A Surface Defect Detection Method Based on Positive Samples

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Abstract. Surface defect detection and classification based on machine vision can greatly improve the efficiency of industrial production. With enough labeled images, defect detection methods based on convolution neural network have achieved the detection effect of state-of-art. However in practical applications, the defect samples or negative samples are usually difficult to be collected beforehand and manual labelling is time-consuming. In this paper, a novel defect detection framework only based on training of positive samples is proposed. The basic detection concept is to establish a reconstruction network which can repair defect areas in the samples if they are existed, and then make a comparison between the input sample and the restored one to indicate the accurate defect areas. We combine GAN and autoencoder for defect image reconstruction and use LBP for image local contrast to detect defects. In the training process of the algorithm, only positive samples is needed, without defect samples and manual label. This paper carries out verification experiments for concentrated fabric images and the dataset of DAGM 2007. Experiments show that the proposed GAN+LBP algorithm and supervised training algorithm with sufficient training samples have fairly high detection accuracy. Because of its unsupervised characteristics, it has higher practical application value.

Keywords: Positive samples · Surface defect detection · Autoencoder · GAN

1 Introduction

Surface defect detection plays a very important part in industrial production process. It is of significant impact on the quality and reputation of the final products in the market. Traditionally, surface defects are inspected by human vision, which is subjective, costly, inefficient and inaccurate.

Machine vision system is a possible substitution of human vision, but it also encounters many problems and challenges in practical applications, especially during those years when traditional image features used to discriminate defects and non-defects are designed manually based on experience. The characteristics of traditional image feature extraction operators are usually at low level. In the case of complex scene variations such as illumination change, perspective distortion, occlusion, object deformation and so on, the extracted features are often not robust enough to handle them so that many

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algorithms are not applicable in practical contexts. Recently, deep learning has been demonstrated to be very powerful in the extraction of image features. The convolution neural network has achieved the highest precision in all kinds of supervised problems, such as classification, target location, semantic segmentation and so on.

Faghih-Roohi et al. [1] uses deep convolution neural network to perform defect detection on rail surface. It divides rail images into 6 categories, including 1 category of non-defect images and 5 categories of defect images, and then DCNN is used to classify them; Liu et al. [2] proposed a two-stage method which combines the region proposals by selective search and the convolution neural network. It detects and identifies the obtained regions, and then completes the detection of the surface defects of the capsule; Yu et al. [3] uses two FCN [4] semantic segmentation networks to detect defects. One of them is coarse positioned, and another one is fine positioned. It can accurately draw the outline of defects, and has achieved higher accuracy than the original FCN on the dataset of DAGM 2007 [12] and can be completed in real time.

All of the above algorithms has used supervised schemes to detect defects. Two problems are necessary to be considered in the practical application of industrial detection:

Lack of Defect/Negative Samples in Training Samples. In practical problems, there are always fewer defects in the training samples because it is hard to collect many defect samples beforehand. Therefore, the number of positive and negative samples in the training process is extremely unbalance so that the generated model may be unstable or invalid. In the scene where the defect appearance is variable and unpredictable, supervised detection methods often fail to reach the required precision.

Manual Labelling is Expensive. In the actual defect detection applications, there are usually many different kinds of defects, and detection standards and quality index are often different. This requires a large number of training samples to be manually label for specific needs, which needs so much human resources.

In view of the problems existing in the practical application of the above supervised learning algorithm, a defect detection method based on positive sample training is proposed. The training process only needs to provide sufficient positive samples, without the need to provide defect samples, and without manual labeling, the effect of defect detection can be achieved.

2 Related Work

2.1 Defect Repair Model Based on Positive Samples

The inspiration for the model we have proposed comes from a series of GAN [5] based repair and detection models. As shown in the Fig. 1 is the schematic diagram of the GAN principle. The generator G receives a Gaussian random signal to generate a picture, the discriminator D receives a true or false picture, and outputs the probability of the picture is true. The reality degree of the generated picture will be improved in the continuous game of the generator and the discriminator.

