Fabric Defect Detection Using Deep Learning Techniques And RPCA

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Abstract

The detection of defects refers to locating irregularities and damages present on fabric in a systematic way. The project uses deep learning methods and techniques which have been found very effective for feature extraction and further computations for fabric defect detection. Defects in fabrics that are invisible to the naked eye can be brought out using image processing algorithms. We aim to detect defects that vary in shape and sizes on both patterned fabric and un-patterned fabric efficiently.

Keywords— Convolutional Neural Network (CNN), RPCA, Fabric Defect Detection, Fabric Defects, Deep Features, Defect Visualization.

I. INTRODUCTION

Using machine vision to perform the task of detecting defects in fabrics as compared to common practice of visually conducting it by humans ensures efficiency. Humans are prone to visual fatigue and are limited by the skill set. Each individual might have a different efficiency in performing defect detection owing to difference in skills. Hence it is very important to automate the process of defect detection. It has also been found that identifying the defects can help prevent the fabrics from selling at prices 45%-65% less than the price it was intended to be sold at [1]. A few methods that exist can be used for specific fabrics and hence it is important to develop robust and scalable techniques to adapt to different kinds of fabrics. Hence it will be useful to study this topic further.

There are a few existing methods for defect detection. These methods can be broadly classified into two categories based on what type of fabric they work on. The first category of these methods works well on unpatterned fabric as shown in Figure- 1(a). A few examples of the first category are statistical based method [2], spectral analysis method [3], model based method [4] and dictionary learning based method [5]. The second category of these methods works well on patterned fabric as shown in Figure-1(b), some of the methods in this category are Elo rating method [6], Motif based method [7] and convolutional matching pursuit (CMP) dual-dictionary method [8]. The above mentioned methods use template matching approach to localise and detect defects, which requires using a suitable template and specific alignment.

Using techniques such as convolutional neural network (CNN) has given good results on image classification, localisation and detection. There is very less literature on CNN based defect segmentation due to the lack of a large training image set with pixel-level annotations. CNN has convolutional layers that resemble neurons that enable vision in humans and dense layers behave like higher-level deduction and decision making, hence it is a most influencing approach for learning the representation of the features automatically.

Robust principal component analysis can be used to separate an image into low-rank and sparse part. Since the non-defective region or the background of the fabric images are highly disposable and homogenous, and these regions can be considered as the low-rank sub-space. The defective regions are sparse and they deviate from the low-rank subspace. Hence RPCA can be used to detect defects [9]. However, the images of fabrics can contain noise and interference which are also sparse in nature, causing the image to be wrongly classified as belonging to the defective category. This problem can be solved by introducing a non-convex total variation regularization term into the RPCA. Non-convex solution is preferred as it is more approximate to the original solution.

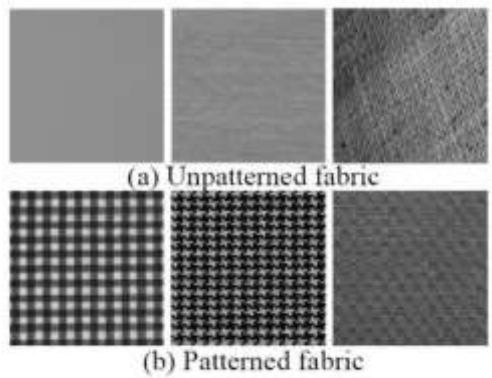


FIGURE 1: Fabric images: (a) Unpatterned fabric images, including plain fabric, twill fabric and plain weave fabric respectively; (b) Patterned fabric images, including box-, star- and dot-patterned fabric respectively.

II. RELATED WORK

A. *FABRIC DEFECT DETECTION*

The fundamental thought of the statistical – based method is to separate the test picture into blocks, and each region is evaluated by estimating its statistical properties and defect in the region will show distinct statistical properties. Nevertheless, it is hard to bring out suitable statistical features and such techniques are delicate to adapt to change in the fabric texture. Spectrum analysis method modifies the test image into a spectrum, and then find the imperfect fabric by calculating the energy of responses. The model-based methods identify defects in fabrics by two methods, modeling and by estimating the parameters. In [4], Markov random fields (MRF) is employed as the texture model and a transform called Karhunen-Loeve is suggested for defect detection. Susan et al [10] used a non-extensive entropy calculated by Gausian mixture model to compute the regularity index to discover the defects, even so the methods based on models are tough to be enforced because of the high machine complexness. Labeled samples are used in training defect classifiers based on dictionary learning methods. Tong et al.[5] suggested a non-locally centralized sparse representation model to predict the non-defective class. Nonetheless small defects are difficult to detect.

