Automated Visual Inspection of Fabric Image Using Deep Learning Approach for Defect Detection

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ABSTRACT

As a popular topic in automation, fabric defect detection is a necessary and essential step of quality control in the textile manufacturing industry. The main challenge for automatically detecting fabric damage, in most cases, is the complex structure of the textile. This article presents a two-stage approach, combining novel and traditional algorithms to enhance image enhancement and defect detection. The first stage is a new combined local and global transform domain-based image enhancement algorithm using block-based alpha-rooting. In the second stage, we construct a neural network based on the modern architecture to detect fabric damage accurately. This solution allows localizing defects with higher accuracy than traditional methods of machine learning and modern methods of deep learning. All experiments were carried out using a public database with examples of damage to the TILDA fabric dataset.

Keywords: fabric defect detection, image enhancement, deep learning, segmentation.

1. INTRODUCTION

Fabric defects in the textile industry are huge costs. Automatic detection of fabric defects is critical to ensure the quality of the final product. Automatic fabric defect detection systems for high-quality textiles are increasingly in demand. Detection of defects on the fabric surface is carried out using technical vision systems, image, and video processing methods. In industrial, this task is challenging due to the complexity of textile textures, defects, and intraclass differences.

Usually, detection of textile defects is accomplished by visual inspection by a human. However, the human factor does not achieve high efficiency due to carelessness, optical illusion, and small defects [1-3]. According to experimental studies in [4], a person can recognize only 50-70% of all fabric defects. Thus, automatic fabric inspection based on visual analysis approaches is one of the most important tasks in intelligent textile manufacturing to ensure high-quality textile products and reduce costs.

Most fully, the current state-of-the-approaches is presented in [5]. Some methods for visually detecting fabric defects are discussed below. Defect detection methods can be divided into two categories: traditional and learning-based algorithms [5]. Traditional algorithms are based on previously known functions based on spectral, structural, statistical, model approaches.

Spectral approaches are widely used to detect fabric defects due to the criss-cross surface structure. Thus, methods based on the Fourier transform allow detecting deviations from the criss-cross structure. However, many of these deviations are not defects, which leads to a large number of false positives. The disadvantage is the lack of local information in the spatial domain and insensitivity to small defects [6]. In [7] combines the modulated Gabor wavelet and the correlation function, which allow obtaining information about the texture; fuzzy c-means clustering (FCM) is used to detect the defective area. The experimental results have shown good results in detecting small defects. In [8], the authors use a multiscale wavelet transform and a Gaussian mixture model to detect textile defects automatically. Experiments demonstrate the efficiency of the described algorithm for detecting and segmenting defect images. Spectral approaches show high efficiency for textures with a high degree of periodicity; however, the use of methods of this group is not advisable for fabrics with a random texture.

Statistical approaches use first and second-order statistics to extract texture features in texture classification [9]. Most of the approaches of this group are based on Local Binary Patterns (LBP), the spatial distribution of gray values in images [10, 11], for example, Gray-Level Co-occurrence Matrices (GLCM), autocorrelation analysis, and features of fractal dimension [5]. The methods in this group compare the input image with known defect-free images, which saves computing power. In [12], the authors combine the Curvelet Transform (CT), Gray-Level Co-event Matrices (GLCM), surface examination, and k-closest neighbor, making the defect features more distinguishable. These approaches allow demonstrating high efficiency for detecting even small defects. Fabric defects can be detected using a variety of methods for detecting and setting thresholds. Thus, manual adjustment of the algorithms' algorithms for each new fabric is required, making them impractical for industrial use.

Model-based approaches solve the problem of defect detection by building an image model [13]. Model parameters are important for feature capture and texture synthesis [14]. In [15], the defect detection algorithm consists of the following stages: feature extraction using a Gabor filter bank and principal component analysis (PCA) and defect-recognition based on the Euclidean metric. In [16], the authors used Gaussian Markov fields to simulate a defect-free texture on tissue images, but they are not effective for detecting small defects. The methods of this group are suitable for imaging surfaces that may have changed due to defects such as yarn breakage and needle breakage [17]. The methods of this group are computationally expensive for working in real-time.

