Research on automatic defect identification technology of electronic components

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Abstract. Aiming at the problems of low efficiency and low accuracy caused by manual defect detection of electronic components, FCN, SegNet/DeconvNet and DeepLab and other deep learning technologies are studied. Using Caffe, Keras, PyTorch and other frameworks, an automatic defect identification system for electronic components is developed to distinguish qualified products from unqualified ones, so as to realize intelligent defect detection of electronic components. At the same time, the detection accuracy rate is greatly improved, and the quality of electronic components is guaranteed.

1. Introduction

In the process of production and use of electronic components, defect detection is very important to ensure the quality of components. Its purpose is to inspect the packaging quality of electronic components and identify the damage of samples in the process of packaging, transportation, installation and testing. Only when the defects of components can be detected accurately can the yield and reliability of components be ensured.

The defect detection of components is called external visual inspection in national standards, which has the characteristics of strong subjectivity. Defect detection is different from other tests. There is no data to quantify. The text on the standard seems easy to understand, but the actual situation is very different. For example, different crack shapes will affect the judgment of whether it is qualified or not. In fact, there is too much experience in doing a good job of inspection and not miss inspection.

At present, the appearance defect detection is mainly carried out by manual method, that is, the inspectors observe the external morphology of electronic components, find out the defects, and judge whether the devices are qualified according to the standard criteria and experience. This requires that the inspectors have rich experience, and qualified external visual inspection personnel of electronic components needs years of training. At the same time, with the continuous improvement of production efficiency and process level, the packaging forms of electronic components are more and more, and the number and tasks of detection are also increasing. Thousands of samples in a single batch bring great pressure to the testing personnel. The inspection time is extremely long, which causes the visual fatigue of the inspectors, increases the risk of wrong inspection, and buries hidden dangers for the later use of products. Therefore, the traditional manual detection has been unable to match with the
automatic production line. To solve these problems, the detection system is required to develop towards automation and intelligence, and integrate with the emerging artificial intelligence technology.

Along with the rapid development of machine learning and deep learning, artificial intelligence has been widely used in the field of image recognition and speech recognition. At present, it has reached the level of human image recognition, and even more than the human expert recognition level of medical chest X-ray image recognition system has been reported. Therefore, the use of artificial intelligence technology for automatic identification of electronic components defects can effectively improve the efficiency and accuracy of detection, and reduce the cost and time of personnel training [1, 2].

Traditional machine vision methods for electronic component image defect detection often rely on a large number of features extracted manually. Moreover, the traditional machine vision method is usually difficult to meet the accuracy requirements of practical application for defect samples with small difference and noise. Compared with the traditional machine vision method, deep learning has the ability to extract the deeper complex features of the image, and performs better in image classification. Therefore, this paper uses image defect detection method based on deep learning [3].

2. Establishment of component defect database

2.1. Data set preparation

Due to the deep learning model for image classification and recognition needs a large number of sample data, through sufficient training, we can accurately extract the features of samples. Therefore, the number of samples plays a key role in the whole process of training and learning. But so far, there is no public database similar to ImageNet in electronic component defects, so this paper needs to collect enough pictures [4].

Electronic components are widely used in many fields, so there are many kinds of them. The defects of various components are simplified, mainly including the following categories:

1) Defect, as shown in Figure 1.
2) Scratch or scratch, as shown in Figure 2.
3) Deformation, as shown in Figure 3.
4) Rupture, as shown in Figure 4.
5) Discoloration or blistering, as shown in Figure 5.

Fig.1 Defect of cladding or porcelain cap
Fig. 2 Scratch or scratch on coating surface
Fig. 3 Cap pit
The defect images are collected according to the product packaging category and defect category. If the number of images collected does not meet the training requirements due to the scarcity of products, the following methods are used to expand the number of samples to meet the requirements of the training set for the number of images:

1) Random rotation: randomly rotate the image by one angle.
2) Random clipping: local images in different positions can be obtained by random clipping.
3) Contrast Transformation: randomly set a contrast transformation factor on the image to adjust the contrast of the image.
4) Flip transform: flip the image vertically or horizontally.

