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Surface Scratch Defect Detection of Titanium Spacer Ring in Hard Disk based on Convolutional Neural Network

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In terms of quality management in the metal machining industry today, most of the defects are classified and judged by the human eye. The decision of the human eye will be affected by the external environment and mental fatigue problems, and small defects will also cause misjudgment due to lack of experience. In this research, aimed at the titanium metal spacer ring inside the hard disk inspection, surface scratch defects are identified. Because of the different depths of scratches and placement angles, shallow scratch features cannot be identified. To fully capture the defect features, referring to the distribution concept of bright field and dark field, a set of the lighting system with a single light source and motor control is designed, which can acquire multiangle images at one time. Due to the large difference in the shape and intensity of scratches, it is difficult to detect defects using the traditional digital image processing method. In this study, the deep learning network architecture was used. First, the images were pre-processed to reduce the interference of noise, and the number of image data increased through data augmentation. Then, the FasterRCNN and Unet models are used for training and prediction. The final experimental results showed that the success rate of defect identification was 95% and 82%, respectively.

NOMENCLATURE

Resnet = AI model for image classification
Unet = AI model for image segmentation
FasterRCNN = AI model for object detection
FOV = Field of view

1. Introduction

Currently, automatic optical inspection technology is widely used in industry to assist in determining workpiece defects, improving not only product quality but also inspection time. However, there are still some tiny and irregular surface defects, and most of them need to be intervened by a human. Generally, in the grinding and polishing process, metal parts are easily scratched due to contact during the process of moving and handling. In terms of machine vision detection technology, such tiny scratches can be divided into traditional digital image processing technology and AI deep learning technology. In traditional digital image processing technology, one uses the fast discrete curvelet transform (FDCT) and texture analysis with a greyscale co-occurrence matrix [1] to estimate the threshold value, and the other is based on a texture orientation histogram through the minimum enclosing rectangle method [2]. However, the above methods all require a stable light source system, and this takes a lot of time during the conversion process. Another method is the design of the light source system. Images captured in the bright field and the dark field are fused [3], and there are also multi-angle light sources to highlight the defect characteristics [4]. Although these methods can obtain the defect information, the grayscale value of each image defect is different, and there is a lot of background noise interference in the conversion process, which requires individual processing. In deep learning AI technology, the more classic model for image classification is Resnet [5], but this is used for the detection of small scratches, which will cause the ratio of background features to defects to be out of balance and requires more data and computing resources. In addition, the image segmentation is Unet [6]. Although the image size needs to be reduced in the training process, only a small number of samples are needed to obtain a good recognition effect. In the object detection model, there is FasterRCNN [7], which is also widely used in more complex parts.

This research focuses mainly on the detection of surface scratches and defects in the titanium metal spacer ring inside the hard disk. We collected a total of 60 defective samples. The number of images is increased through data augmentation technology and multi-angle image acquisition, and two models of Unet and FasterRCNN are used for training and prediction through deep learning technology.

2. Overview of the spacer ring

In the process of processing metal workpieces, there are often various defects, such as yellow marks, scratches, grind non-uniform, bumps, burrs and other abnormal dimensions and materials, and the proportion of scratch defects in the whole is second only to the yellow mark, and the characteristics of scratches are tiny and complex than other defects.

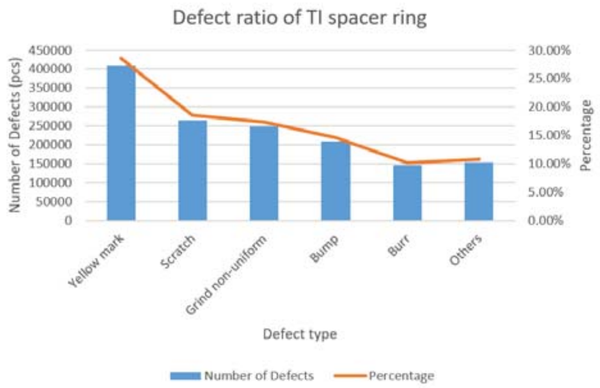


Fig.1 shows the defect ratio of the TI spacer ring.