Structural approaches consider texture as a composition of texture primitives [9]. The composition of simple textured structures determines the general structure of the texture pattern. The reliability of structural approaches is low. Structural approaches are only reliable when separating tissue defects from texture, the pattern of which is very regular [17-18].

Convolutional neural networks (CNN) are gaining popularity among learning-based approaches. In [6], a CNN-based defect detection method is presented, which consists of three stages. First, the tissue image is divided into local areas - patches, and each local area is marked. The marked patches are then transferred to the deep CNN for learning. Defects are detected during the verification step by sliding across the entire image using the trained model, and the category and location of each defect are determined. In [11], the authors use CNN to track a single yarn (as opposed to other existing methods that learn from defects), then the yarns can be tracked over the entire image, which allows existing defects to be localized. Thus, this neural network is used to detect defects in textiles without the need to annotate defects. Ultimately, however, a learning-based approach relies on both defect-free and defective samples to train the network. Without prior knowledge of the fabric, this technique cannot be used to detect defects.

Summing up, we can conclude that no universal approach will work on all types of tissue and automatically detect all kinds of defects in real-time.

In this paper, we investigate a new method for detecting fabric defects. The proposed method is based on deep learning, followed by accurate detection of defect boundaries using the support vector machine.

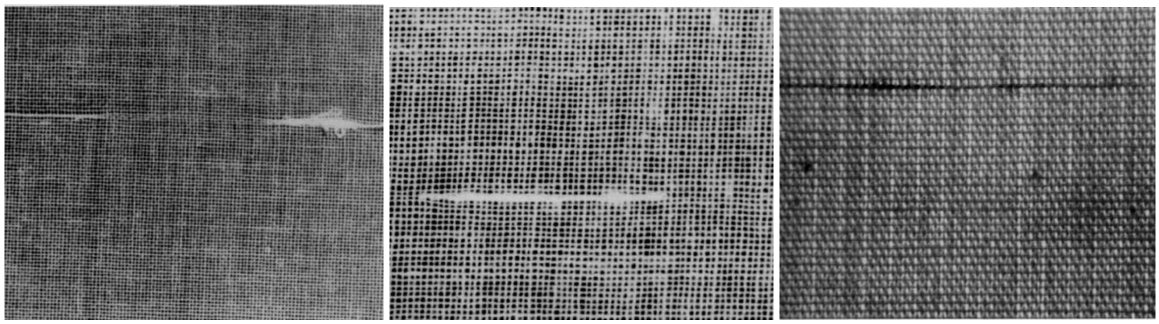
2. PROPOSED METHOD

2.1 Fabric defect model

Defects of fabric connections represent any deviations from the parameters of connections set by normative documents formed due to violation of the technological process of fabric. Such violations may be errors associated with the choice of technology, violation of the process, materials of poor quality, etc. Total, there are five main types of defects in fabric: cracks, cavities and pores, solid inclusions, violation of the shape, and other defects (Figure 1) [19]. In our case, the mathematical model of the image containing the defect can be represented as follows:

$$Y_{i,j} = (1 - d_{i,j}) \cdot S_{i,j} + d_{i,j} \cdot c_{i,j},$$

where $Y_{i,j}$ - image containing various defects, $i = \overline{1,I}$ and $j = \overline{1,J}$ spatial coordinate, where I and J - height and width of the image in pixels, $S_{i,j}$ – undamaged image, $d_{i,j} \in \{0,1\}$ a binary mask of defects, which shows exactly what area in the image was damaged, $c_{i,j}$ – mask, which contains the brightness values of defects.



a) b) c)

Figure 1. Examples of fabric defects.

2.2 General scheme of the method

The proposed method consists of three main steps: preliminary localization of the defects using morphological filtering, defect classification using a convolutional neural network, an accurate determination of the boundaries of the defects using a fully connected neural network [20]. The general scheme of the proposed method is shown in Figure 2.