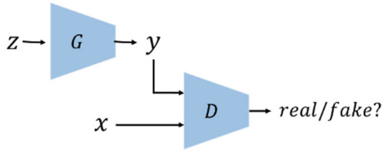

Fig. 1. The architecture of GAN

Yeh et al. [6] uses GAN for image repair. First, it uses a no defect picture to train a GAN model in a general process. Then, when repairing a known location defect, we optimize the input z of the generator G, so that we can find the best z, which makes y and the normal part of a defective picture similar to the greatest extent. The picture y is the restored image. Schlegl et al. [7] implements defect detection on the basis of image repair. First, it uses the reconstruction error of the middle layers to complete a repair module without knowing the location of the defect in advance. Second, it makes the difference between the restored picture and the original one. Where the difference is large, that is the defect. Because of the error of reconstruction and repair, the disadvantage of this model is that it is difficult to distinguish the reconfiguration error and the small defect by the direct subtraction.

The obvious disadvantage of these two models is that they use gradient optimization to find the right z, and then get the repair picture further. This process needs to consume a lot of time, which is so unpractical. So we expect that using autoencoder to restore the defect image.

2.2 Autoencoder

Pix2pix [8] uses autoencoder to cooperate with GAN to solve the task of image translation. It can generate sharp, realistic images. In order to achieve better results in details and edge parts, pix2pix uses the structure of the skip connections, like Unet [9]. This structure is not suitable for removing the whole defect, so it is not used in our model. The general image translation task refers to the task of coloring black and white pictures, translating simple strokes into photographs, and so on. We use a similar structure to achieve the transformation of the defect picture to the restored picture.

On the basis of the above research, the following work has been completed in this paper: (1) We use the autoencoder to restore the image. We can complete the image repair function in real-time and improve the quality of the picture with GAN loss; (2) We use artificial defects in training, and we do not rely on a large number of full and real defect samples and manual label; (3) We use LBP [10] to compare the restored image and the original one to find the location of the defect more accurately.

To sum up, we propose a defect detection model, which is based on the training of the positive example without manual label.

3 Method

The general framework of the model presented in this article is shown in the Fig. 2. At the training stage, x is a random picture taken randomly from the training set. $C(x^{\sim}|x)$ is a artificial defect module. Its function is to automatically generate a damaged, defective sample. $x^{\sim}$ is its output. EN and DE constitute an autoencoder G. EN is an encoder, and DE is a decoder, and the entire autoencoder can be seen as a generator in the GAN model. The task of G is to fix a defective picture. D is a discriminator, and the output of D is the probability that its discriminant is a true positive sample.

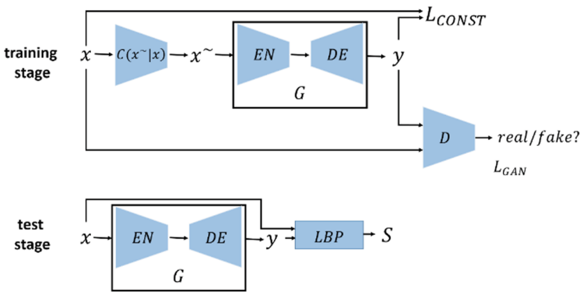

Fig. 2. The framework of our model

At the test stage, we input the test picture x into the autoencoder G, get the restored image y. Then use the LBP algorithm to extract the features of x and y, and compare the features of each pixel of x, where the feature difference between x and y is large, that is the defect.

