Ball Grid Array Solder Void Inspection Using Mask R-CNN

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ABSTRACT

The ball grid array is one of the packaging methods that used in high density printed circuit board. Solder void defects caused by voids in the solder ball during the BGA process do not directly affect the reliability of the product, but it may accelerate the aging of the device on the PCB layer or interface surface depending on its size or location. Void inspection is important because it is related in yields with products. The most important process in the optical inspection of solder void is the segmentation process of solder and void. However, there are several segmentation algorithms for the vision inspection, it is impossible to inspect all of images ideally. When X-Ray images with poor contrast and high level of noise become difficult to perform image processing for vision inspection in terms of software programming. This paper suggests the solution to deal with the suggested problem by means of using Mask R-CNN instead of digital image processing algorithm. Mask R-CNN model can be trained with images pre-processed to increase contrast or alleviate noises. With this process, it provides more efficient system about complex object segmentation than conventional system.

Key Words : Computer vision system, Digital image processing, BGA, Automatic X-Ray inspection, Solder joints void, Object segmentation, Deep learning

1. Introduction

In BGA, one of the packaging technologies, the roll of solder ball is very important. The solder ball connects the chip and the substrate so that an electrical signal is transmitted. In this case, the shorter connection can minimize inductance, resistance, electrical delay, and thermal path. It also includes more I/O and takes the advantage of being able to use the back side of the chip for cooling. When the defective solders like voids are not detected in the packaging process, it may cause electrical failure, which will lead to a fatal problem in its functionality.

Currently, the most used method for solder void inspection is optical inspection using X-ray images. The biggest advantage of using the X-ray optical inspection method is non-destructive inspection which provide non-contact inspection to the PCB. However, the quality of X-ray images is largely affected by the environmental conditions of lighting and cameras. This leads to poor contrast and unexpected noises, and it degrades the accuracy of the inspection. In this paper, we use Mask R-CNN [1], a representative image segmentation deep learning model, to solve the problem of object segmentation in inspection using conventional image processing. The experiment uses image of a large amount of solder voids that present in the actual PCB, which was provided by sec company. First, we test the performance of the Mask R-CNN model from which the original images that have not been pre-processed is trained. Second, a contrast enhancement technique, histogram stretching, CLAHE [2], to enhance for the poor contrast of the X-ray images is applied to the original images, and the performance of the Mask R-CNN model trained with the

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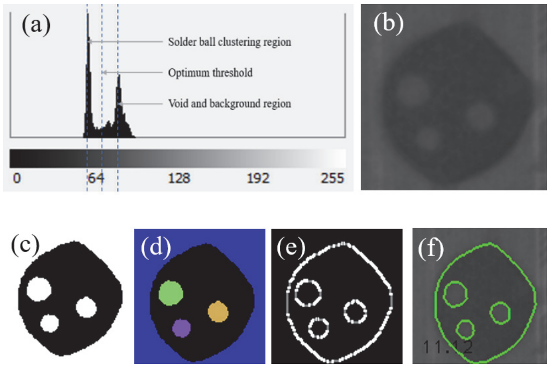


Fig. 1. Conventional inspection process of ideal image: (a) Histogram of original image, (b) Original image, (c) Binary image, (d) Image that is labeled with each class, (e) Image that is detected edge, and (f) Inspection result of original image.

applied images is evaluated. Through the results of the experiment, we evaluate the utility of solder void inspection using Mask R-CNN. We also evaluate whether the contrast enhancement technique is effective as a pre-processing process for deep learning model training for images with poor contrast.

2. Solder void inspection process

2.1 Conventional inspection of solder void

The most important process in the solder void inspection process is the segmentation process of solder and void. In the class segmentation process using the conventional segmentation algorithm, intensity-based segmentation methods or edge-based segmentation methods are usually used.

When performing intensity-based segmentation, first find the optimum threshold in the histogram using adaptive thresholding algorithm [3] or Otsu thresholding algorithm [4]. After that, the solder class and the void class can be segmented by thresholding based on the optimum threshold like the second dotted line in Fig. 1 (a). When the image like Fig. 1 (c) in which the area is divided by thresholding is labeled using Hoshen Kopelman labeling Algorithm [5], the area of the solder and the void area can be obtained, respectively. Fig. 1 (d) is an image with labels assigned to each area. Using an image with a label as shown in Fig. 1 (d), the area of solder and void can be obtained, and the defect rate can be found by substituting this into Equation (1). The edge-based thresholding method is used to print inspection results. The edge-based segmentation method mainly uses first-order differential edge detection [6,7], second-order differential edge detection [8], and canny edge detection [9]. Fig. 1 (e) is an image obtained by extracting the edge of a binary image, and using this image, the inspection result is output as shown in Fig. 1 (f).

