Unsupervised defect detection based on the pseudo-defect generation

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Abstract. With the progress of industrial production, more and more products need to be tested to ensure product quality. Detecting and locating surface defects become a challenging and practical problem. In previous researches, the supervised training needs a lot of manual annotation data and defective product data. And the unsupervised method based on image inpainting can’t reconstruct complex images with high precision. In this paper, we proposed an unsupervised defect detection method based on the pseudo-defect generation to solve the problem of insufficient defective samples and the detecting accuracy problem. We conducted experiments on the AITEX dataset which get 93.3% DR, 3.2% FAR, and 35.5% MIOU. And it also shows outstanding effects in real industrial scenes.

1. Introduction

With the increasing demand for product quality, surface defect detection has become a hot topic. The development of deep learning makes the supervised defect detection developed to high accuracy. The FCN network[1] and U-net[2] use the semantic segmentation method to make the pixel-level high-precision defect detection possible. However, these semantic segmentation methods based on supervised learning need a lot of manual annotation data for training to have high accuracy. A small dataset may cause the overfitting problem.

In order to solve these problems, many unsupervised defect detection methods are proposed. They use the image inpainting algorithm to reconstruct images without defects. Then the residual image generated by the difference between the two images is used for defect detection. Part of it does image reconstruction based on generative adversarial networks(GANs)[3]. Radford et al.[4] made a breakthrough in fabric defect detection by using the generation model. The training of the generation model only needs positive samples. However, the quality of the reconstructed image is affected by the complexity of the background. In some cases, the reconstruction effect of Autoencoder will be more limited. Some results are shown in Figure 1.

In response to the above problems, we proposed the unsupervised defect detection method based on the pseudo-defect generation. Firstly, this method randomly generates defects on positive sample images, because we generate them ourselves, we know the pixel-level information of the generated defects. We can make semantic labels based on pixel-level information. Then the problem can be transformed into supervised learning. We can use a high-precision semantic segmentation algorithm[5-6] or object detection algorithm[7] to deal with subsequent problems. Our method only needs positive sample data and it doesn't need a lot of manual annotation. We can generate defects directly from a large number of original industrial data to increase the diversity of training data and reduce overfitting. And for the background of a complex text pattern, we can directly detect the existence of defects instead of generating them. We also use this method to get excellent results in the defect detection of the Industrial
Product Dataset[8]. Experiments show that our method has a good performance in the defect detection of print.

Figure 1. Text details cannot be recovered using the image reconstruction algorithm. The left is the original image, and the right is the reconstructed image.

Figure 2. The positive samples are transformed into negative samples and labels after the defect generator and then are given to the segmentation network for training.

2. Materials and methods

Our method is mainly divided into two steps. First, we generate the defect to make the training dataset and then use the train dataset to training the semantic segmentation model. The algorithm pipeline is shown in Figure 2.

2.1. The pseudo-defect generation

This paper takes the defect detection of print as the main research object. Defect generation is divided into two parts, shape generation, and color generation.

2.1.1. Color generation

Most of the defects are stains or scratches. The defect is white, gray, black, etc. We select these colors as the base colors, and then attenuate from the center to the edge of the defect according to the Gaussian kernel distribution as shown in equation (1). \( \text{center}_i, \text{center}_j \) are the center coordinates. \( \sigma, \mu \) set according to the actual situation. Random noise is also added in order to be close to the real situation.

\[
\text{color}_{(i,j)} = \text{color}_{\text{base}} \times \frac{1}{2\pi\sigma^2} \exp \left( - \frac{(\text{center}_i - \mu)^2 + (\text{center}_j - \mu)^2}{2\sigma^2} \right) + \text{noise}
\]  

(1)
2.1.2. **Shape generation**
The generated defects are mainly divided into regular graphics and irregular graphics. Regular graphics generally generate rectangles, lines, triangles, convex polygons, etc. Irregular graphics we mainly require are smooth, continuous, and closed. Therefore we use cubic Bezier curves to connect random points.

2.2. **Semantic segmentation network**
With the pseudo-defect labels, we now start to use the training set for semantic segmentation training. For this part, we can use any semantic segmentation model. Because the richness of the defect we made is not as high as in the real world, we should try to expand the training set to avoid overfitting. Since the task is defect detection, our network output should be binary classification, not multi-classification of traditional semantic segmentation.