3.1 Objective

The samples with defects should be equal to the original positive samples after being autoencoder. Here we refer to pix2pix using L1 distance as a similar basis for them. L1 distance preferred less blurred images than L2 distance. The refactoring error is defined here:

$$L_{CONST}(\mathrm{G}) = \underset{x \sim p_{data}(x)}{E}\left[\|x - \mathrm{G}(x^{\sim})\|_1\right] \tag{1}$$

If the reconfiguration error is used only as the target function, the edges of the obtained images are blurred and the details are lost. According to the experiment in pix2pix, a discriminant network is introduced and GAN loss can be added to improve the image blurred problem and enhance the fidelity of the image. The objective of a GAN can be expressed as:

$$L_{GAN}(\mathrm{G,D}) = \underset{x \sim p_{data}(x)}{E}\left[\log \mathrm{D}(x) + \log(1 - \mathrm{D}(G(x^{\sim})))\right] \tag{2}$$

So the overall optimization goal is to find the parameters that generate the network G, and make it satisfied:

$$G^{*} = \arg\min_{G}\max_{D}(L_{GAN}(\mathrm{G,D}) + \lambda L_{CONST}(\mathrm{G})) \tag{3}$$

λ is the parameter to balance the GAN loss and the reconstruction error, which is determined by the experiment. The introduction of GAN loss, to some extent, will compete with the refactoring error, but it can improve the quality of the picture and the description of the important details.

3.2 Network Structure and Artificial Defects

The network structure of our proposed model is referred to as DCGAN [11]. In the generator and discriminator network, batchnorm layer is added. The LeakyRelu layer is used in the discriminator network, and the Relu layer is used in the generator network. The encoder structure is roughly similar to the discriminator.

In our model, the autoencoder only needs to repair the original map to the nearest example sample, which does not need to know the specific form of the defect. So the network will be able to learn the information of the repair map when enough random defects are attached to the sample. In actual training, we manually generate random blocks, locations, sizes, grayscale values, and the number of defect blocks added to the picture, as shown in Fig. 3, training network to automatically repair defects.

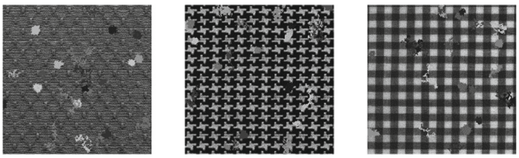

Fig. 3. Artificial defect schematic diagram

For data augmentation, we adopt random resize between 0.5 and 2, and additionally add random rotation between −180 and 180°, and random Gaussian blur for the images.

3.3 To Get the Position of the Defect

Because there are some errors in the detail information of the restored picture, we should not directly divide the restored picture and the original picture to get the position of the defect directly. We use the LBP [10] algorithm for feature extraction, and then search for the most matched pixels around each pixel. The LBP algorithm is a nonparametric algorithm which has the characteristics of light invariance and is suitable for the dense points.

The steps to get the defective picture as shown in the Fig. 4. The original picture x and the restored picture y are processed by LBP algorithm to get the feature map x^{+} and y^{+}. For each pixel point of the x^{+}, search the nearest eigenvalue point at the corresponding location of the y^{+}, which is the point of the pixel as the matching point. Make the difference between the eigenvalues of the two matching points and get the absolute value. The smaller the value you get, the lower the possibility that the point is a defect. Then using the fixed threshold binaryzation, you can get to the position of the defect.

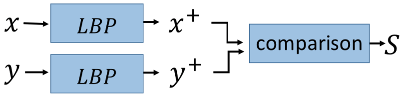

Fig. 4. The process of getting the defect position

4 Experiment

4.1 Preparation

This paper uses the fabric picture and the texture surface picture to test the performance of the experimental model. There are 3 kinds of fabric pictures and 1 kind of texture surface pictures. The image of the fabric comes from the database [13], and the texture surface image is from the dataset of DAGM 2007 [12]. In this paper, we compare the supervised semantic segmentation model [4] and the proposed model in defect detection.

The develop environment is as follows: CPU: Intel® Xeon(R) E5620@2.40GHZ*16, GPU: GTX1080, memory: 16 G, python 2.7.12 and mxnet. We train by Adam, and set the initial learning rate to 0.0002, and set the batch size to 64.

4.2 Result

We use the average accuracy of the whole picture as the evaluation index of the model performance in the experiment.

