A Flexible Quality Inspection Robot System for Multi-type Surface Defects

Mingwei Li
Research Center of Precision Sensing and Control, Institute of Automation, University of Chinese Academy of Science,
Chinese Academy of Science
Beijing, People's Republic of China
limingwei2020@ia.ac.cn

Xiuqin Shang
Research Center of Precision Sensing and Control, Institute of Automation, University of Chinese Academy of Science,
Chinese Academy of Science
Beijing, People's Republic of China
xiuqin.shang@ia.ac.cn

Qianyu Zhou
Research Center of Precision Sensing and Control, Institute of Automation, University of Chinese Academy of Science,
Chinese Academy of Science
Beijing, People's Republic of China
zhouqianyu2018@ia.ac.cn

Yali Shi
Research Center of Precision Sensing and Control, Institute of Automation, University of Chinese Academy of Science,
Chinese Academy of Science
Beijing, People's Republic of China
yali.shi@ia.ac.cn

Zhengtao Zhang*
Research Center of Precision Sensing and Control, Institute of Automation, University of Chinese Academy of Science,
Chinese Academy of Science
Beijing, People's Republic of China
zhengtao.zhang@ia.ac.cn

Abstract—**Automatic defect detection is an essential part of quality inspection in industrial production. It can improve the effectiveness and reduce the cost for labor. Most of the detection systems are designed for specific tasks and they usually could not adapt to multiple types of objects simultaneously. In this paper, a general and flexible defect detection system is established for multi-type surface defects, it can achieve defect detection tasks for complex 3-demential surface with different types and material, which has a precision of 95.3% and recall of 96.2%. A database of surface defects is also built to help the system to manage the data, recognize unknown defects and analyze the possible problems in the production line.**

Keywords—surface defect detection, robot system, 3-demential surface

I. INTRODUCTION

As the development of automation technology, the automatic production line has been widely applied in industrial production, in some fields like high-end chips, workers only need to set the program and the machines will do all the production work automatically. However, in the field of industrial defect detection, the extent of automation is still in a low level. The products need to be checked manually before leaving the factory, 30%-50% workers in the factory are hired to do this labor-intensive work. And what's more, for some fine detection work like optimal elements, the high intensity work can cause vision damage to workers, most of them can only do this work for less than one year. With the rising labor cost, automatic quality inspection system is needed in many industrial fields, which is not only for the steady operation of the product line, but also for the health of the workers.

In recent years, with the improvement of artificial intelligence algorithm and industrial vision technology, automatic defect detection has been applied in industrial production. Cha et al. [1] adopted Faster R-CNN [2] to detect structural defects on steels, Liu et al. [3] proposed a positioning method for catenary support components based on SSD[4]. Yuan et al. [5] utilized Generative Adversarial Network (GAN) [6] to get defect regions. Tong et al. [7] proposed a method based on nonlocal sparse representation to detect defects on fabric. Zou et al. [8] established DeepCrack network which is based on SegNet[9], and achieved good performance on crack detection. For detection system, Tao et al. [10] designed a surface defect detection system for large aperture optimal elements. Cao et al. [11] proposed a optimal surface detection system with high dynamic range. Jiang et al. [12] established a detection system of solder paste on printed circuit boards.

However, most detection systems are designed for specific tasks. Most of the devices are fixed and when the detection target changes, the system usually can not adapt to the new tasks well. What's more, for objects with multi-type 3-demential surface, it's hard for a detection system to acquire images that cover the whole surface.

In this paper, a general and flexible defect detect system is established that can achieve the defect detection of complex 3-demential surface for multi-type, multi-material inspected objects. The system achieved a precision of 95.3% and a recall of 96.2%. A database of the surface defects is also built, and the system can classify and grad each defect and analyze the possible problems in the production process according to it. When there are unknown kind of defects, the system can give an alarm and it can also be trained to adapted to the new defects if the new class have been confirmed manually. Our system can be integrated into the product line, which can improve the production efficiency greatly through the automatic defect detection.