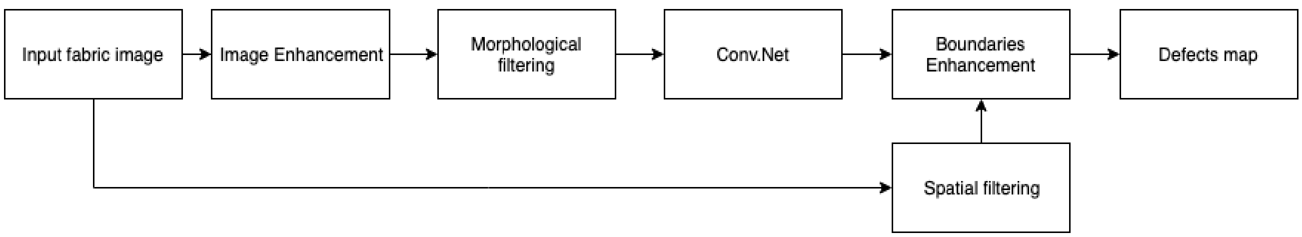


Figure 2. General scheme of the proposed method.

2.3 Image enhancement step

For image enhancement we combined local and global transform based on multi-scale block-rooting processing [21]. The basic idea is to apply the frequency domain image enhancement approach for different image blocks [22]. The parameter of transform coefficient enhancement for every block is driven through optimization of the Agaian's cost function (image enhancement non-reference quality measure) [21]. The flowchart of the proposed enhancement algorithm is shown in Figure 3. The proposed algorithm is a four-stage procedure: (a) block splitting using extraction blocks with different sizes, (b) block matching and combine them to the 3-D group, (c) block-rooting and return the estimates to their original locations and (d) optimization enhancement parameter.

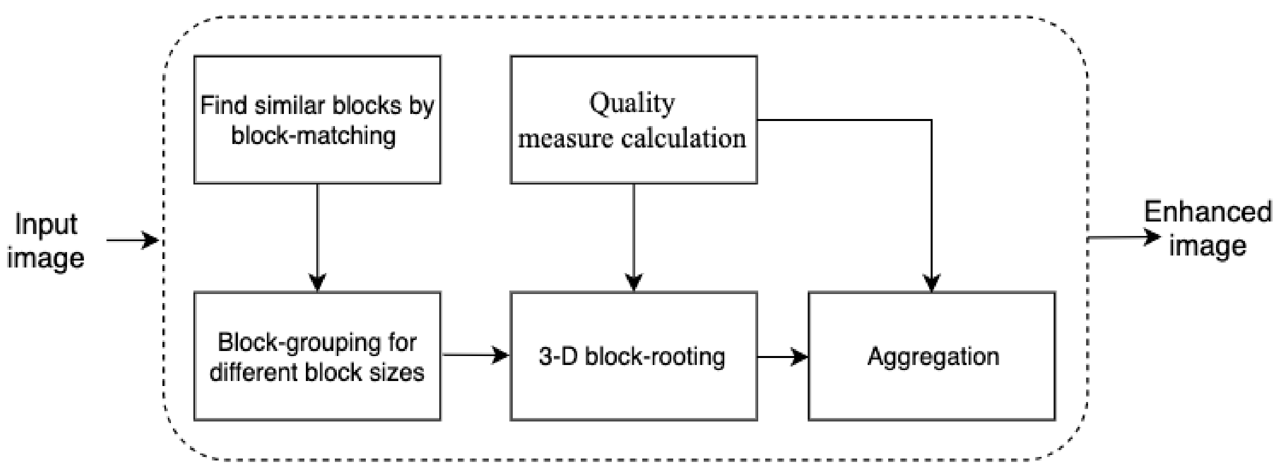
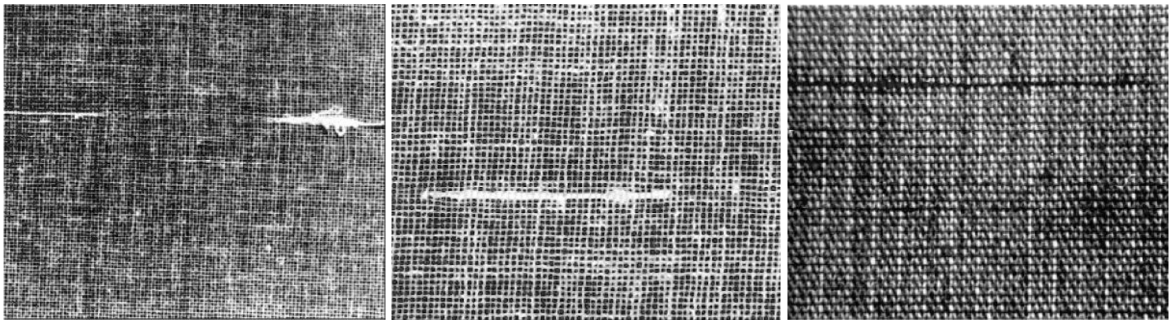