Texture Surface. Texture surface has good consistency, so they have enough defect samples on the training set to learn (Tables 1 and 2).

Table 1. Test information of texture surface

Training set	400 images without defects for ours 85 (defective) + 400 (no defect) for FCN
Test set	85 images with defects
Picture size	512*512

Table 2. Test result of texture surface

Model	Mean accuracy	Time cost
FCN(8s)	98.3547%	80.3 ms
Ours	98.5323%	52.1 ms

As shown in Fig. 5, it is an example of some defect detection results.

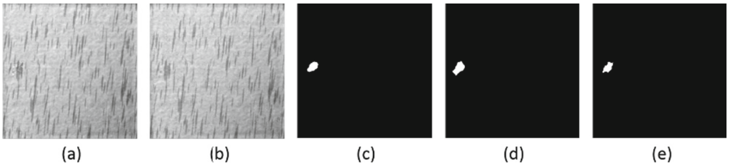

Fig. 5. (a) Initial input images. (b) Restored images (c) Results of ours. (d) Results of FCN. (e) Ground truth.

Fabric Picture. Due to the different form of fabric samples in real scenes, the defect samples in training set are relatively scarce. In this experiment, there are 5 types of defects. There are 5 pictures in each form, and 25 positive pictures. For the supervised semantic segmentation model, 3 of each form of defect picture is used as a training set, and 2 is used as a test set (Tables 3 and 4).

Table 3. Test information of fabric picture

Training set	75 images without defects for ours 45 (defective) + 75(no defect) for FCN
Test set	30 images with defects
Picture size	256*256

Table 4. Test result of fabric picture

Model	Mean accuracy	Time cost
FCN(8s)	81.6833%	31.2 ms
Ours	94.4253%	22.3 ms

As shown in Fig. 6, it is an example of some defect detection results.

Experiments show that in a regular pattern background, our model can obtain and supervised semantic segmentation accuracy when the labeled defect samples are sufficient, and our model can obtain higher precision when the defective sample with annotation is not sufficient. In terms of time consumption, our model can achieve real-time detections.

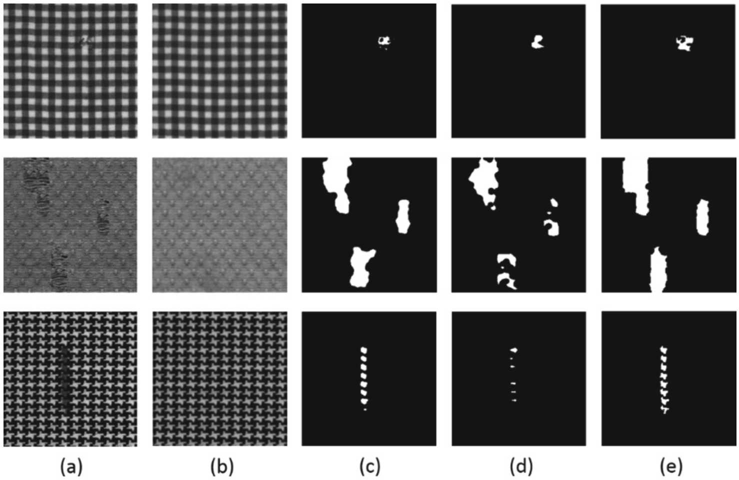

Fig. 6. (a) Initial input images. (b) Restored images (c) Results of ours. (d) Results of FCN. (e) Ground truth.

5 Conclusion

In this paper, we combine autoencoder and GAN to propose a defect detection model based on positive sample training without manual label. In training, combined with artificial defects and data enhancement methods, the model can automatically repair the defects of regular pattern texture images, and get the specific location of defects through comparing the features of the original picture and the restored picture. The position of the defect can be detected in real time on the image of the fabric and the plane of the texture. Moreover, we can get better results than supervised semantic segmentation when training defect instances are scarce.

If the background is too complex and random, it is difficult for the autoencoder to reconstruct and repair the picture. The related defect detection problem remains to be studied in the future.

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