AI-Driven BGA Solder Joint Failure Detection of PCB Assembly

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AI-Driven Solder Joint Failure Detection of PCB Assembly

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Abstract

This paper introduces an AI-driven approach to bolster the reliability of automatic solder joint failure detection for PCB Assembly development. Our method employs a 2-stage framework integrating localization and classification. To address domain specific challenges, we propose a post-training correction method based on a fixed solder joint arrangement. Our work is validated on unseen data acquired in a field.

I. Introduction

Solder joint defect analysis is crucial for ensuring reliable PCB Assembly development. Among the various physical failure analysis techniques for solder joints, dye&pry relies on visual inspection, where human labor is exhaustively spend to analyze defective types of dyed solder joints. For example, creating manual defect maps for a PCB Assembly takes approximately 3.5 hours. In addition, due to the relative bias among analysts, there exists variations between defect maps which needs to be eliminated and standardized. Therefore, use of AI-driven techniques is highly necessary for efficient and fair investigation.

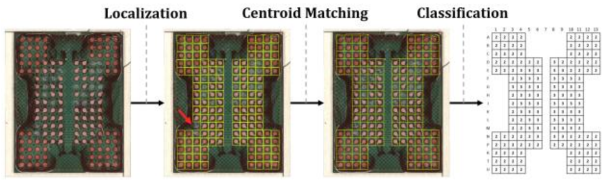

Figure 1. Overview of our framework

Recent studies on image classification [1] and object detection [2] have shown overwhelming performance on natural images. However, the direct application of these models to different domains [3] often leads to inferior performance, possibly due to the domain specificity. For better performance, a modification using domain knowledge is required.

In this regime, we propose to utilize fixed arrangement of solder joints as post-training correction method that localizes missing solder joints on the detection model. For the correction method, we adopt a 2-stage detection framework consisting of localization and classification. In the classification, since solder joint failures do not occur frequently, we adopt a focal loss [4] to tackle this skewed distribution.

Our work brings the following contributions: 1) We successfully apply an AI model to BGA PKG (Ball Grid Array Package) solder joint failure mode classification, which is accurate and significantly faster than visual inspection, 2) the proposed correction method can be applied to other BGA PKG with various ball array.

II. Methods

As in Figure 1, our framework follows a sequential process comprising solder joint localization and fail mode classification. Centroid Matching serves as an ad-hoc hedge for localization.

2.1 Solder Joint Localization & Centroid Matching

Solder joint localization aims to identify the solder joints without classifying the fail type. In this regard, we label the solder joints as the foreground. We employ Faster-RCNN [5] over YOLO [6] due to accuracy being the primary issue in this domain rather than operation time. Since the number of solder joints is fixed, the maximum prediction number is limited through confidence-wise order in prediction head.

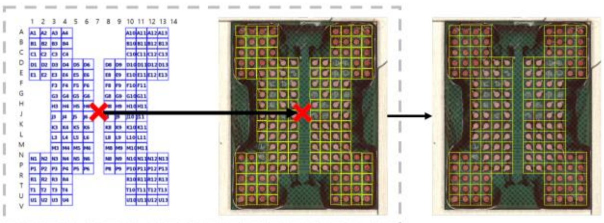

Figure 2. Description of Centroid Matching

Even if the localization model shows high accuracy, false positives (e.g. wrongly defined as solder joints) or false negatives (e.g. missing solder joints) may occur. Even one false case is critical as the corresponding solder joint cannot be fed into a classification model. However, the remaining large number of true cases, combined with domain knowledge, allows us to cope with it. In the case of PKG with 152 solder joints, as shown in Figure 2, few outliers out of 152 solder joints do not affect true centroid much. While each input images differ in margin outside of PKG, solder joints locate in fixed location inside the PKG like a grid. Simply moving the grid to match its centroid with predicted one can provide aligned localization and ensure every solder joint is identified.

2.2 Fail Mode Classification

After the centroid matching, cropped solder joint images according to the aligned coordinates are fed to a classification model. There are 6 classes indicating the solder joint fail mode (e.g. 0: Solder Crack, 1: No Solder Crack, 2: PCB Cratering, 3: No PCB Cratering, 4: PKG Cratering, 5: No PKG Cratering). Due to the domain specificity, our training data is highly imbalanced due to different frequencies of defect types. To deal with this, we adopt focal loss in classification.

Ⅲ. Experimental Setting

3.1 Dataset

Figure 3. Train and Test data distribution

The data is an image of the bottom side of the PKG, and to obtain the image, the PKG is mounted on the PCB surface and environment or mechanical test is performed. After test, detached the PKG from the PCB and take images. Both training data and test data are obtained by actual evaluation or harsh processing on SK Hynix to generate more defective data, as the data of pass modes are overwhelmingly large in a general evaluation situation. For localization, we prepared 284 PKG images for training, and 106 images for test.

Corresponding solder joint images are cropped and used for classification. The solder joint image can have one of the 6 modes, three pass modes and three fail modes, that occur in the solder joint. Among the fail modes, class 4 (PKG Cratering) has the lowest frequency of occurrence compared to other modes, causing data imbalance as visualized in Figure 3.

3.2 Experimental Setup

3.2.1. Data Pre−processing

In localization, we pad the PKG images for batch−processing and downsampled into half. In classification, we resized the input solder joints images to (140, 140). To mitigate the color gap across images, we applied color−jittering of 0.15 for brightness, contrast, saturation and hue. Also, training images both in localization and classification were horizontally or vertically flipped with 0.5 probability.

3.2.2. Training Details

Stage	Localization	Classification
Model	Faster R−CNN	ResNet−18
Learning Rate	5e−6	1e−3
Batch Size	32	1024
Weight Decay	1e−3	1e−3

Table 1. Hyperparameters

We adopt Faster R−CNN and ResNet−18 each for localization and classification, following the settings of [3] and [7]. Our whole framework was trained with AdamW optimizer [8] along with cosine learning rate [9]. We summarized the details in Table 1.

3.3. Metrics & Baseline

Since the maximum number of predictions was regulated in Section 2.1, we adopt the Accuracy@IoU=0.70 as the evaluation metric. If a ground truth solder joint overlaps more than 70% with any prediction, we regard it identified. Then, the metric can be formulated as $\frac{\#Identified@IoU=0.70}{\#Ground\ Truth}$.

For solder joint classification, due to the skewed data distribution, the F1−score is adopted as the metric together with accuracy.

3.4. Performance Evaluation

Method	Faster R−CNN	Faster R−CNN + Centroid Matching
Accuracy	0.980	1.000 (+0.020)

Table 2. Evaluation on Localization

Table 2 shows the effect of Centroid Matching. Using our domain knowledge on each package, our post−training method compensates model's mistake and better align every solder joint in given PKG images.

Loss Function	Accuracy	F1−Score
Cross−Entropy Loss	0.9764	0.8943
Focal Loss [4]	0.9741	0.9001

Table 3. Evaluation on Classification

While focal loss doesn't show increase on accuracy compared to cross−entropy loss, F1−score, which is more critical, has increased. Furthermore, considering that human error is about 3~5%, our results are feasible to replace the human effort in the field.

Ⅳ. Conclusion

We proposed a two−stage framework suitable for accurate solder joint failure mode classification. Based on the PKG structure, we restricted the number of solder joint predictions to those of the ground truth. Then, we proposed centroid matching, which again uses the structure to suggest more refined predictions. On these localized solder joints, adopting focal loss on our work can tackle the data skewness problem. Our framework is validated on the evaluation data for both localization and classification, and can be extended to other PKG types.

Acknowledgement

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