Study on Shot peening Coverage of Metal Surface Based on Deep Learning

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Abstract. The surface shot peening coverage of industrial parts will affect the performance of the parts. Therefore, it is of great significance for the identification of the metal surface shot peening coverage area and the uncovered area for the metallurgical process. This paper uses the idea of image semantic segmentation, using CCD industrial camera to select and shoot the metal surface of 67%, 89% and 98% shot peening coverage. Based on UNet and UNet++ model, the shot peening area is segmented. After training 200 epoch, the network converges and the training accuracy can reach 98.45%. Comparing the two kinds of network training results, using the UNet++ model with good results to predict the selected 18 metal surfaces, the proportion of shot peening coverage area and uncovered area is counted, and then the K-means clustering algorithm is used to classify. The classification accuracy can reach 100%.

1. Introduction

Along with the development of information technology, the "metallurgical industry Internet" has become inevitable development trend[1]. In order to realize the accurate detection of metal surface, the traditional manual detection method is replaced by the image segmentation algorithm based on machine learning and deep learning[2-3]. Shot peening is a kind of artificial injection treatment on the surface of the part. By spraying a large number of high speed shot peening on the surface of the part, the metal surface is deformed violently and a certain thickness of deformation hardening layer is formed. It has obvious strengthening effect on the fatigue resistance of the material[4]. However, different shot peening coverage will lead to different morphology characteristics on the metal surface during shot peening strengthening. Therefore, it is very important for metallurgical process to quickly divide the shot peening covered area from the uncovered area and to classify the metal surface with different shot peening coverage.

Nowadays, most studies on the surface morphology of metal after shot peening are based on the angle of image recognition. Xu Mingbo et al[5] used scanning electron microscope to observe and record the morphology, thickness and porosity of the surface oxide layer before and after shot peening to characterize the densification effect of shot peening on metal surface. For the study of the morphology of metal surface shot peening, there is a lack of relevant literature using deep learning[6].

In this paper, deep learning and image semantic segmentation are used to analyze the coverage of metal surface shot peening. In such areas, in 2014, Long et al[7] proposed a FCN approach to apply deep learning to image segmentation for the first time. UNet model was proposed by Ronneberger et al[8] in
MICCAI in 2015, which has good effect on medical image segmentation; On this basis, Lv Y[9] proposed AA-UNet for retinal vascular segmentation. On the basis of UNet model, Zongwei Zhou et al[10] made an optimized model called UNet++. Since the model extended by UNet network has good performance in medical image segmentation, the researchers have also extended the application field of UNet model. Liu Chang et al[11] proposed a combination of UNet and classification neural network for magnetic tile surface defect detection. Zhang haichuan et al[12] put forward a application of asphalt pavement image crack segmentation method. Meanwhile, through research and proofs, UNet++ is also suitable for the development in the field of remote sensing images[13]. The above research also provides reference for this paper.

Inspired by some previous studies, UNet and UNet++ model are selected to study the coverage of metal surface shot peening. By comparing the image segmentation performance of the two models, the recognition and segmentation of shot peening coverage area and the verification and calculation of shot peening coverage are carried out, and the accurate detection method of surface shot peening coverage is explored.

2. Model and work

2.1. Outline

The idea of this paper is to first use CCD industrial camera to take pictures of metal surface with \( i \) shot peening coverage. Each class contains \( j \) pictures. For the first picture in the picture of the \( i \) coverage, the code name is \( m_{ij} \). Then, using the method of random cropping, \( k \) sub-pictures are adopted, which are divided into two groups \( n_{1k} \) and \( n_{2k} \), input into the UNet and the UNet++ model respectively. Through the training and iteration of the network, the test images are predicted by using the trained results. Thus, the shot peening coverage area is separated from the uncovered area. For the results of two model training, we use the following two indicators as evaluation criteria:

- Accuracy-Miou.
- Shot peening coverage.

The network with the larger value of these two indicators is selected as the prediction network of this batch shot peening. Through the continuous circulation of the above process, the network with better prediction results can be selected for different batches of shot peening, thus improving the accuracy of the results. The workflow diagram for this article is shown in figure 1 below.

Figure 1. Workflow.
Therefore, according to the idea of our model design, based on the above two network structures, this paper carries on the multiple sampling for the actual metal surface with different shot peening coverage area, and carries on the experiment through the flow in figure 1.