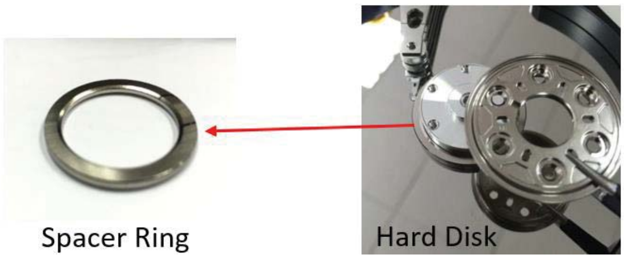


Fig.2 Spacer ring inside the hard disk

2.1 Specification of the spacer ring

A spacer ring separates the magnetic area inside of a hard disk. Fig. 2 shows the spacer ring inside the hard disk. It is made of aluminum alloy and titanium alloy. This research focuses mainly on the titanium alloy material for defect detection. Its appearance size is 32.6mm in diameter and 4 mm in surface width and 1.7 mm in thickness. The grayscale value of the scratch feature will show differently when the spacer ring is photographed at different angles, most of them are small shallow scratches, and the minimum flaw feature is 200 μm, as shown in Fig.3.

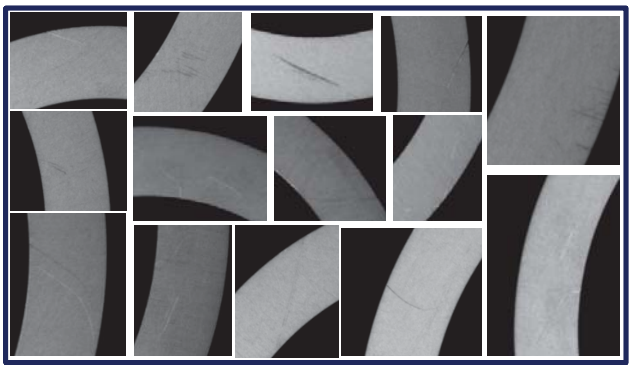


Fig.3 Surface defects in the spacer ring caused by grinding, polishing, and handling

3. Design of the Lighting System

To fully capture the features of defects, we designed a low-cost, high-efficiency lighting system, which can clearly capture the sample surface through a set of external coaxial white light and a set of 5 million pixels industrial cameras. Image information is shown in Table 1. In addition, a set of motors is used to control the rotation of the sample to achieve multiangle shooting. It also solves some scratches that need to be shot at a specific angle.

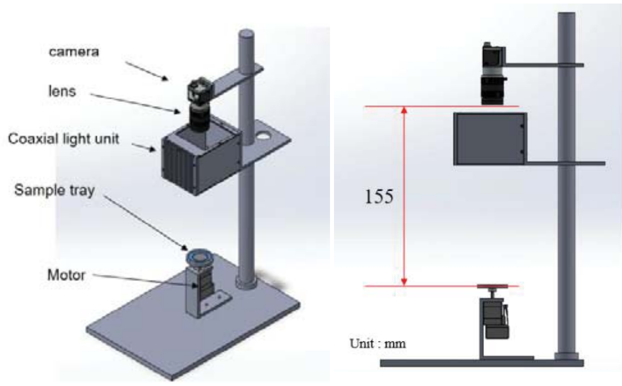
Table 1 Image information

Image size	2048*2448 pixels
Pixel size	0.018*0.018 mm^2
FOV	36.86*44.06mm^2

3.1 Overview of the system

Fig. 4 is a schematic of the proposed light system. The detailed specifications of the hardware are as follows:

- Industrial camera: Basler acA2440-35um with Sony IMX264 CMOS sensor delivers 35 frames per second at 5.0 MP Resolution
- Lens: ICL-C3514M with 2 mm extension ring for FOV
- Lighting: OPT-RIA211-W external coaxial light
- Lighting controller: OPT-DPA-1024-E4
- Driver: Oriental Motor AZD-KD
- Motor: Oriental motor AZM24AK



(a) (b)

Fig.4 Schematic diagram of the light system (a) isometric view (b) side view

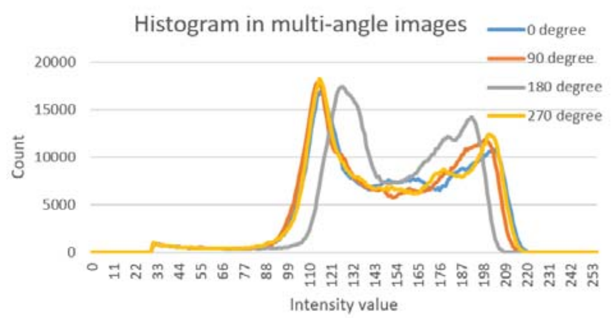
Fig.5 four angles for shooting

4. Methodology

In order to obtain image information from different angles, we design four angles for shooting, 0 degrees, 90 degrees, 180 degrees, and 270 degrees, and control the motor through the program. Each time shooting, the motor will automatically rotate to these four angles, and the camera will Simultaneous acquisition. Fig.5 is four-angle images.