Figure 3. The block diagram of the image enhancement method.

Figure 4 demonstrate the image enhancement results obtained by enhancement algorithm.



a) b) c)

Figure 4. Examples of enhanced images.

2.4 Morphological filtering

Morphological image filtering is one of the popular techniques used for the preliminary localization of defects in the image. It reduces the computational cost of the entire algorithm and, in some cases, reduces the probability of false alarms [20]. In our work, we use the "top" and "bottom hat" transform. "Top" and "bottom hat" transform based on four operations of binary mathematical morphology (opening, closing, erosion, and dilation):

$$BottomHat(Y_{i,j}, B) = ((Y_{i,j} \oplus B)\Theta B) - Y_{i,j}$$

$$TopHat(Y_{i,j}, B) = Y_{i,j}^{(k)} - ((Y_{i,j}^{(k)}\Theta B) \oplus B)$$

where $Y_{i,j}$ is a grayscale image, B is a structural element, $(Y_{i,j} \oplus B)\Theta B)$ - morphological operations "Close", $(Y_{i,j}\Theta B) \oplus B)$ - morphological operations "Open," Θ and $\oplus$ correspond to "Erode" and "Dilate" operations.

The size of the structural element B in our work is set by 20×20 pixels. The threshold value is set manually and is equal to 0.01.

2.5 Defects Classification using a convolutional neural network

After preliminary localization of defects, each pixel marked with a unit is classified using a convolutional neural network. Convolutional neural networks have several advantages compared to traditional methods of machine learning: no need to use different texture descriptors, high accuracy of data classification, the ability to effectively use graphics accelerators to speed up the training and classification processes [23].

The architecture of the proposed convolutional neural network is illustrated in Figure 5.

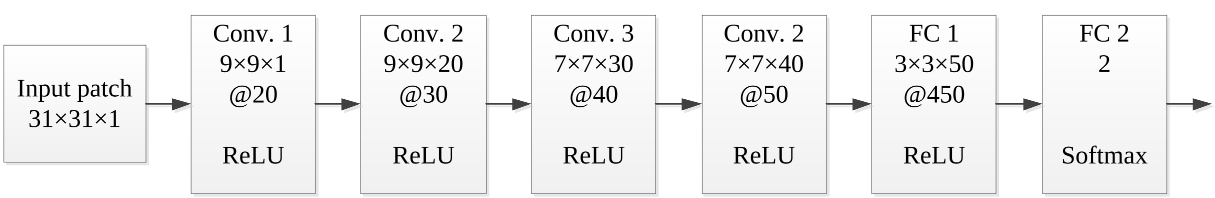


Figure 5. The proposed architecture of the convolutional neural network.

In hidden layers, a rectified linear unit (ReLU) is used as the activation function [23]:

$$f(x) = \max(0, x)$$

where x is the input value of the feature vector.

To determine the losses in our work, we use the cross-entropy function according to the expression:

$$H_{y'}(y) = -\frac{1}{m}\sum_{l=1}^{m} y'_l \log(y_l)\,, \tag{7}$$

where y - prediction Conv.Net, y'_j - true value.

The architecture of the proposed neural network includes four hidden layers and two fully connected layers. The first convolutional layer includes 20 feature maps, the second 30, the third 40, the fourth 50. The first fully connected layer has a dimension of 450 bins. The momentum is 0.001. Training took approximately 60 epochs. For training, the method of optimization “Adam” is used.