The remainder of this paper is arranged as follows. Firstly, the overall design is briefly introduced in Section II, including the instruments and the software, the detection procedure is also introduced in this section. Secondly, the 3 modules of the system will be introduced in detail in Section III. The experiments are reported to evaluate the performance of our system in Section IV. Finally, the conclusions are presented in Section V.

II. System Design

A. Defect detection instruments

The defect detection instrument is composed of recognition, loading and detection three modules, which is shown in Fig.1. The recognition module consists of a recognition camera and circle light source. A 6-DOF loading robot, an area of temporary storage, fixtures and their quick-change table are in the loading module. The temporary storage area is divided into four parts: qualified area, unqualified area, repairable area and undetected area, there are sensors on the template to detect whether there are objects occupying each vacancy. In the last module includes a 6-DOF detection robot, detection camera and five light sources. All these are placed on a workbench and they are controlled by a industrial control computer through programmable logic controller (PLC) device. The instruments can achieve high flexibility, accuracy and stability through the high-speed DC servo-control system. With the cooperation of 6-DoF robotic arm and rotatable table, our system can plan the trajectory automatically and move along it, so that the system can detect entire surface of the objects.
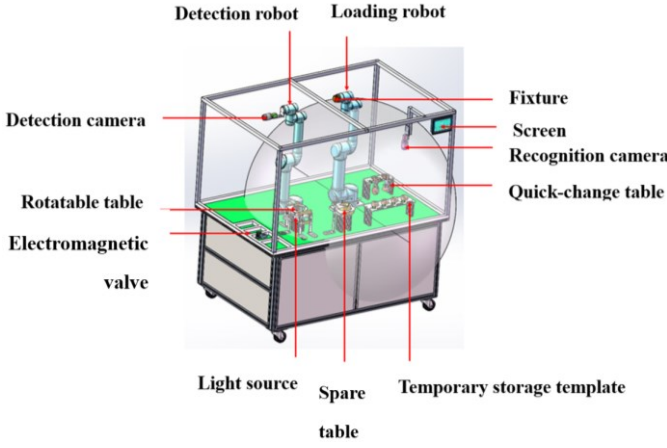

Fig. 1. Defect detection instruments

B. Defect detection software

Together with the instruments, we also developed software for the system. We designed an interactive interface for the software, which can help us finishing programming work easily through dragging command modules. The software can control the imaging system, lighting system and motion system through the PLC device. After creating proper detect model in the software, the system can achieve image acquisition of the 3-dementional surface according to the model. Then, image processing and defect detection will be done by the software. The software integrates our general deep learning defect detect algorithm library, which can meet the needs for detecting, classifying, measuring, grading the defects and so on. The software will also establish databases with the detecting procedure, which can analyze the data and give the possible reason to make defects.

C. Detect procedure

The flow chart of the detect process is shown in Fig. 2. To begin with, the automated guided vehicle(AGV) will send objects to the undetected area of the template. When it is detected by the sensor, the recognition camera will take a picture of it and the system will judge which type the object belongs to. Then, the grab robot will grab the object and place it on the rotatable table.

With the help of loading robot, the detection camera will take several pictures of the objects in the following order: the first picture will be taken from the top, and then the loading robot will turn the object over. The second picture is taken from the same position, which will show the bottom of the object. Then the detection robot will move to the side and take pictures with the rotation of the platform until every angle of the side have been taken in pictures. The system will detect the objects and judge whether it is qualified, unqualified (irreparable) or repairable. The loading robot will put them to the different areas of the template and the AGV will send them to different places of the production line.
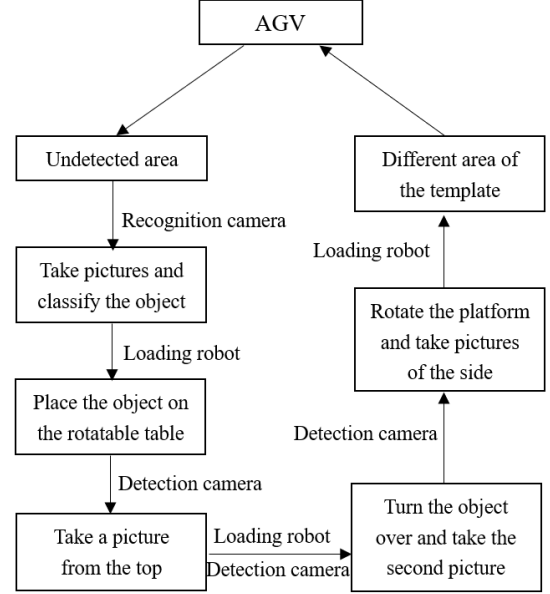

