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Fabric Defect Detection Using Activation Layer Embedded Convolutional Neural Network

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***Abstract*— Loom malfunctions are the main cause of faulty fabric production. A fabric inspection system is a specialized computer vision system used to detect fabric defects for quality assurance. In this paper, a deep-learning algorithm was developed for an on-loom fabric defect inspection system by combining the techniques of image pre-processing, fabric motif determination, candidate defect map generation, and convolutional neural networks (CNNs). A novel pairwise-potential activation layer was introduced to a CNN, leading to high accuracy of defect segmentation on fabrics with intricate features and imbalanced dataset. The average precision and recall of detecting defects in the existing images reached, respectively, over 90% and 80% at the pixel level and the accuracy on counting the number of defects from a publicly available dataset exceeded 98%.**

Keywords- Convolutional neural network, activation function, fabric defects, imbalanced dataset.

I. Introduction

A faulty mechanical motion or a yarn breakage on a loom can cause the weave structure to differ from the design, yielding a warp, weft, or point defect, such as harness misdraw, endout, mispick, and slub. Defects can reduce fabric price by 45% to 65% . In the modern weaving factories, weavers are required to check the fabric in weaving for intricate defects by cruising a number of looms periodically because some of the fabric defects are preventable or correctable if detected on time. Hence, the textile industry has been moving toward automating fabric inspection for consistent evaluation of fabric quality. Compared to the 60-75% defect detection accuracy of human visual judgment , a typical state-of-art automatic fabric inspection system can achieve a detection rate up to 90% .

Most auto-fabric inspection systems are based on computer vision techniques including image acquisition and defect segmentation algorithms. The fabric defect detection algorithms can be categorized into statistical, spectral, modelbased, learning, structural, and hybrid approaches. The first five approaches for defect segmentation were reported to be sensitive to noise, computationally intensive , limited to certain types of defects], and

inconsistent to changes in fabric structures and background . For the past decade, the hybrid approach has been adopted for higher robustness in handling variations in weave structures and defect types. Concepts from other fields, i.e., Bollinger Bands (BB) – a statistical chart of a financial instrument, and Elo rating (ER) – an evaluation method of player performance, have also been introduced to the fabric defect detection. Although BB and ER achieved a detection rate above 96% on patterned fabrics, they failed to detect defects smaller than the repetitive unit of a patterned fabric .

Recently, convolutional neural networks (CNN) have been demonstrated for effective image semantic segmentation. The CNNs, e.g. FCN , U-Net , SegNet , and their successors, all share the basic components—convolution, pooling, and activation functions, in which the pooling layer plays a role of avoiding overfitting and reducing the spatial dimensions. A deep network could reach over a hundred convolutional layers. For example, the VGGNet has 16 layers, while the ResNet possesses 152 layers. However, deep networks provide features with a global semantic meaning and abstract details that are not suitable for fine structure segmentation in an image, mainly because the traditional convolutional filters have large receptive fields, and fine structures are further reduced by pooling layers . From the perspective of computer vision, most fabric defects are considered as fine structures since they are indicated only by a small number of pixels in an image. To improve the fine structure segmentation, further processing is needed to be embedded in a CNN to fine tune the coarse outputs of the CNN. Another common problem in the neural network learning process is that samples from a real-life application may not always evenly distribute among classes. Applications, such as medical diagnosis, credit fraud detection, computer vision, etc., are brimming with imbalanced datasets. The methods of handling an imbalanced dataset can be categorized into datalevel, algorithmic-level and hybrid approaches . As of the data-level approach, over-sampling and under-sampling are the common strategies to adjust the class distribution of a dataset. A synthetic minority oversampling technique (SMOTE) allows samples to be randomly created based on the density distribution . The algorithmic-level approach assigns different cost values to minority and majority samples . It is difficult, however, for such a cost-sensitive approach to unify a general framework since it is often specific to a paradigm. AdaBoost algorithms bridged the sampling and cost-sensitive approaches together by iteratively updating cost weights. Yuan et al. introduced a regularization term in the SAMME algorithm to penalize the weight of a classifier that misclassifies the second-roundmisclassified examples .