Fig. 2. Problem due to unexpected causes.

$$Defect\ Ratio = \frac{\text{Area of Void}}{\text{Area of Void + Area of Solder}} \tag{1}$$

However, this existing method has a fatal drawback. The reason is that exception handling programming is required for unexpected noises or exceptional pixel characteristics. It has unnecessary noise in the X-ray image. Because it is an image obtained through an object. Fig. 2 shows inspection failures caused by various types of noise captured at the same time when an X-ray image was captured. In addition, since the contrast of X-ray images is also poor, high technical skill is required for ideal segmentation. For these reasons, there inevitably exist an image that cannot be ideally inspected using conventional segmentation algorithms.

2.2 Inspection of solder using Mask R-CNN

Various noise reduction, contrast enhancement, and image segmentation techniques exist, but it is impossible to perform ideal segmentation for all unexpected cases. In this paper, to overcome this problem, a deep learning method that extract the features of objects well while being robust to various distortions and noises of an image is used for solder void inspection. To obtain the solder area and void area, a deep learning model that can segment objects for each pixel is required, not simple object detection. Therefore, we use the Mask R-CNN model, which can obtain the resulting image with a class assigned to every pixel. The Mask R-CNN model is a combined model of Faster R-CNN [10] model and FCN [11] model, and it has a feature of using an ROI align method instead Table 1. Hyperparameters applied to the training process of an ROI polling method when calculating a bounding box. We evaluate the solder void inspection performance of Mask R-CNN trained in this experiment. And considering that the images to be inspected are X-ray image with poor contrast, we also evaluate whether the way the model is trained after pre-processing the image with contrast enhancement technique affect the inspection performance.

Table 1. Hyperparameters applied to the training process

Experiment Hyperparameters	
Loss rate	0.001
Epoch	50
Batch size	14
Train Val ratio	7:3
Data augmentation	X

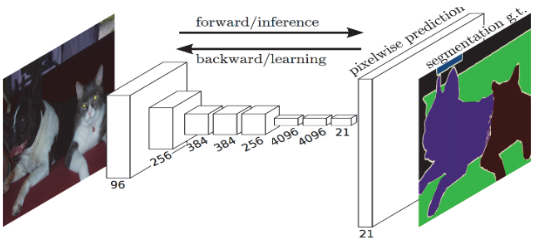


Fig. 3. Mask R-CNN Architecture.

Fig. 3 shows the operation mechanism of the Mask R-CNN. Each time the original image passes through the convolution layer, it is transformed into a small and compressed 3D matrix, and the final matrix has probability information corresponding to each class of pixels. Finally, the last matrix is stretched to the size of the original image, and the image with the highest probability class per pixel is obtained. Using the mechanism of Mask R-CNN, the original solder void image is converted into an image that is divided into a solder class and a void class. If an image in which the solder class and the void class are divided is obtained, the defect inspection result can be obtained using Equation (1). Fig. 4 gives a brief overview of the experiment, and in the following section we will show the detailed experimental method.

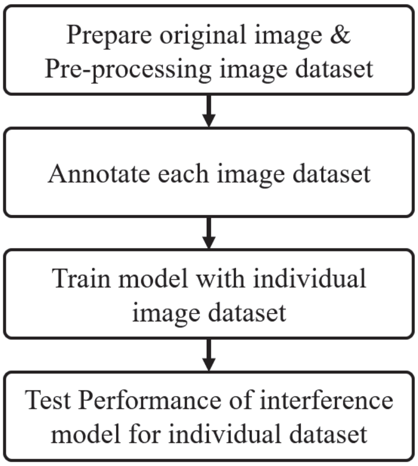


Fig. 4. Experiment Flow Chart.

3. Experiment method for Deep Learning Model

3.1 Preparing Dataset

The dataset used for the experiment is a total of 5,489 images of solder void taken with X-ray. The size of the original image is different from each other, and the size of the smallest image is 50×50 pixels. However, if the size of the image is too small, the features of the image will be limitedly extracted, whereas if it is too large, it will be difficult to process and recognize the image in a short time, so adjust the size of the image to 120×120 pixels [12].