3. **Results and discussion**
The proposed method is evaluated on two datasets including AITEX detection datasets[9] and an industrial product dataset provided from the real production line. The proposed model is trained on one NVIDIA Titan X GPU with batch size of 16 with images of resolution 128*128.

3.1. **Result**
On the AITEX[9], we use the segmentation network is U-net[2]. This network has a small number of parameters and is widely used. We compare our training results with DCSNet[10] which is an unsupervised method based on image reconstruction. To be fair, we use the same test method as the DCSNet[10]. The result is shown in Table 1. Our method got 93.3% DR, 3.2% FAR and 35.5% MIOU. These performances are better than baseline[9] and DCSNet[10]. Figure 3 shows some sample results.

\[
DR = \frac{\text{Number of defective samples correctly detected}}{\text{Total number of defective samples}} \times 100\% \quad (2)
\]

\[
FAR = \frac{\text{Number of defect free samples detected as defective}}{\text{Total number of defect free samples}} \times 100\% \quad (3)
\]

| Models   | DR   | FAR  | MIOU  |
|----------|------|------|-------|
| Baseline[9] | 86.1%| 11.4%| -     |
| DCSNet[10]  | 84.4%| 4.2% | 34.2% |
| Ours      | 93.3%| 3.2% | 35.5% |

3.2. **Application**
We used our method in the industrial dataset[8] competition and achieved outstanding results compared to other unsupervised methods[10]. Some samples are shown in Figure 4. The final correct rate of our method is 0.8619[8]. The overkill rate and the escape rate can be adjusted by adjusting the threshold.
Figure 3. In the figure, the first column is the real sample pictures, the second column is the ground truth defect parts marked, and the third column is the pixel-level result calculated using our method.

Figure 4. Some examples in industrial data[8]. The first line is the picture of the industrial product that contains the defect. The second line is the pixel-level result calculated using our method.

4. Conclusions
In this work, the performance of our proposed method has improved compared to traditional methods based on image reconstruction on the dataset[9]. This method can solve the problem that supervised learning requires a lot of manual annotation data and traditional methods cannot cope with complex backgrounds. And it also has outstanding performance in industrial scenes.

However, the quality of the generated defects will also have a partial impact on the results. This problem will also be studied later.

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References
[1] Yu, Z., Wu, X., Gu, X.: Fully Convolutional networks for surface defect inspection in industrial environment. In: Liu, M., Chen, H., Vincze, M. (eds.) ICVS 2017. LNCS, vol. 10528, pp. 417–426. Springer, Cham (2017).
[2] Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation[C]. International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015: 234-241.
[3] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherijl Ozair,
Aaron Courville, and Yoshua Bengio, Generative adversarial nets, In Advances in neural information processing systems (2014) 2672–2680.

[4] Radford A, Luke M and Chintala S., Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint (2015) 1–16.

[5] Chen et al., 2017 L.C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A.L. Yuille Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs IEEE Trans. Pattern Anal. Machine Intell., 40 (2017), pp. 834-848.

[6] V. Badrinarayanan, A. Kendall, R. Cipolla SegNet: a deep convolutional encoder-decoder architecture for image segmentation IEEE Trans Pattern Anal Mach Intell, 39 (12) (2017), pp. 2481-2495.

[7] Ren et al., 2017 S. Ren, K. He, R. Girshick, J. Sun Faster r-cnn: Towards real-time object detection with region proposal networks IEEE Trans. Pattern Anal. Machine Intell., 39 (2017), pp. 91-99.

[8] JiangSu association of Artificial Intelligence, (2020). National Campus Machine Vison Application Competition. https://www.marsbigdata.com/competition/details?id=5293671830016.

[9] Silvestre-Blanes, J., Albero-Albero, T., Miralles, I., Pérez-Llorens, R., & Moreno, J. (2019). A Public Fabric Database for Defect Detection Methods and Results. Autex Research Journal, 19(4), 363-374.

[10] Wang Yuxiang et al., (2021) DCSNet: A Surface Defect Classification and Segmentation Model by One-Class Learning. J. Phys.: Conf. Ser. 1914 012037.