Fig. 2. Flow chart of the detection process

III. Realization of different functions

To introduce more details of our system, we divided our system into 3 modules: recognition module, loading module and detection module. These modules will cooperate with each other to achieve the detecting tasks.

A. Recognition module

This module is first step of our system. Objects will be sent to this module by the AGVs, and then this module will classify the object for the system to decide how to accomplish image acquisition tasks. The recognition camera and the light source are placed on the top of the temporary storage template.

In this paper, we adopt ResNet-18[13] network as the classifier, the design of residual structure makes it easy for weights to be trained. Because the objects are placed in fixed places, so we can cut out some background area of the images before sending them to classification network.

B. Loading module

After identifying the class that the object belongs to, the loading module need to put the object to the detection area and help turning over the object during the imaging process. We use an UR robot with a fixture at the end to do this work. To grab different kinds of objects, an shortage template is set near the robot, different kinds of fixtures are placed on it for quick change. The design of this module in shown in Fig.3.
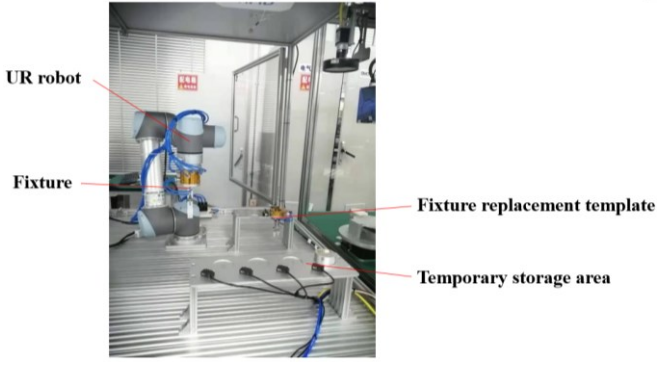
Fig. 3.   Loading module

C. Detection module

This is the core module of our system. The design of the module is shown in Fig.4. To achieve the generality and flexibility of imaging tasks, the detection camera is fixed on an UR robot, so that it can adjust its position and angle for different tasks. We also design a set of lighting sources for better imaging quality. As is shown in Fig.4, there is a circular lighting source on the top of the rotatable table and two parallel lighting sources at the side of it, we also placed a circular lighting source around the camera on the robot to raise the light intensity of imaging area. The light intensity can be adjusted automatically or manually.

After acquiring enough images of the objects, we can now do the detection work. We choose Faster R-CNN as the basic architecture of the detection network. Faster R-CNN is an effective method for object detection and it can achieve high mAP in some open datasets. To adapt to the industrial images better, we adapt a network that combines ResNet and DenseNet[14] as backbone for feature extraction. The improved Faster R-CNN network performs well in our surface defect detection tasks.
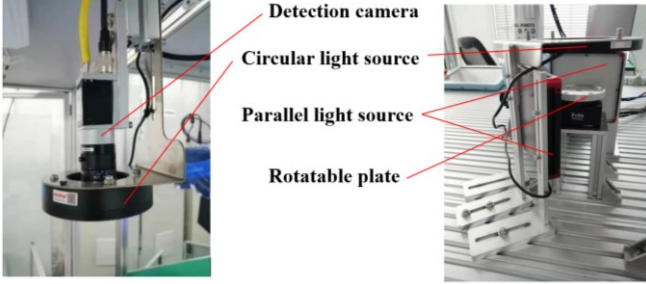

Fig. 4.   Detect camera with circular lighting resource(left) and rotatable plate with a set of lighting resources (right)

IV. EXPERIMENTS

The experiment system are established as we described in Section II. We choose Basler acA2440-120gm and Computar 35mm varifocal lens as the detect camera, the size of the optimal element is 8.4mm×7.1mm and the image size is 2448×2048 pixels. Two UR5 robots are used in grab and detect module as the robotic arms.