2.6 Spatial filtering

The spatial filtering block shown in Figure 2 is used to extend the number of input modalities by spatially filtering the source image in our work used: the image obtained by morphological filtering “bottom hat,” and the size of the structural element 20 pixels, the image obtained by enhancing, and the image obtained by gamma correction with parameter g=0.5. This procedure allows creating an imaginary multimodal source dataset used in the block of accurate determination of the boundaries of defects.

2.7 Accurate determination of the boundaries of the defects

One of the disadvantages of convolutional neural networks is the precise definition of the object's position of interest in the image. This problem is caused by the high volatility of the object of interest inside the patch for classification [20].

We use the support vector machine (SVM) [23] to reclassify the boundary pixels to solve this problem. Using SVM allows to more accurately separate pixels belonging to a defect from pixels close to the defect but belonging to the background. The vector machine used a linear function with a soft margin of 0.05 to construct the separating hyperplane in our work support. The vector passing through the imaginary modalities described above is used as the initial data.

3. EXPERIMENTAL RESULTS

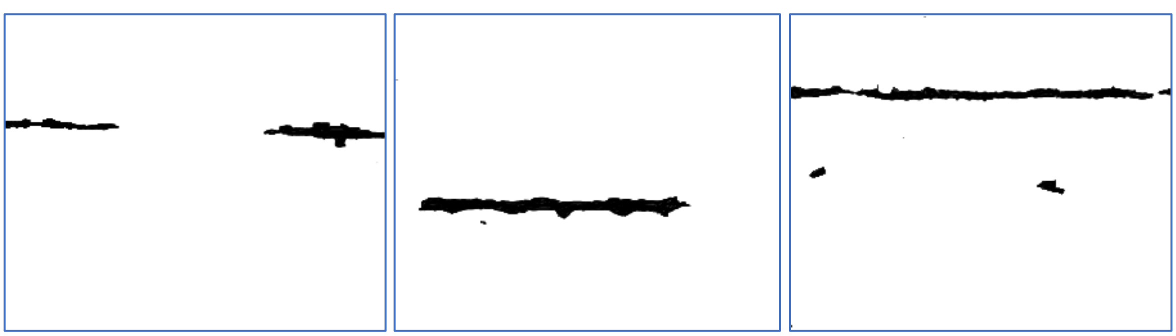
To estimate the effectiveness of the proposed method in our work as the initial data, we use the TILDA fabric dataset with examples of damage [24]. TILDA is a textile texture database with eight sorts of classes for each kind of textile.

As quantitative metrics are used:

$$FA = \frac{FP}{AllPix - DefPx}, \quad P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad F1 = \frac{2PR}{P + R}$$

where FA - is probability false alarm, P - is precision, R - is recall, $F1$ - is F1-measure, $AllPix$ - is the total amount of pixels image and $DefPx$ - is the total amount of defect pixels.

Figure 6 shows an example of defect detection for the test images.



a) b) c)

Figure 6. Illustration of the defect detection for the test images.

Table 1 summarizes the quantitative metrics for the test images.

Table 1. Experimental results for the test images.

Dataset	Proposed Method	F1-measure
TILDA	Conv.Net.	0.3834
	MF + Conv.Net	0.5145
	MF + Conv.Net. + EB	**0.5534**

Analysis of the results shows the high efficiency of the developed method. The additional use of the support vector machine as a post-processing technique has significantly reduced the likelihood of false alarms.

4. CONCLUSION

We proposed a two-stage approach, combining novel block-based alpha-rooting image enhancement and defect detection algorithms based on deep learning. The main distinguishing feature is the post-processing of the defect map to reduce the probability of false alarms caused by excessive thickening of the defect boundaries. To do this, we use a support vector machine that uses imaginary modality as input. As a pre-processing in our work, we use morphological filtering, which allows us to reduce the computational cost and reduce the probability of false alarms. The analysis of the experimental results confirmed the high efficiency of the developed method compared to the pure classification method based on the use of a convolutional neural network.

5. ACKNOWLEDGMENT

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