3.2 Model Training Environment

Training and testing process take place on Supervisely, a web platform for computer vision. The experiment is conducted using the "Deep Learning AMI (Amazon Linux 2) Version 46.0" and the "p3.2xlarge" hardware instance of Amazon AWS EC2, and the training hyperparameters are specified in Table 1.

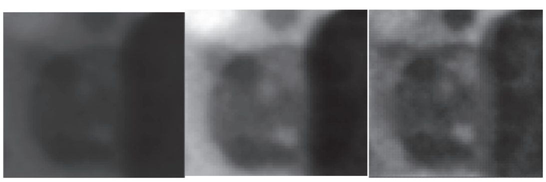
3.3 Training with Pre-processed Dataset

In the experiment, we evaluate the performance of the

Mask R-CNN model trained on three kinds of datasets. The three datasets consist of the original dataset like Fig. 5 (a), the dataset like Fig. 5 (b) that pre-processed using histogram stretching, and the dataset like Fig. 5 (c) that pre-processed with CLAHE. The contrast is poor because the original image is an X-rayed image. Therefore, the histogram stretching and CLAHE, which are methods to improve the contrast, are used as pre-processing methods. Fig. 5 (b) is an image with improved contrast by converting all grayscale pixel values $f(x,y)$ of the image of Fig. 5 (a) to $g(x,y)$.

$$g(x,y) = \frac{f(x,y)-G_{min}}{G_{max}-G_{min}} \times 255 \tag{2}$$

The image Fig. 5 (c) is an image in which CLAHE is applied to the image Fig. 5 (a). The tile size is 8×8, and the clip limit is set to 4.



(a) (b) (c)

Fig. 5. Three datasets used in the experiment: (a) Original image, (b) image with histogram stretching applied, and (c) image with CLAHE applied.

4. Results & Discussion

Two of the performance evaluation indicators of the trained model were used. The first metrics are train loss and validation loss, which indicate how identical the input and output images are during the training process. The second evaluation metric is mAP [13]. It is a widely used method for performance evaluation of object detection algorithms. In the training process of 50 epochs, we tested the mAP by loading the inference of the model with the lowest loss value. 200 sampled images were used as input image for the mAP test. This dataset is a dataset composed by sampling 25 sheets each of 8 cases representing the total dataset of 12,816 sheets.

Train loss and validation loss showed no significant difference in all three datasets. Through the mAP result, mAP of the model is high even if the model is trained only with the original images. The model pre-processed using histogram stretching did not differ significantly from the model trained using only the original image in mAP, and the model pre-processed using CLAHE had the highest mAP among the three models.

Table 2. Loss and mAP results of model trained with each three datasets

Value		Original image	Histogram Stretching	CLAHE
Train loss		0.125	0.120	0.136
Validation loss		0.223	0.248	0.328
Recall	Solder	0.975	0.995	1.000
	Void	0.965	0.958	0.965
AP	Solder	0.975	0.995	1.000
	Void	0.948	0.938	0.965
mAP		0.962	0.966	0.983

5. Conclusion

Due to the characteristics of the X-ray image taken through the object, it is difficult to ideally segment the image using the conventional image processing method due to various noises. Since the inspection method using deep learning can overcome these shortcomings, so it shows high accuracy even when inspecting complex types of inspection object. If we analyze the performance of the inference model of the dataset pre-processed using CLAHE among the experimental results, the fact that the solder class recall and AP both have a value of 1 means that the inspection model has the same performance as human visual inspection 100% do. Void detection is relatively difficult compared to solder ball. However, considering the recall and AP value of 0.965, it indicates that the inspection model has excellent performance with an error of 3-4 % compared to human visual inspection. As a result, for complex images, the solder void inspection method using deep learning is more effective than the inspection method using traditional image processing. CLAHE pre-processing showed an effect in alleviate black noise(caused by other components) that is common in solder void images taken by X-ray.

In the case of solder void inspection, only two areas of solder and void need to be extracted, so it shows high segmentation performance even without pre-processing the input image. However, for images with poor contrast, when the model was trained by applying the contrast enhancement method as a pre-processing method, the model showed slightly better performance. Therefore, when the model is trained by pre-processing the input image according to the image characteristics, performance improvement can be expected in the inspection performance.

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