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Void detection in solder bumps with deep learning

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ABSTRACT

Wafer level chip scale packages feature large numbers of solder bumps. These bumps are prone to having voids arising for instance from outgassing during the solder reflow. These voids are considered a reliability risk for the thermo-mechanical strength of the solder connection. Screening of bumps on void percentage is therefore required for quality control. Voids are well captured with X-ray radiography. Void detection in X-ray images is the topic of this paper. The large number of solder bumps necessitates the detection to be automated. In this article we first employ conventional threshold based methods to identify voids. Then, we apply a deep learning model to void percentage detection. We will demonstrate that with a proper training data set deep learning can successfully bin solder bumps on their void percentage.

1. Introduction

WLCSP devices are prevalent in the industry as they enable a large number of IO pads, contacted by solder bumps, without excessive die area. After mounting devices on PCBs, voids may be present in the solder bumps. These voids can have various origins, for instance outgassing or contraction stresses, both during the reflow process. Voids in solder bumps are considered a reliability risk since they are believed to degrade their thermo-mechanical strength if their total area becomes too large [1]. It is therefore of importance to inspect solder bumps for the presence of voids.

X-ray radiography is well suited to visualize such voids in a 2D fashion. Namely, a void appears as a bright region in a dark surrounding since X-rays will be absorbed less in the projected volume of material of which the void is part, since that volume has lower density because of the void. Further, the high resolution of X-ray radiography, on the order of 0.5um, is much smaller than solder bumps and voids, implying that void content can be mapped accurately. In this work a 180 kV Phoenix Nanomex X-ray inspection tool was used to collect all X-ray images. The sheer quantity of bumps and voids within necessitates that the detection of voids is done automatically. Analysis of such images is however complicated in that voids may for instance be masqueraded by PCB copper traces, vias, or components (on the rear side of the PCB). Besides, the overall image contrast and brightness will also vary as a function of magnification, device and PCB, X-ray operator, etc. This makes the automatic detection of voids a challenging task, since the algorithm needs to cope with all these variations [2].

One way out would be to reduce the number of variations by imposing for instance strict X-ray machine settings and having different algorithms for different devices, all this at the cost of versatility. Another way would be to implement several pre-image analysis steps that bin the images and each bin has its own void detection algorithm, at the cost of program complexity. In this article we try a different approach, namely to involve a deep learning [3] model that is trained to detect solder bumps and voids within. Training a deep learning model requires in general a significant data set that we generate by classifying X-ray images in a conventional way, namely by detecting voids with threshold techniques, that require adjustment based on the contents of the image.

The article is organized as follows; first we discuss the threshold techniques employed to detect voids. Then we describe the deep learning model used and show the results it gives on a broad image type data set that comprises images of various devices capturing a rich image variation.

2. Void detection based on conventional thresholding

X-ray images give a 2-dimensional representation of the solder bump void content. A typical example image is given in Fig. 1. Threshold techniques can be employed to detect solder bumps and voids within. In general, thresholding can be global, that is, a single threshold for all image pixels, or local, i.e. an individual threshold for every image pixel. Solder bumps are well detected with global thresholding, such as the isodata algorithm. This would identify the bumps, together with other objects that have a similar image contrast, as for instance the vias in Fig. 1. What is a solder bump can then be identified

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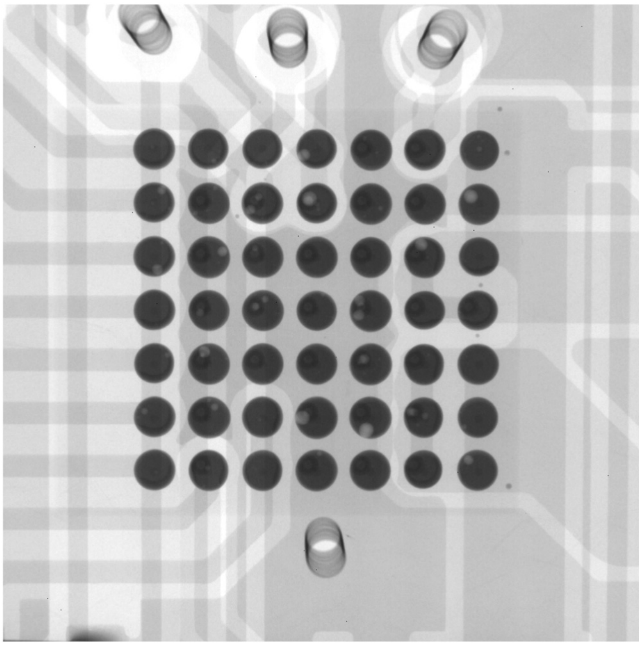