In this proposed system, we adopt a hybrid approach that utilizes statistical defect information and a CNN for fabric defect detection. The motif of a fabric is firstly calculated using the autocorrelation of a fabric image to represent the repeated texture in the fabric. A motif-center-point map, namely node map, is then generated by normalized cross-correlation (NCC) taking the motif as the template. The distributions of node points can indicate the regularity of fabric textures in the image, from which a statistical rule can be derived to relate the node point count in a motif region to the defect judgment. The statistical rule can be utilized as an activation reference, called pairwise potential activation layer, in a newly designed CNN to improve the fabric defect detection performance. significantly influence the success rate and the response speed of object recognition . In a similar way, a convolutional neural network selects only suitable ones from a tremendous amount of generated features for object identification.

II. RELATED WORK

A. *ACTIVATION LAYER IN CNN*

To identify an object, a human brain tries to pick up useful information, such as shape, color, smell, feeling, and prior knowledge. Among these features, prior knowledge can significantly influence the success rate and the response speed of object recognition [28]. In a similar way, a convolutional neural network selects only suitable ones from a tremendous amount of generated features for object identification.

B. *FINE STRUCTURE SEGMENTATION ON CNNS*

Different approaches were proposed to improve the segmentation of fine structures. Firstly, the method of retrieving the features from earlier layers was presented in [29] and [30] to better estimate fine structures, such as boundary, hollow area, etc. An alternative way was to conduct a super-pixel representation of an original image to enhance the localized details [31]. The main drawback of this strategy is that it leads to a poor prediction if wrong features are retrieved in the very beginning.

Secondly, a nonlinear model was applied to produce accurate semantic segmentation based on a label map. The nonlinear model can be a support vector machine (SVM) [32], a random forest [33], or a Conditional Random Field (CRF) [34]. The DeepLab is the pioneer that utilized the CRF as a post-processing procedure after a CNN. The DeepLab treated the prediction of a CNN as the unary potential and took the generated energy map as the pairwise potential to form a CRF presentation. Because the potentials of a CRF integrate the prior probability, the pairwise potential, and the Gaussian smooth term that encourages similar pixels having similar posterior [35], [36], a CRF is able to assist recovering the details of the CNN output. Although the CRF post-processing significantly improves the fine structure segmentation in an image, it does not fully take advantage of the strength of a CRF since it is isolated from the CNN learning process. It

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needs to be noted that a simple combination of a CNN and a CRF may not be an optimal solution since it wastes many features generated by the CNN because of limited latent features in CRF. Zheng et al. formulated dense CRF as a Recurrent Neural Network (RNN) so that the CRF energy could be calculated during the CNN training [21], but its performance relied on the recurrently computed forward pass, which was time-consuming [37].

III. METHODS

A. DEFECT PROBABILITY MAP GENERATION

The autocorrelation measurement of an image I(i, j), i ∈ (0,N), j ∈ (0, M), is to shift the image in the vertical and horizontal direction with different scales, which the function is described as,

ρ (x, y) = PN−1 i=0 PM−1 j=0 I(i, j)I(i + x, j + y) PN−1 i=0 PM−1 j=0 I(i, j) 2 (2)

where x and y represent the image shifting scales in the horizontal and vertical directions. The efficiency of this calculation can be improved by the Fast Fourier Transform (FFT) in (3),

ρ (x, y) = ABS(IFFT 2(FFT 2 (I). ∗ Conj(FFT 2 (I)))) PN−1 i=0 PM−1 j=0 I(i, j) 2 (3)

Fig.1a is a fabric image containing defects, Fig. 1c illustrates its autocorrelation map, and Figs. 1d and 1e are the side views of the autocorrelation map in the warp and the filling directions. The average period intervals are about 7 pixels in the warp direction, and about 16 pixels in the filling direction, which define the size of the weave repeating unit (fabric motif). The fabric motif can be generated by averaging pixels in every 7 × 16 non-defective area. In this research, if either the horizontal peak interval or the vertical interval is 3 pixels above the corresponding averaged interval, this area will be excluded from the fabric motif calculation. The calculated fabric motif of Fig. 1a is shown in Fig.1b. The red –box in Fig. 1e indicates a defect region in Fig.1a. However, the approximate 16-pixel peak-to-peak interval of the defect region is not distinguishable with other regular fabric texture. Therefore, further processing is needed. Using the calculated motif image (Fig.1b) as a template, a fabric motif map of the image (Fig.1a) can be generated by calculating its localized correlations with the template. Compared to the sum of absolute difference (SAD), the sum of squared differences (SSD), and the hamming distance (SHD), the normalized cross-correlation (NCC) proves to be more robust for calculating motif center points. To eliminate the intensity differences between the template and the image, the mean values should be subtracted. Therefore, the zero-mean NCC (ZNCC) is used for the fabric motif map generation. The calculation of the ZNCC on an image

