

LETTER

Combining Fisher Criterion and Deep Learning for Patterned Fabric Defect Inspection

Yundong LI^{†a)}, Member, Jiyue ZHANG[†], and Yubing LIN[†], Nonmembers

SUMMARY In this letter, we propose a novel discriminative representation for patterned fabric defect inspection when only limited negative samples are available. Fisher criterion is introduced into the loss function of deep learning, which can guide the learning direction of deep networks and make the extracted features more discriminating. A deep neural network constructed from the encoder part of trained autoencoders is utilized to classify each pixel in the images into defective or defectless categories, using as context a patch centered on the pixel. Sequentially the confidence map is processed by median filtering and binary thresholding, and then the defect areas are located. Experimental results demonstrate that our method achieves state-of-the-art performance on the benchmark fabric images.

key words: deep learning, fabric defect inspection, stacked autoencoders, Fisher criterion

1. Introduction

Fabric inspection is highly important to fabric quality control. Research has been intensively focused on plain and twill fabric. Compared with detecting plain and twill defects, patterned fabric inspection is far more complex. A summary of methods of patterned fabric defect detection can be found in earlier work [1], [2]. Ng et al. presented a novel method of decomposing the fabric image into a cartoon structure and repeated patterns according to the image decomposition method (ID), which is superior to other methods on benchmark images [2], [3].

Conventional methods of fabric defect detection proceed in a two-phase fashion: feature extraction and feature identification. The key issue lies in the process of designing a distinguishing feature. In contrast to existing methods which exploit hand-crafted features, we take a different approach inspired by the powerful feature learning capability of deep architectures.

This Letter presents a discriminative deep learning architecture based on Fisher criterion, in an attempt to identify the defects in fabric images. The probability of each pixel belonging to defect areas is predicted by a stacked autoencoders (SAE) according to the context centered on the pixel. Then the confidence map is processed to obtain the defect areas. This research has two contributions. First, we propose a Fisher criterion based stacked autoencoders (FCSAE)

with the objective of improving discrimination. Second, we propose a context prediction method based on deep learning, which is different from the block-wise comparison fashion used in other learning methods [4]. To our best knowledge, no any previous work has done this before.

2. Fisher Criterion Based Stacked Autoencoders

SAE [5] is one of the popular deep architectures, which has been applied to image classification successfully. However, fabric defect detection is slightly different from image classification due to the lack of negative samples. Negative samples, i.e. pixels in defect areas, only have a very small proportion in the fabric images. It is motivated by the facts that a good feature is expected to preserve separability between the defective and the defectless patches. Thus, we bring Fisher criterion into the loss function of SAE. Optimization of Fisher criterion can guide the learning direction of deep network, which makes the extracted features more distinguished.

We construct a SAE with the encoder part of several pre-trained autoencoders and a softmax classifier. The weights of the pre-trained autoencoders are used to initialize SAE. Suppose we have a fixed training set $\{(x^{(1)}, y^{(1)}), \dots, (x^{(n)}, y^{(n)})\}$ of n training samples, the deep networks are trained using the standard back-propagation algorithm to minimize the following objective:

$$J_{(W,b)} = \frac{1}{n} \sum_{i=1}^n \left(\frac{1}{2} \|h_{w,b}(x^{(i)}) - y^{(i)}\|^2 \right) + \lambda \frac{J_{intra}}{J_{inter}} \quad (1)$$

The second term in (1) is the Fisher criterion of the feature space, λ is a ratio factor. It is noted that Fisher criterion optimization is performed on the last layer features. Training samples are divided into L classes, and each class has m_i samples, $i = 1, 2, \dots, L$. J_{intra} and J_{inter} are the intra-class and inter-class distance of feature space, which are defined as (2) and (3) respectively:

$$\begin{aligned} J_{intra} &= \frac{1}{2} \sum_i^L \sum_{k=1}^{m_i} \|h_{w,b}(x^{(k)}) - M^{(i)}\|^2 \\ &= \frac{1}{2} \sum_i^L \sum_{k=1}^{m_i} \sum_{j=1}^s (f(z_j^{(k)}) - M_j^{(i)})^2 \end{aligned} \quad (2)$$

$$J_{inter} = \frac{1}{2} \sum_{i=1}^L \sum_{j=i+1}^L \|M^{(i)} - M^{(j)}\|^2 \quad (3)$$

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[†]The authors are with School of Electronic and Information Engineering, North China University of Technology, Beijing, 100144 China.

