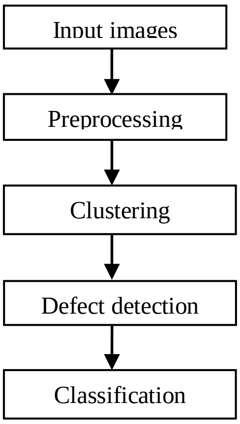

***Figure 1:** Flowchart of the defect detection model.*

KPCA
KPCA is a method for speeding up feature extraction and it is an improved PCA. This scheme widely used for nonlinear 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 spaces through a nonlinear 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:

- Pick k random points as cluster centre positions.
- Assign each point to the nearest centre.
- Recompute each cluster mean as the mean of the vectors assigned to that cluster.
- If centers moved go to 2. The algorithm requires a distance measure to be defined in the data space and euclidean distance is used.

Image Restoration
For Image restoration, non-locally centralized sparse representation (NCSR) method is applied. In NCSR, each patch is coded using adaptive sparse domain selection strategy method.

Adaptive Sparse Domain Selection
In this method, a set of compact sub dictionaries is learnt from high quality image patches. The image patches are clustered as many (k number of) clusters. A cluster consists of many patches with same patterns. Compact sub dictionary is learned for each cluster. PCA technique is used to learn the sub dictionaries. Calculate distances to means of the clusters, using this distance measures, check which cluster falls into, then PCA sub dictionary is of this cluster is selected for coding. The best sub dictionary is selected such that which is very close to the given patch is selected for coding the image patch. Then given image patch is represented by the adaptively selected sub dictionary. The whole image is reconstructed accurately than the usage of universal dictionary. It is a simple technique. It improves the effectiveness of sparse modeling and image restoration results.

Multi SVM Classification

The features extracted from the local binary pattern method are used to train the support vector machines. Support vector machine is a binary classification method of 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. The first approach is to qualify the design of the SVMs to unite the multi class learning in the quadratic solving algorithm. The 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.

RESULTS AND DISCUSSION

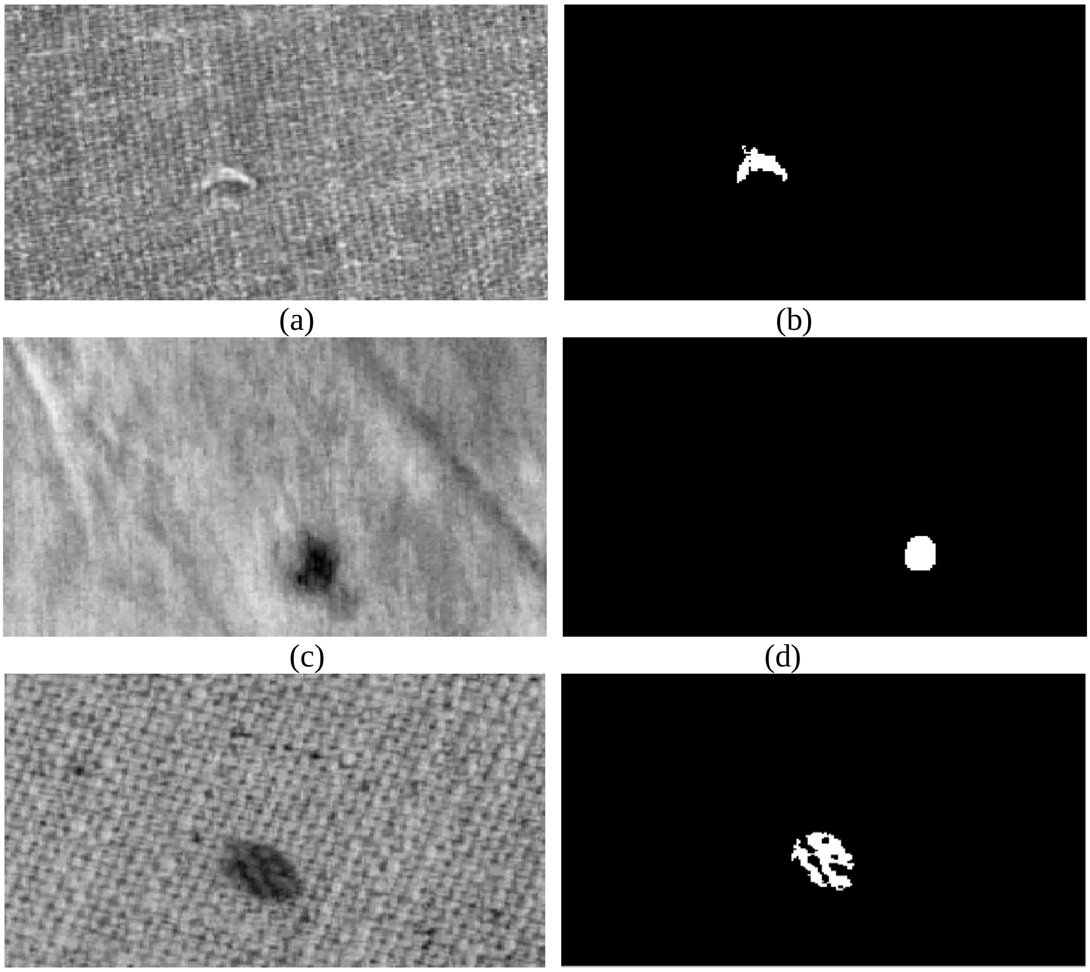

Figure 2: *Detection and classification results of small defects. (a),(c),(e) –Input images, (b),(d),(f)- Output images*

In this paper, fabric detection and classification model is done using TILDA databases. This database contains most common types of defects that always appear in the textile industry. Four measurements (expressed as percentages) are used to judge the performance of defect detection models.

- Precision = TA / TA+FA
- Sensitivity = TA / TA+FN
- Specificity = TN / TN+FA
- Accuracy = TA+TN/TA+TN+FA+FN

Where, true abnormal (TA) means correct detection with good localization, which is recorded only the defect area is covered by white pixels in the binary feature image. False abnormal means white pixels appear in the binary feature image of a defect free sample. True normal means white pixels not appeared in the defect free sample. False normal means white pixels is not appeared in the binary image though it is affected by the 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.

CONCLUSION

We have proposed a new frame work based on principal component analysis and adaptive sparse domain selection. We have successfully applied our approach to texture differentiation. Our approach yielded better detection results than recent state of the art methods. Future works will focus on extending our approach to uniform patterned fabric and non-uniform patterned fabric.

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