Our software is developed in Visual Studio 2017 environment and the interface is developed with Qt. The basic interface of the software is shown in Fig.5.
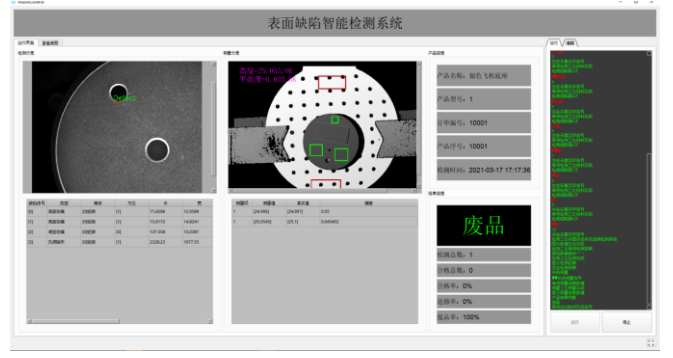

Fig. 5.   Basic interface of the software

In this paper, we choose two objects as the detection targets. As is shown in Fig. 6, the left picture is a rotate solar ornament, it is composed of 6 components of different size and materials, which is shown in picture 1-6 in Fig.7. The right picture in Fig.6 is a model plane bases, and it is composed by a base and a nameplate, which is shown in picture 7-8 in Fig.7. We choose some of these objects to do our surface detection.

Fig. 6.   Rotate solar ornaments(left) and model plane base(right)

Fig. 7.   Different components of the objects

A. Objects classification and Image acquisition

We established a dataset for classification of 347 samples, including 167 pictures of the model plane base, 88 pictures of the solar ornament base and 92 pictures of the plastic pad of solar ornament. The dataset is divided into train set of 208 samples, validation set of 69 samples and test set of 70 samples. We rotate of flip the samples in train set with a 50% probability as data augmentation. The ResNet-18 network achieved an accuracy of 100% for classification. Some of the results are shown in Fig.8.
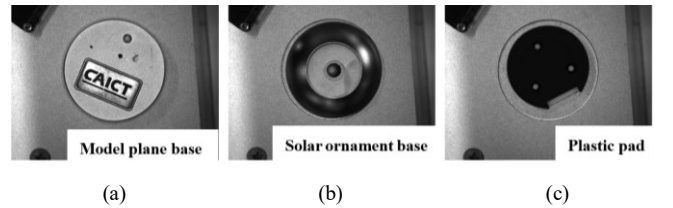

Fig. 8.   (a) model plane base   (b)solar ornament bas   (c)plastic pad

After the classification, the objects will be sent to imaging area by the grab module. The imaging process has

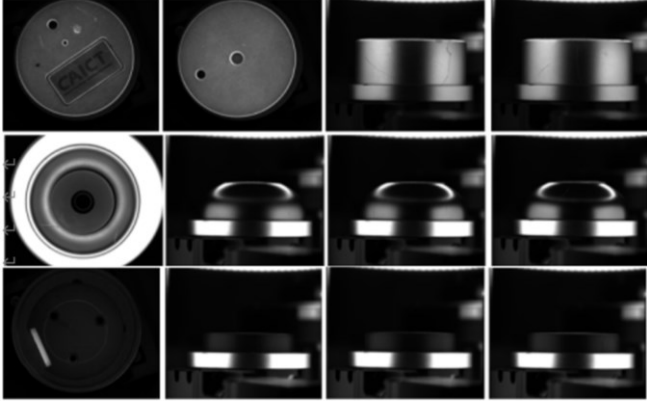been described in Section II. Some of the images are shown in Fig.9.