Tsang et al.[6] proposed an Elo rating (ER) method for defect detection , where the test image is divided equally into image block with typical size, and then the matches between different patches are updated by Elo point matrix, and furthermore image blocks are characterized into defect blocks or defect -free blocks.

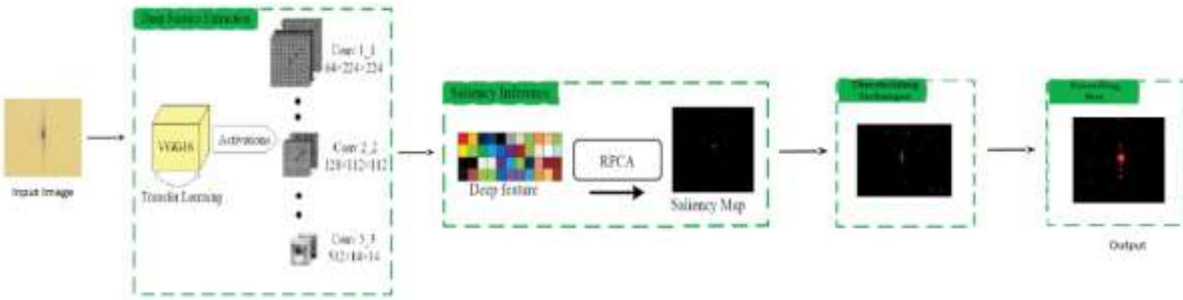
B. *CNN BASED FABRIC DEFECT DETECTION*

The success of the deep learning methods largely depends on how well the CNN is trained. Another important advantage of such techniques is that humans have not developed the feature layers. The features are learnt by a general-purpose learning method and hence they reduce the dependence on domain specific knowledge. This has motivated the CNN's activations to be used as descriptor for feature representation.

C. *RPCA BASED FABRIC DEFECT DETECTION*

The performance of RPCA model depends on efficiency of feature descriptor, where the above-mentioned methods use conventional handcrafted feature descriptor to describe the texture surface, which isn't adequate for the fabric images with complex surface and they can't deal with different kinds of fabric images. So, to overcome the problem fusion of deep features from different levels and RPCA is proposed in this work.

III. PROPOSED METHOD



The proposed method can be partitioned into five steps as described in Figure-2. A pre-trained CNN model, VGG16, is employed to extract multilevel deep features to represent the fabric image.

FIGURE 2: System Architecture

A. MULTILEVEL DEEP FEATURE EXTRACTION

Extracting features is one of the most important steps for the fabric defect detection based on RPCA model. The conventional handcrafted features require cautious designing and significant skills. Whereas convolutional neural networks(CNNs) can automatically learn hierarchical and representative features via a layer-to-layer successive propagation pipeline. To enhance the ability of CNNs to extract features, a well-trained neural network is necessary, which in turn requires a large number of labelled images. Since there isn't any large amount of public datasets available, a pre-trained model, which is trained over ImageNet database is used because ImageNet database has a huge quantity of images of complex textures and a technique called transfer learning approach is applied.

A pre-trained model, VGG16, is used to extract features, model consist of 13 activations layers corresponding to 13 feature extractors. The features extracted from deep layers of input images include semantic properties, which are important to find the important areas. The features extracted by the shallow layers contain spatial structural detail, which is important to distinguish boundaries. Hence the features taken out from shallow layers are more crucial than the features extracted from deeper layers for performing fabric defect detection. The feature map size is irregular due to convolution followed by pooling and hence should be resized to a size similar to that of the input images.

Activations from feature maps at the same location of pixel is concatenated to form the deep feature.

$$f_i = [x_{i1}, x_{i2}, ..., x_{il}]$$

Here i = 1, 2,….., NxN.

Deep feature maps are divided into image blocks such that each block is of the same size, n_bx n_b. For each image segment R_k a mean of feature vectors f_k hat is calculated and it is considered to be the feature of this image block.

$$\hat{f}_k = \frac{\sum_{f_j \in R_k} \sum_{j=1}^{n_b \times n_b} f_j}{n_b \times n_b}$$

Piling up all the features of all image blocks generates the deep feature matrix.

$$F = [\hat{f}_1, \hat{f}_2, ..., \hat{f}_{N_b}]$$

B. SALIENCY INFERENCE WITH ROBUST PRINCIPAL COMPONENT ANALYSIS (RPCA)

There is a regularity in the pattern and texture of a fabric as it is woven by warp and weft in a particular way. This regularity is broken whenever a defect occurs. The background of the fabric image is highly redundant and it lies in low-dimensional subspace, on the other hand the defect covers small areas which implies that it is sparse. Hence RPCA can be used to separate the background and defect.