B. PAIRWISE POTENTIAL ACTIVATION LAYER

Unlike the prediction on a standalone sample by traditional discrete classifiers, a Conditional Random Field (CRF) considers sample's neighbors to be a random variable distribution in an undirected graphical model. Of an image, a single pixel is meaningful only if its neighbors is taken into account. Therefore, the application of a CRF can be extended to the image segmentation, in which random fields describe the correlations among different pixels sharing similar properties. Let's denote an image as I, which has a pixel vector X = {x1, x2, ... , xn} and a corresponding label set L = {l1, l2, ... , ln}. According to the Hammersley-Clifford theorem, CRF obeys the Gibbs distribution .

C. NETWORK ARCHITECTURE

Figure presents a CNN for the fabric defect detection. To achieve state-of-art detection result, the fabric defect probability map is introduced to the network as a dynamic activation layer, namely pairwise potential activation layer (PPAL). The probability map, which contains the prior knowledge or defect statistical rules, is critical to the judgment of the probable defect areas. The new 7-layer CNN includes, (1) the original image input layer. (2) the first hidden layer – the first convolutional layer with 32 × 5 × 5 kernels. (3) the second hidden layer – another convolutional layer with 16 × 5 × 5

(4) the pairwise potential activation layer. Instead of using activation function, each feature in the output of the previous convolutional layer is multiplied by this specific activation map with one 3×3 convolutional kernel, which takes more pixels' properties into consideration.

(5) the fourth hidden layer with 8×5×5 kernels to convolute the 16 prior knowledge (statistical rules) imposed feature maps.

(6) the last hidden layer – single 5 × 5 kernel is used to generate the output image.

(7) backpropagation with loss calculation is performed by taking ground truth images as references.

(8) the middle position insertion of the PPAL is to ease off the influence of the probability map. If the PPAL is inserted at the output layer, the output will be similar to the probability map, which weakens the convolutional features.

IV. EXPERIMENTS

A. DATASETS

To evaluate the effectiveness of the proposed PPAL convolutional neural network (PPAL-CNN), we created a fabric defect dataset using our designed on-loom fabric imaging system. The dataset contains 1160 fabric images of 500 × 500 pixels, which include vertical defects, horizontal defects, isolated defects, and defect-free fabrics, as shown in Fig. 4. In order to provide the ground truth information for the CNN training, each image was manually inspected to mark defects areas. We also used the TILDA—a Textile Texture Database developed by the texture analysis group of the DFG (Deutsche Forschungsgemeinschaft) as a verification set. Each TILDA image has a text description about defect areas in the image.

B. EVALUATION ON DIFFERENT ACTIVATION FUNCTIONS IN NEURAL NETWORKS

A visual comparison on loss curves was performed among four CNNs that have the same structure with different activation functions, i.e. Sigmoid, Tanh, ReLU, and PPAL. In order to avoid small gradient issues in the flat regions of Sigmoid and Tanh activation functions, the cross-entropy loss function was chosen. Two different learning rates, 10−10 (slow) and 10−4 (fast), were used to check if the learning rate influenced the network learning process. Fig. 5 lists the loss curves calculated from the output layer during the 106 learning iterations of the networks with the four different activation functions under the two learning rates. Regardless of learning rate, the three activation functions, Sigmoid, Tanh and ReLU, show fluctuation, and the network with Sigmoid or Tanh activation function is not convergent. ReLU loss curve at the 10−4 learning rate has a sudden decrease after the firstthousand iterations. This may be because the fast learning rate causes the learning to be trapped in the local minimum a normal learning process that start converging after 2 × 105 iterations . However, the same network seems difficult to be convergent at the 10−10 learning rate. Thus, the 10−4 learning rate was chosen for the PPAL-CNN in the fabric defect detection. displays the prediction results of using the CNNs that have the same structures with the four aforementioned activation functions of the 106 th training-iterationmodel at the 10−4 learning rate. In comparison with the ground truth , the predicted result of each activation function is consistent with the loss curves depicted in. Among the four activation functions, Sigmoid appears to be the worst because of the highest loss value, and PPAL-CNN demonstrates the best defect detection result.