2.2. Label
Since all the images that can be collected are images without data labels, manual annotation is a very time-consuming process for pixel level image segmentation. Labelme tool is used to label the image, and the marked file should be stored in a folder separately. Because the size of the existing images is not uniform, in order to avoid problems in training and occupy more video memory, it is necessary to compress the original images [5].

The final data set includes 6 different packaging forms and 10 different defect forms of electronic components defect library. The number of pictures is 1523, including 1211 defect pictures and 312 defect free pictures. After the data set is completed, 200 images with defects can be selected randomly, and 50 images without defects can be randomly selected as test set, which is used to preliminarily test the recognition accuracy of trained convolutional neural network; the rest of the images are used as training sets to train the convolutional neural network.

3. Research on deep learning technology of component defect

3.1. Research on automatic recognition method
The success of convolution neural network in image classification has led to the development of other visual tasks. Many kinds of backbone convolution networks, such as AlexNet, VGGNet, GoogleNet and ResNet, have sprung up, constantly refreshing the accuracy of image classification [6]. Visual tasks mainly include classification, detection and segmentation. In the classification problem, the category information of the target is given according to the content of the input image. The target location is marked in the form of bounding box or bounding box while the category is given R-CNN algorithm to complete the end-to-end target detection task SSD, Yolo algorithm, the candidate frame
extraction method is more advanced, detection accuracy and speed almost reached the limit. Image segmentation usually includes semantic segmentation and instance segmentation. The difference between them is whether to further segment the same category of objects.

The semantic concept of image domain is to complete the understanding of image content and connotation. The classification task does not provide accurate location information, and target detection is only applicable to a single center distributed target. For the targets running through the image such as roads and buildings, the detection result is generally the whole image. Semantic segmentation provides fine edge contour and category information at the same time. More fine-grained pixel segmentation meets the needs of the development at this stage. The purpose of this paper is to identify defects automatically, which requires that the system can identify defect areas and calculate some feature sizes of defects. Therefore, the purpose of this paper cannot be achieved only by classification method, but also by semantic segmentation method.

At present, the basic algorithms for image semantic segmentation include FCN, SegNet/DeconvNet, DeepLab and so on [7, 8].

1) FCN

FCN (full convolutional networks) proposed by Long et al. in 2015, it realized image semantic segmentation based on end-to-end convolutional neural network for the first time. The accuracy of the test set is much higher than that of the non-deep learning scheme, and the complexity of the process is greatly reduced.

2) SegNet/DeconvNet

SegNet/DeconvNet was proposed in 2015, which is a codec structure designed for the problem of image loss in FCN. The feature extraction part is called the encoder, and the part that transforms the extracted feature map into the prediction graph is called the decoder.

3) DeepLab

DeepLab is the research achievement of Google team in the field of image semantic segmentation, which is divided into DeepLab V1, DeepLab V2, DeepLab V3 and DeepLab V3+. In DeepLab V1 version, the algorithm combines the deep convolution neural network (DCNNs) and probability graph model (DenseCRFS). DeepLab V2 is optimized to solve the problems of V1, such as low feature resolution, multi-scale object and DCCN translation invariance. In V3, in order to solve the multi-scale problem of segmented objects, multi-scale hole convolution cascading or parallel is adopted to capture multi-scale background. DeepLab V3+ version continues to improve the framework of the model. In order to integrate multi-scale information, the encoder decoder framework, which is commonly used in semantic segmentation, is introduced. In the encoder decoder architecture, the resolution of the feature extracted by the encoder can be controlled arbitrarily, and the accuracy and time-consuming are balanced by hole convolution.

Through comparative analysis, DeepLab V3+ is the most advanced algorithm for image semantic segmentation, so this paper uses DeepLab V3+ version algorithm as the basic algorithm, optimizes it according to the characteristics of component image and defect recognition, and adds conditional random field / Markov random field.

3.2. Analysis of deep learning framework

Common deep learning frameworks include Caffe, CNTK, Keras, MXNet, TensorFlow, etc. Among them, Caffe, Keras and PyTorch are three commonly used deep learning frameworks. Each of the three frameworks has its own advantages and disadvantages [9, 10].