Algorithm 1:

1: **initialize:** $S_0 = Y_0 = 0$, $\mu > 0$.
2: **while** not converged **do**
3: compute $L_{k+1} = \mathcal{D}_{1/\mu}(M - S_k + \mu^{-1}Y_k)$;
4: compute $S_{k+1} = \mathcal{S}_{\lambda/\mu}(M - L_{k+1} + \mu^{-1}Y_k)$;
5: compute $Y_{k+1} = Y_k + \mu(M - L_{k+1} - S_{k+1})$;
6: **end while**
7: **output:** L, S.

C. SALIENCY MAP SEGMENTATION

A threshold operation is used to estimate the upper and lower boundary of threshold value:

$$T = \mu \pm c\sigma$$

Here c is a constant, sigma and mu are standard deviation and mean respectively. Segmentation results are obtained by a binary image m.hat to locate defective regions.

$$\hat{M}(i,j) = \begin{cases} 0, & \mu - c\sigma < M(i,j) < \mu + c\sigma \\ 255, & otherwise \end{cases}$$

This means that the pixel value in output binary image is assigned 0 if corresponding pixel in input saliency map has value between the upper and lower threshold values. Otherwise the pixel value is assigned 255. Pixel value 0 (black) indicates non-defective area and pixel value 255 (white) indicates the defective region.

D. DEFECT VISUALIZATION

To make the defect more visible, a bounding box is drawn around all the defects that are detected by the model. This helps users identify the major defects by highlighting the area in which the defect is present.

Algorithm 2:

1. input: threshold image
2. contours = extract_contours(input)
3. **for** c in contours:
4.   draw_bounding_rectangle(c)
5. **end for**
6. display(output)

IV. *RESULTS AND DISCUSSION*

The system was implemented in Python programming language. The model was tested on 15 un-patterned and 15 patterned fabric images. For un-patterned fabric, the accuracy is found to be 90% and for patterned fabric it is 87%.

Figure 3(A)(1) shows the input plain fabric image and figure 3(A)(2) shows the input patterned fabric image. Figure 3(B) shows the feature maps extracted from the pre-trained CNN model. Figure 3(C)(1) shows the sparse matrix obtained from RPCA for the plain fabric and figure 3(C)(2) shows the sparse matrix obtained for the patterned fabric. Figure 3(D)(1) shows the threshold image obtained by running thresholding algorithm on the sparse matrix of the plain fabric and figure 3(D)(2) shows the same for the patterned fabric. Figure 3(E)(1) shows the defect areas bounded in a red box for the plain fabric and the figure 3(E)(2) shows the bounding box output for the patterned fabric.