C. EVALUATION ON FABRIC DEFECT DATASET AT PIXEL LEVEL

A 4-folder cross-validation was performed on the 1160 fabric images. Since the accuracy is measured by true positive and true negative samples, it will not be suitable for our imbalanced fabric defect dataset. Therefore, the 3-metrics, precision, recall and F1-score, that are derived from the confusion matrix are applied to evaluate the detection accuracy at the pixel level. The precision represents the rate of the correctly detected defect pixels over all the predicted defect pixels. The recall is the ratio between correctly detected defect pixels and defect pixels marked in the ground truth image, which represents the integrity of the correctly detected defect region. The F1-score is the harmonic average of precision and recall. Fig. 7 illustrates the curves of the three metrics of the training set (blue) and the testing set (red) from 5000 to 106 iterations.

Overall, the three metrics monotonically increase with the training iterations, indicating an ascending defect detection accuracy. In the recall chart (Fig. 7b), the training curve is slightly above the testing curve before the 9 × 105 th iteration. At the 9 × 105 th iteration, the testing curve tends to fall, suggesting a convergent point of the training process. Although the precision of the detected defects keeps improving as the training epoch increases, the small drop of the recall (integrity) at the 9 × 105th iteration indicates the reductions in both false positive and true positive defect pixels

D. EVALUATION ON THE IMBALANCED DATASET WITH DIFFERENT PROPORTIONS OF DEFECT PIXELS

According to the proportions of the defect pixels in the fabric ground truth images, we clustered the 1160 fabric images into 21 groups. Group #1 indicates defect-free images, and groups #2 - #20 represent the proportion of defect pixels with 5% increment. Among the 1160 images, there are 432 defectfree images and 635 images with defect pixel proportions being less than 35%. In other words, 92% of the fabric images in the dataset have small proportion or none of defect pixels. Those defect regions above 35%couldbe the fabric selvage regions. The highest proportion (95-100%) of defects does not exist in the dataset.

E. EVALUATION ON DETECTION ACCURACY ACCORDING TO DEFECT COUNT

In the 1160-fabric-image dataset, totally 1191 fabric defects were found in 728 fabric images. We inspected each predicted defect image according to its corresponding ground truth image. If the predicted defect pixels occupied over 50% in the bounding box of the defect area in the ground truth image, the prediction was considered to be correct. Therefore, according to the defect counts in the dataset, 1177 of 1191 defects were correctly detected, yielding a 98.82% detection accuracy. It is found that there were 51 over counted defects that should be defect-free areas in the 38 ground truth images. In the 38 false predicted fabric images, 13 of them should be defect-free images. Therefore, at the image level, the detection rates of defect-free images, defect images, and total 1160 fabric images are (432 − 13)/432 = 96.99%, (728 − 25)/728 = 96.57%,(1160 − 38)/1160 = 96.72%, correspondingly.

F. EVALUATION ON TILDA DATASET

The TILDA dataset provides 43 sample images, and each of them represents a type of fabric texture. Table 5 presents the defect detection results of the 11 images from TILDA.

The 11 sample fabric images have variations in textures, lighting conditions, and defect morphologies. Visually, most detection results show the same defect locations as in the ground truth images, even if the detection integrities of the defects are smaller than the ground truth. Due to the possible fabric texture incompletion near the image edges,
5-pixel regions around image edges were omitted during the defect segmentation process, which explains the failure defect detection around the bottom area in images 5 and 6 of PPAL-CNN.

The results of the 3-metrics evaluation on TILDA are listed in Table 6. The higher precision and the lower recall are in agreements with the visual judgment. Moreover, the recall and precision of the TILDA images are consistent with the previously used 1160 images, which demonstrates the reliability of the proposed algorithm. PPAL-CNN seems able to detect various types of fabric defects on diverse textures under different imaging conditions. Figure 8 illustrates an F1-score comparison among the proposed method and other four state-of-the-art fabric defect detection methods (BVM, TDVSM, PGLSR and LSF-GSA), which demonstrates the superiority of the proposed method. At the image level, the defect detection rate on TILDA was 95.34%.

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