4.1 Image analysis

Depending on the degree of scratching, the grayscale intensity of images from different angles is analyzed. Through image J software, the intensity information is exported. It can be found that there are obvious differences in the grey-scale intensity at different angles. As



shown in Fig.6, to reduce noise interference during training, we make the sample tray black, so that we can easily use image binarization for image preprocessing.

Fig.6 Intensity value of four-angle images

4.2 Pre-processing

The first step is to remove the background of the image. Since we use external coaxial white light, the light source is concentrated on the surface of the sample, which can be easily implemented through the OpenCV binarization function library, so interference of the background can be eliminated during training. The second step is defect labeling using the CVAT image labeling program. Scratches and other defects are marked using the polygon tool, and the grayscale value of the defect marks is adjusted to 255 to facilitate inspection. The third step is data augmentation. To increase the number of samples. The Augmenters function is used to mirror the image horizontally and vertically, and then mirror it again after vertical flipping, so that the image can generate the corresponding information in the four quadrants. This approach allows the original information of only 60 samples, through four angles of shooting and data augmentation, so that our image data is expanded to 720 images. The fourth step is the distribution of the data. In the training data set, 80% of the data is used for training, 10% is used for verification, and the other 10% is used for testing, as shown in Table 2.

Table 2 Distribution of training dataset

Training	576 images
Validation	72 images
Test	72 images
Total	720 images

The final step is to select the AI model. In this study, the classical Unet model for image segmentation and the popular FasterRCNN for object recognition were selected for experiments. Fig.7 shows a block diagram for image processing and its main steps.

(a) Unet cannot perform high-pixel operations under this model due to the limitation of the training host memory. To solve this problem, we directly change the original image size to 512 × 512 pixels for training, and Table 3 shows the model parameters.

Table 3 Training information(Unet)

Model name	Unet
Images size	512 × 512 pixels
Training images	576
Validation images	72
Learning rate	0.0001
Epochs	40
Steps per epoch	400
Batch size	1

(b) FasterRCNN will import COCO register COCO, so the training data can be converted to COCO data format before training. This is essential to start the training. Table 4 lists the model parameters used during training.

Table 4 Training information (FasterRCNN)

Model name	FasterRCNN
Images size	2048 × 448 pixels
Training images	576
Validation images	72
Learning rate	0.01
Epochs	50
Steps per epoch	500
Batch size	1

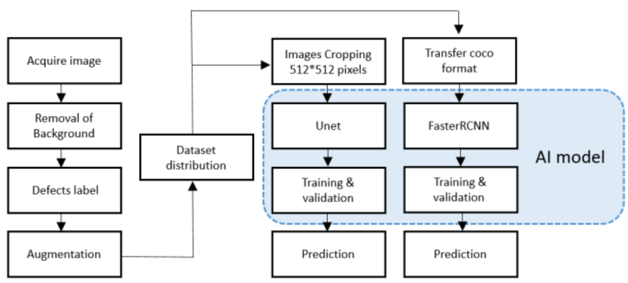


Fig.7 Image Processing Fetch Chart

Table 5 Prediction results for Unet model

Defect type	Number	Number of successful detections	Number of failed detections	Success rate
Scratch	72	59	13	81.94%

Table 6 Prediction results for FasterRCNN model

Defect type	Number	Number of successful detections	Number of failed detections	Success rate
Scratch	72	69	3	95.83%

5. Experimental results

In this batch of experimental samples, 72 images are reserved for prediction. The following Unet predicts the results, as shown in Fig.8. The overall statistical results of the defect detection for the defective spacer ring are shown in Table 5. The following FasterRCNN predicts the results, as shown in Fig.9. The overall statistical results of the defect detection for defective spacer rings are shown in Table 6.