a) E-mail: liyundong@ncut.edu.cn

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where $f(\cdot)$ is sigmoid function, $f(z_j^{(k)})$ is the j -th element of the last layer features extracted from the k -th sample. $M^{(i)}$ is the average feature of the i -th class, which is defined as:

$$M^{(i)} = \frac{\sum_{k=1}^{m_i} f(z_j^{(k)})}{m_i}, i = 1, 2, \dots, L \quad (4)$$

Minimizing the Fisher criterion term of (1) will shorten the intra-class distance, meanwhile, increase the inter-class distance. $J_{(w,b)}$ is minimized by batch gradient descent algorithm in an error back-propagation fashion. The residual error of the last layer is crucial in the calculation procedures. Equation (5) gives the residual error definition of the Fisher criterion term in the last layer:

$$\delta_j = \frac{J_{inter} \frac{\partial J_{intra}}{\partial z_j} - J_{intra} \frac{\partial J_{inter}}{\partial z_j}}{J_{inter}^2} \quad (5)$$

Once the residual error of the last layer is obtained, the residual errors of other layers can be calculated as same as that in the traditional error back-propagation algorithm.

3. Context Prediction Method

In the learning methods of fabric defect detection, images are always divided into small patches, and features extracted from the patches are compared to those of reference images to identify the patches which contain defects [4]. This

method can only label the blocks contain defects, but cannot locate the defect pixels accurately. In this letter, we take a different approach, by predicting the confidence of each pixel according to the context of the pixels.

The context of a pixel is defined as a rectangular area centering this pixel, with the width of w and the height of h . Whether a pixel belonging to defect areas is related to its context. The grayscale values of pixels in the rectangle are arranged to construct a one dimension pattern vector. Let q_i be the pattern vector of the i -th pixel, and p_i be the probability of the i -th pixel belonging to defect areas, then the mapping between q_i and p_i is presented as:

$$f(q_i) = p_i \quad (6)$$

FCSAE is trained to learn this mapping from reference images. We feed the pattern vectors of test image into trained FCSAE, and then we could get the confidence map of the test image. The noises are removed from the confidence map by median filtering. Finally, binary thresholding is employed to determine the defect areas. The flowchart of the proposed method is shown in Fig. 1.

4. Experimental Results

To evaluate the performance of FCSAE method, we compared it with ID method [2] and SAE method. The box-patterned fabric images used in [2] were employed as the benchmark images. There are five types of defects in the dataset, namely, “Broke End”, “Hole”, “Netting Multiple”,

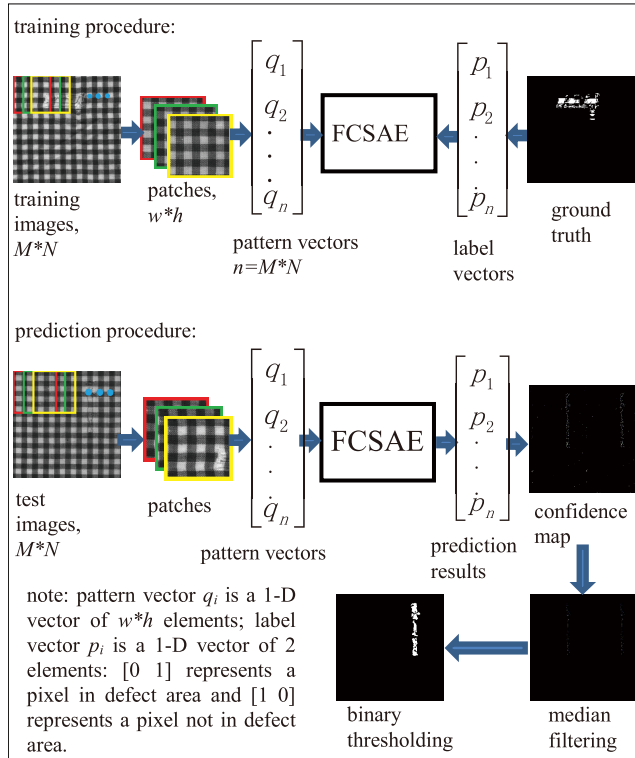


Fig. 1 Flowchart of defect inspection based on FCSAE.