3. Testing of metal surface shot peening coverage

3.1. Setting of experimental environment and parameters
The experiment is trained under GPU RTX3090(24G), the environment is anaconda integrated environment, and the network model is built under the framework of Pytorch.

During this experiment, the number of iterations is set to 200 iterative training. In order to improve the generalization ability of the model, the data are randomly scrambled before each epoch to make it more consistent with the sample distribution under natural conditions. The Batch Size is set to 4, the learning rate is 0.0001, the Loss function is cross entropy function, and the RMSProp optimizer is selected.

3.2. Experimental data and preprocessing
The metal surface shot peening image used in this paper is the image of different shot peening coverage taken by CCD industrial camera. The original image size $1920 \times 1080$, total shot peening amount is 67\%, 89\% and 98\% three types.

Each type of 6 images, a total of 18 images, some of the original images are shown in figure 2 below.

![Figure 2. Partial raw image data.](image)

In order to segment the original image semantically, it is necessary to make the label picture, usually the label picture is a binary image. By using labelme software, the shot peening coverage area in the original image is marked, and then converted into binary image. Random selection of 5 images of each category of a total of 15 images to label, and random clipping, rotation and other ways to expand the original image into each category of 100 images, and resize them into $512 \times 512$, to form a total of 300 groups of images and labels datasets. Some of the new datasets obtained are shown in figure 3 below.

![Figure 3. Partial new datasets.](image)

3.3. Miou
For determining the performance of the model, $\text{Miou}$ is used as the evaluation index of the accuracy of the segmentation model, and the corresponding calculation formula is as follows.

$$
\text{Miou} = \frac{1}{k+1} \sum_{i=0}^{k} \frac{p_{ii}}{\sum_{j=0}^{k} p_{ij} + \sum_{j=0}^{k} p_{ji} - p_{ii}}
$$
The $k$ represents the number of classified pixels, the $p_{ii}$ is to predict the correct number of pixels, the $p_{ij}$ is the real number of metal shot peening pixels, and the $p_{ji}$ is the number of pixels in the non-peening region.

3.4. Classification of shot peening coverage

For the output results, by calculating the ratio of the number of pixels representing the shot peening area to the total number of pixels, the ratio of shot peening area to non-peening area in each picture can be obtained, and finally the K-means clustering is used. The clustering results of each shot peening image are obtained. The expression of the algorithm is as follows.

$$E = \sum_{i=1}^{k} \sum_{x_i, x_i \in m_j} \| x_i - m_j \|^2$$

The $x_i$ is the position of the $i$ center point and the $m_j$ is the position of the class $j$ sample point.

4. Results and analysis

Through the training of the prepared datasets into the UNet and UNet++ model, the training results of the network can be obtained as shown in figure 4 below.

In figure 4, the loss of the UNet++ model converges earlier than the UNet, and the loss of the final training is smaller, which is 0.4069, and the loss of the two models tends to converge, which indicates that the network training is better; The accuracy of UNet++ is higher than that of UNet, which is 98.45% for $MIOU$. Hence, we choose the results of UNet++ network training as the model for the final prediction of shot peening coverage area; For the above two models and the final results after edge smoothing, the final predicted partial binary diagram is shown in table 1 below.

| Raw test data | UNet Output |
|---------------|-------------|
| ![Raw test data](image1) | ![UNet Output](image2) |
Therefore, according to the results in table 1, we can see that the UNet++ and edge smoothing process output are better, so we select this method to predict 18 images. By calculating the ratio of shot peening coverage area to uncovered area in each image, the clustering results of K-means cluster analysis can be obtained in figure 5 below.

According to the results of the clustering analysis in figure 5, we can see that the points corresponding to 18 pictures are all clustered to the vicinity of the three regional central points of 67%, 89% and 98%. After testing, each picture is classified into the corresponding process category, and the classification accuracy can reach 100%. Therefore, the prediction results of our model are good, and the results are good for classifying different shot peening processes.
5. Conclusion
This paper uses the method of image segmentation, uses UNet and UNet++ to segment the metal surface shot peening coverage area and the uncovered area, and calculates the area ratio of the two types of regions. Finally, the K-means clustering algorithm can be used to classify the pictures with different shot peening coverage. A series of shot peening process images of 67%, 89% and 98% were taken by CCD industrial camera. Repeat the above process, the accuracy of UNet++ network training is 98.45%, and according to the calculated results, 18 pictures are classified by K-means clustering algorithm. The accuracy of classification can reach 100%.

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