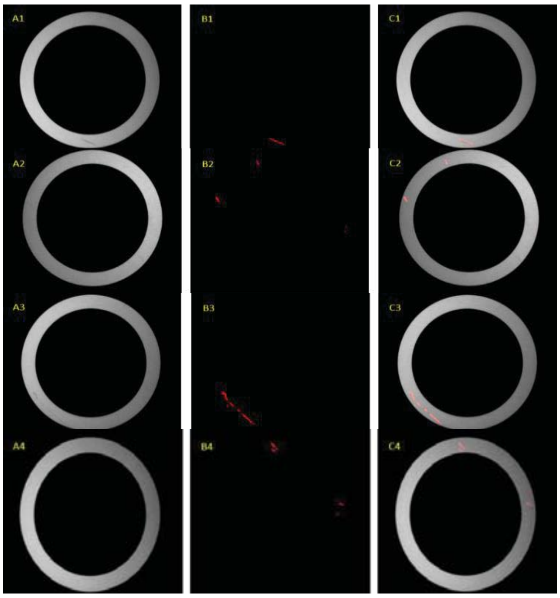


Fig.8 Unet model predicted results: A1-A4 Source images; B1-B 4 defects predicted; C1-C4 images results

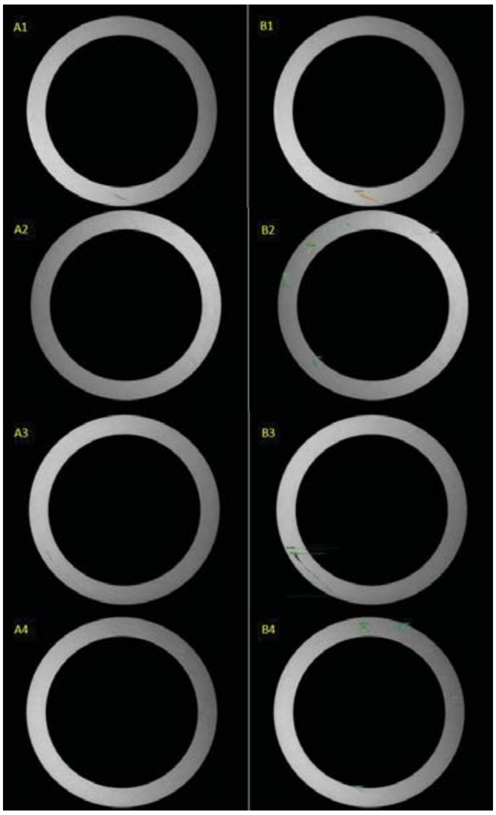


Fig.9 FasterRCNN model predicted results: A1-A4 Source images; B1-B4 predicted results.

6. Conclusions

Scratches defects have the characteristic that they can only be inspected at a specific angle, and scratches that are too small are difficult to inspect with the naked eye, so in this paper, we designed a lighting system that can shoot from multiple angles. One sample can take multiple images, which can increase not only the training data but also the characteristics of defects. The experiments show that a higher success rate of image prediction, and the time spent for each image prediction, Unet is 45ms, FasterRCNN is 254ms, which also meets the detection standards of the industry.

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REFERENCES

[1] Xueqin Li , Honghai Jiang , Guofu Yin, “Detection of surface crack defects on ferrite magnetic tile,” NDT&E Int.,62(2014), pp.6-13

[2] Jiangang Lin, Dongxing Wang, Hongzhi Tian and Zhaocai Liu, “Surface defect detection of machined parts based on machining texture direction, ” Meas. Sci. Technol., 32 (2021), 025204 (12pp)

[3] S. Satorres Martínez, C. Ortega Vázquez, J. Gámez García, J. Gómez Ortega, “Quality inspection of machined metal parts using an image fusion technique,” Measurement 111,(2017),pp.374-383

[4] Bin Liu, Yiqian Yang, Shangshang Wang, Yang Bai, Yuduo Yang, Jianxin Zhang, “An automatic system for bearing surface tiny defect detection based on multi-angle illuminations,” Optik, 208(2020),164517

[5] Y.-F. Chen, F.-S. Yang, E. Su, and C.-C. Ho, “Automatic defect detection system based on deep convolutional neural networks,” ICESI, 2019, pp.1-4.

[6] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in International conference on medical image computing and computer-assisted intervention, 2015, pp. 234-241.

[7] Yuanbin Wang, Minggao Liu, Pai Zheng, Huayong Yang, Jun Zou, “A smart surface inspection system using faster R-CNN in cloud-edge computing environment,” Advanced Engineering Informatics,43(2020),101037