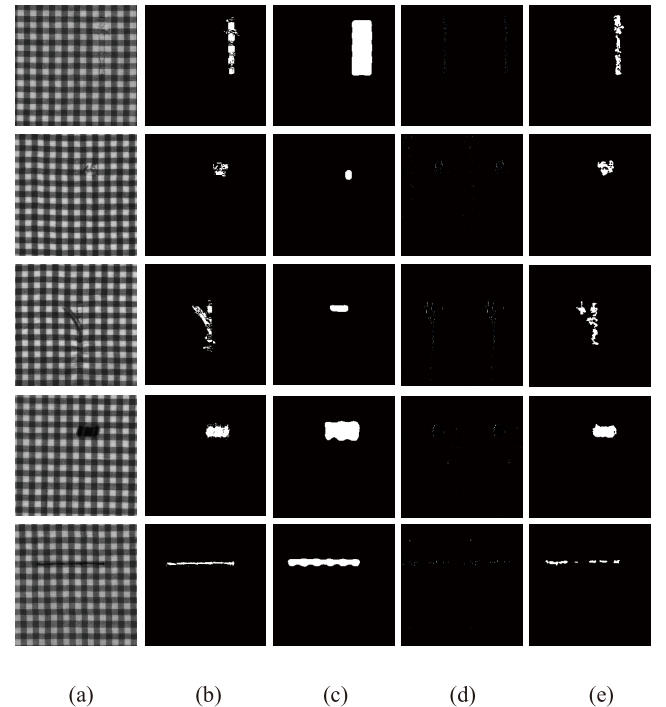


Fig. 2 Detection results of ID and FCSAE methods. (a) Original images. (b) Ground truths. (c) Results of ID. (d) Confidence maps after media filtering. (e) Final results after binary thresholding.

Table 1 Detection accuracy comparisons of ID, SAE and FCSAE methods.

Defects	Methods	Image 1 (%)	Image 2 (%)	Image 3 (%)	Image 4 (%)
Broken End	ID	81.9	79.7	83.7	85.1
	SAE	84.8	81.9	85.1	81.6
	FCSAE	87.7	83.7	90.0	85.5
Hole	ID	70.7	69.1	54.6	67.5
	SAE	81.6	80.2	83.6	80.5
	FCSAE	85.0	82.7	85.6	84.4
Netting Multiple	ID	63.7	58.1	64.9	65.8
	SAE	72.2	71.3	77.5	79.6
	FCSAE	73.6	77.9	77.7	82.2
Thick Bar	ID	75.5	87.6	80.4	86.9
	SAE	71.2	93.7	66.1	94.9
	FCSAE	75.7	93.7	68.2	95.3
Thin Bar	ID	81.3	75.9	59.7	82.3
	SAE	73.1	69.7	75.9	85.5
	FCSAE	83.9	76.5	79.2	86.5

“Thick Bar” and “Thin Bar”, and each type has 5 pictures. All the 25 pictures were divided into two groups: 5 pictures for training and other 20 pictures for test. It is noted that all of the five-type defects were included in the training set.

The patch size was 9×9 and the images were padded with 4 rows and 4 columns before training and prediction. The pixel values in the 9×9 rectangle were converted to a 1×81 pattern vector. In this experiment, the numbers of hidden layer were set to 3. The numbers of neurons in each layer were 81, 600, 200, 100, and 2 respectively. The learning rate of FCSAE was set to 0.9, momentum = 0.5, $\lambda = 0.01$.

The detection results of five-type defects are shown in Fig. 2. There are five rows in Fig. 2, which corresponding to “Broke End”, “Hole”, “Netting Multiple”, “Thick Bar” and “Thin Bar” defects. The second column images in Fig. 2 are manual-labeled ground truths. From Fig. 2, we can see that the results of FCSAE are more accurate. Several measurement metrics such as ACC, TPR, FPR, PPV and NPV [2] were further employed to quantify the detection accuracy. Here we adopt the average of these metrics to demonstrate the detection accuracy. The accuracy comparisons of ID, SAE and FCSAE methods are shown in Table 1. FCSAE

got 19 of the highest scores in all 20 test items. As mentioned before, negative samples only have a small proportion in training and test images. Compared to ID and SAE methods, FCSAE can improve inspection accuracy benefiting from make full use of the differences between defective and defectless samples.

5. Conclusions

In this letter, we propose a discriminative deep learning architecture based on Fisher criterion, in an attempt to implement the patterned fabric defect inspection task. The confidence of each pixel is predicted by deep networks, according to the context centered on the pixel. Experimental results show that our method could achieve state-of-the-art performance on the benchmark images. Future work will investigate the effectiveness of the proposed method for defect detection of more complex jacquard fabrics.

Acknowledgments

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