Fig. 9. Images acquired by the detect camera

B. Defect detection

We established a dataset of defects to test our system. The sample numbers of different objects are shown in TABLE I.

TABLE I.   NUMBERS OF SAMPLES IN DEFECTS DATASET

Defects dataset	Train set	Validation set	Test set
Model plane base	150	59	90
Solar ornament base	119	49	70
Plastic pad	85	33	51
Total	354	141	211

We use our system to detect the defects in our dataset. Some of the results are shown in Fig.10.
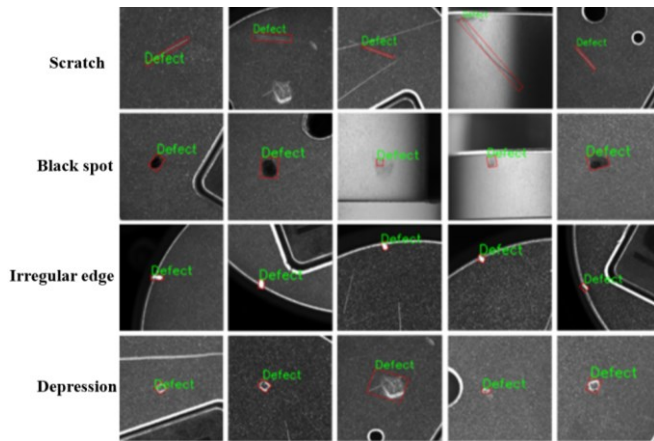

Fig. 10. Some of the defect detection results

We count the numbers of correct detection, false detection and over detection. The results are shown in TABLE II. We use two indexes to evaluate the performance of the system: precision and recall. The calculate method are as follows:

$$precision = \frac{correct\ detecion}{(correct\ detecion + over\ detection)}$$

$$recall = \frac{correct\ detecion}{(correct\ detecion + false\ detection)}$$

The results are shown in TABLE III.

TABLE II.   DEFECT DETECT RESULTS

Object classes	Defect number	Correct detection	False detection	Over detection
Model plane base	90	87	3	4
Solar ornament base	70	67	3	3
Plastic pad	51	49	2	3
Total	211	203	8	10

TABLE III.   PRECISION AND RECALL OF DEFECT DETECTION

Performance	Precision	Recall
Index	95.3%	96.2%

C. Database

Our database module is developed on the basis of SQLite. The interface of the database module is shown in Fig.11. During the detecting process, the system will import the information of defects into the database, for example, class, grade, location, size and so on. We can add, delete or modify the information in database manually and export in word, excel or pdf formats.
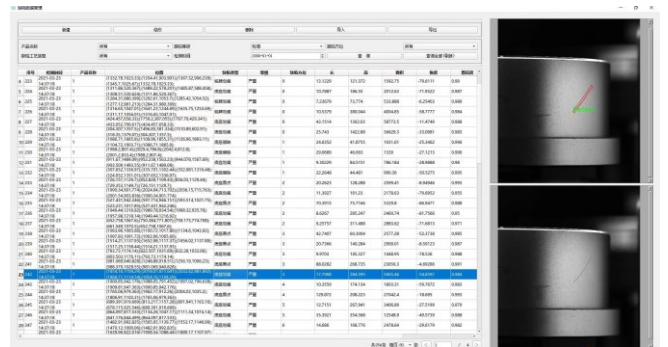

Fig. 11. Interface of the database module

With the database, our system can analyze the possible causes of the defects, and judge where the object should be sent in the product line. For example, as is shown in Fig. 12, when the lack of metal plate on model plane base is detected, our system will show 'assembly repair' and connect the AGVs to send it to the assemble module of the product line.
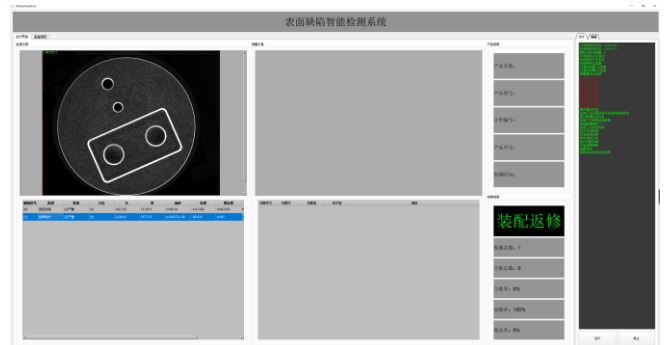