1) Caffe

Caffe is a clear and efficient deep learning framework, and it is also a widely used open source deep learning framework. The main advantages of Caffe framework are relatively easy to use and fast to train, but its disadvantages are inflexible, requiring a large amount of unnecessary redundant code, only a small amount of input format and one output format, which is not suitable for constructing cyclic networks.

2) Keras
Keras is written in pure Python and based on Tensorflow, Theano and CNTK back-end. It is equivalent to the upper interface of Tensorflow, Theano and CNTK. It is called 10 lines of code to build neural network. It is easy to operate, easy to use, rich in documentation and easy to configure environment, which simplifies the difficulty of neural network construction code writing.

Keras has the advantages of simple and easy to use API, complete documentation, good scalability and wide distribution of users. However, Keras has obvious disadvantages, mainly slow speed, especially the program takes up more GPU memory.

3) PyTorch

PyTorch is an open source Python machine learning library based on torch, which is used for natural language processing and other applications. In January 2017, the Facebook Institute of artificial intelligence (FAIR) launched PyTorch based on torch. PyTorch is the same as the torch framework, but it rewrites a lot of content with Python. It is not only more flexible, supports dynamic graph, but also provides Python interface. Compared with the first two frameworks, PyTorch has obvious advantages in several aspects: easier to use, easier to create and debug graphs, and easier to load data.

To sum up, PyTorch is more conducive to researchers to quickly build prototypes. Therefore, this paper adopts PyTorch framework.

3.3. Optimization design of system framework

Because the component defect identification and segmentation algorithm needs to traverse all the pixels in the picture, it will bring a lot of calculation and affect the recognition speed. Therefore, the feature detection module is added to quickly identify, locate and frame the defects, and then the frame out part is handed over to the segmentation module and the micro shape detection module to separate the defect parts. The feature detection module adopts the mature Yolo V4 algorithm, but the network of the algorithm is reduced to some extent, and the unnecessary functions are removed. At the same time, the steps that will bring noise to the image are removed to avoid noise to the image and affect the segmentation accuracy.

Adding the micro shape detection module is to consider that some failure parts are small, which may be removed by the network as noise in the process of processing. Adding the micro shape detection module can effectively ensure the occurrence of such errors.

After the above model framework is determined, the software is completed by programming. After the training of the model, the test set is used to test, and the recognition rate of the test set is calculated and analyzed. At the same time, the loss curve of the test set and the training set is read to analyze the rationality of the model.

According to the test results, the model is improved in two aspects when necessary
1) Changing the size of convolution kernel
2) Reduce network complexity

According to the analysis results, the parameters and super parameters of the network are adjusted to achieve 96% recognition accuracy and ensure certain generalization ability.

4. Construction of automatic defect identification system

Through the above-mentioned deep learning technology research and software construction, combined with high-definition industrial camera and surround light design, an automatic defect identification system for electronic components is developed, as shown in Figure 6.

In order to fully verify the performance of the system, five kinds of packaged devices were selected for automatic defect identification, and three senior testers conducted additional visual inspection and gave comprehensive judgment opinions. By comparing the similarities and differences between the two opinions, it is confirmed that the system performance can achieve the accuracy rate of more than 95%.
5. Conclusion
At present, the defect identification of electronic components mainly depends on manual work, which is inefficient, and the accuracy is greatly affected by human factors. In this paper, the artificial intelligence technology is used to develop an automatic defect identification system for electronic components, so as to realize the automatic identification of defect detection. Compared with the preset judgment, it can distinguish qualified products from unqualified products, and realize the intelligent detection of electronic components defects. In order to meet the increasing demand of component detection tasks, the detection accuracy is guaranteed and the detection efficiency is greatly improved.

Fig. 6 Automatic identification system for component defects

In the future, it is still necessary to strengthen the establishment of defect database of more kinds of components, optimize the deep learning recognition algorithm, reduce the impact of noise on image processing, and ensure the quality of electronic components more comprehensively.

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