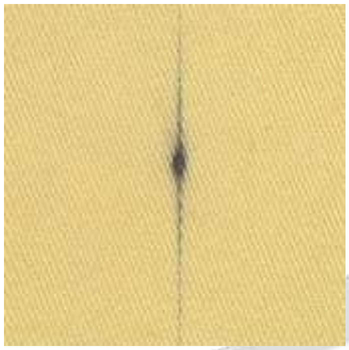


FIGURE 3(A)(1) : Plain Fabric Input Image

FIGURE 3(A)(2) : Patterned Fabric Input Image

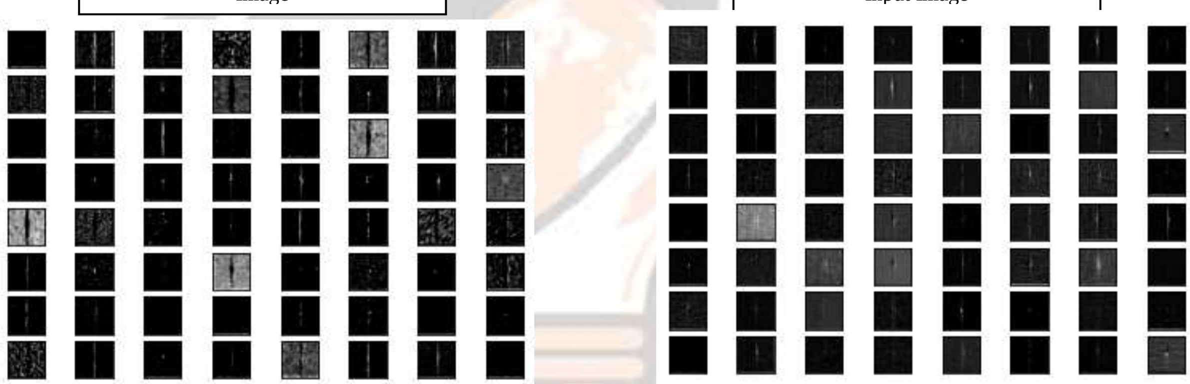


FIGURE 3(B): Feature Maps

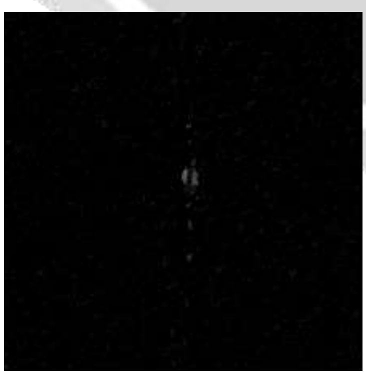


FIGURE 3(C)(1) : Sparse Matrix of Plain Fabric

FIGURE 3(C)(2) : Sparse Matrix of Patterned Fabric

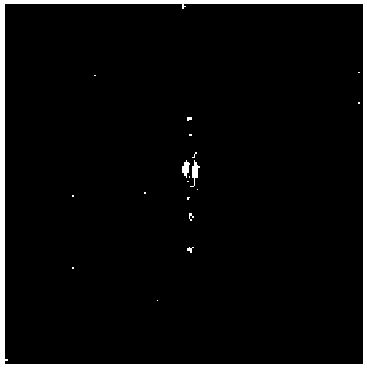


FIGURE 3(D)(1): Threshold Image for Plain Fabric

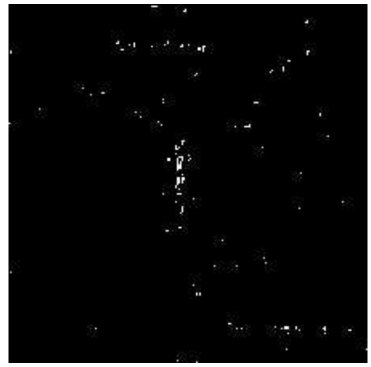


FIGURE 3(D)(2): Threshold Image for Patterned Fabric

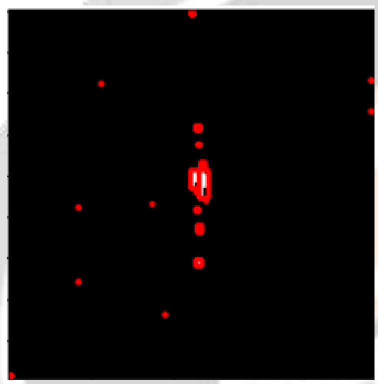


FIGURE 3(E)(1): Output Image of Plain Fabric

FIGURE 3(E)(2): Output Image of Patterned Fabric

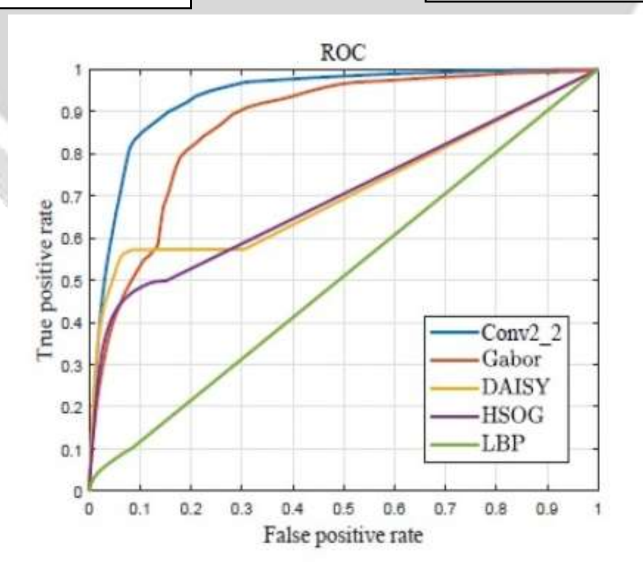


FIGURE 3(F) : Graph showing results of proposed method and existing methods

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