Fig. 12. Lack of metal plate on the model plane base

V. Conclusion

In this paper, a general and flexible defect detection system is established for quality inspection of multi-type 3-dementioal surfaces. More than 3 objects are detected in the experiments and the adaptability and effectiveness of detection system is validated. It is of great significance to improve the efficiency of quality inspection in industrial production. Meanwhile, the system still has some problems, the result of detection may be influenced by the lighting condition, and therefore some defects will be missed.

So for future work, the design of instruments could be updated for stronger anti-interference ability. What's more, the surface defect detection algorithms usually extract texture features, geometric features, transform index features et al. from images, and it's kind of redundant. So choosing dominant features that more efficient for classification or localization of defects may be what we can improve in future work.

Acknowledge

References

[1] Cha, Y., Choi, W., Suh, G., Manhmoudkhani, S. and Buyukozturk, O. Autonomous Structural Visual Inspection Using Region-based Deep Learning for Detection Multiple Damage Types. Computer-Aided Civil and Infrastructure Engineering, 2018, 33(9), 731-747.

[2] Ren, S., He, K., Girshick, R. and Sun, J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. Conference and Workshop on Neural Information Processing Systems, 2015, 91-99.

[3] Liu, Z., Liu, K., Zhang, J., Han, Z. and Zhang, W. A High-Precision Positioning Approach for Catenary Support Components with Multiscale Difference. IEEE Transactions on Instrumentation and Measurement. 2020, 69(3), 700-711.

[4] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. and Berg, A. SSD: Single Shot MultiBox Detector. arXiv: 1512.02325v5.

[5] Yuan, Z., Zhang, Z., Su, H., Zhang, L., Shen, F. and Zhang, F. Vision-based defect detection for mobile phone cover glass using deep neural networks. International Journal of Precision Engineering and Manufacturing, 2018, 19(6), 801-810.

[6] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. Generative Adversarial Networks. arXiv:1406.2661v1.

[7] Tong, L., Wong, W. and Kwong, C. Fabric Defect Detection for Apparel Industry: A Nonlocal Sparse Representation Approach. IEEE Access, 2017, 5, 5947-5964.

[8] Zou, Q., Zhang, Z., Li, Q., Qi, X., Wang, Q. and Wang, S. DeepCrack: Learning Hierarchical Convolutional Features for Crack Detection. IEEE Transactions on Image Processing. 2018, 28(3), 1498-1512.

[9] Badrinarayanan, V., Kendall, A. and Cipolla, R. SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. arXiv:1511.00561v3.

[10] Tao, X., Zhang, Z., Zhang, F. and Xu, D. A Novel and Effective Surface Flaw Inspection Instrument for Large-Aperture Optical Elements. IEEE Transactions on Instrumentation and Measurement, 2015, 64(9), 2530-2540.

[11] Cao, Z, Cui, F., and Zhai, C. Vision Systems with High-dynamic Range for Optimal Surface Defect Inspection. Applied Optics, 2018, 57(34), 9981-9987.

[12] Jiang, J., Cheng, J. and Tao, D. Color Biological Feature-Based Solder Paste Defects Detection and Classification on Printed Circuit Boards. IEEE Transactions on Components Packaging and Manufacturing Technology, 2012, 2(9), 1536-1544.

[13] He, K., Zhang, X., Ren, S. and Sun, J. Deep Residual Learning for Image Recognition. IEEE Conference on Computer Vision and Pattern Recognition, 2016, 770-778.

[14] Huang, G., Liu, Z., Weinberger, K. and Maaten, L. Densely Connected Convolutional Networks. IEEE Conference on Computer Vision and Pattern Recognition, 2017, 2261-2269.