Fig. 1. X-ray image of WLCSP device on PCB. This image is used for the evaluation of the various void detection models described below.

by imposing a circularity constraint on the detected objects, with 80% typically doing the job. In this way, area of interests (AOI) are extracted, each of which constitutes a bump. Then, the process can be repeated on each individual AOI to detect voids within. Again, thresholding is applied but is in general more subtle since the contrast delta between void and bump can be quite small. Typically, different threshold algorithms, both global and local ones, have to be tried to figure out which works best for the image at hand. Moreover, various correction steps have to be applied to prevent for instance identifying the solder bump edge (naturally lower contrast) as a void. One can think here about erosion and dilation steps, and circularity and size constraints. After identifying all likely voids, their percentage of the total bump area can then be calculated for each individual bump. In this way, the algorithm fine-tuned for a single image is found to work quite well for images of multiple devices taken under similar tool settings.

Such a generic optimizable algorithm was constructed using the scriptable image-analysis tool Fiji (ImageJ) [4] and the result of analysing Fig. 1 on voids is shown in Fig. 2. It should be noted that the threshold algorithm does not always identify all voids but with some fine-tuning the far majority can be captured. A downside of the thresholding is that the calculated void area will also depend on the fine-tuning which therefore gives an additional variation in results.

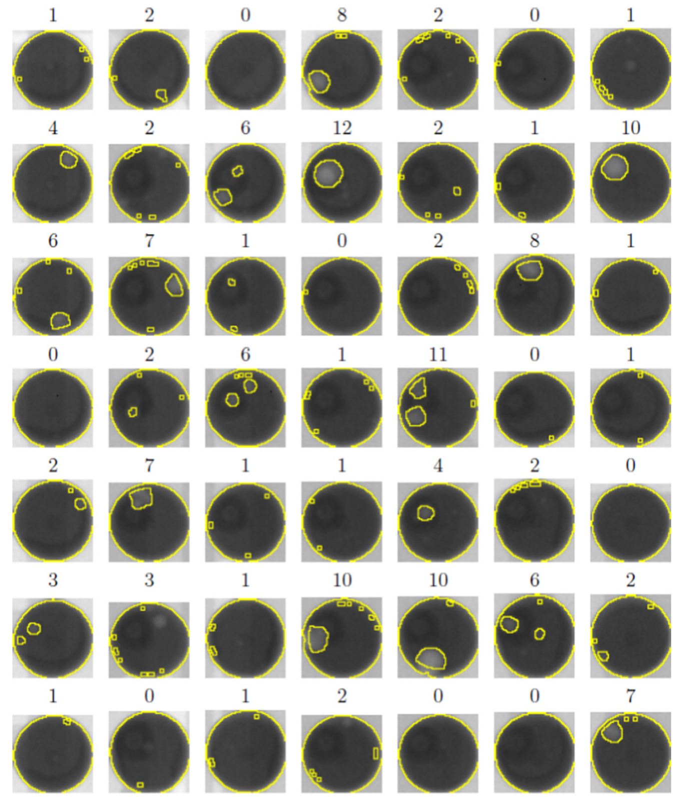

Fig. 2. Individual solder bumps of Fig. 1 with calculated void percentage written above each bump, as found using the threshold model.

3. Void detection with deep learning

3.1. Model description

Deep learning has in recent years taken an enormous flight and is now applied to numerous tasks ranging from machine translation to object detection. Various software libraries exist that allow a straightforward implementation of complex neural networks (NN). In this work we use Tensorflow [5]. Furthermore, proven models can be readily employed to new tasks by retraining them with a new dataset.

Images are typically analysed with convolutional neural networks since these are sensitive to local areas of the image, also called receptive fields, that are likely spatially correlated. Multiple layers of neurons (deep network) allow for the detection of increasingly global image features.

Image analysis can be of several types, namely, classification (determine the class the total image belongs to), object localization (find the bounding box of an object in an image), object detection (locate multiple objects in an image), segmentation (find the boundary of an object in an image). Here, we choose to use a deep learning model that does object detection in order to find individual bumps and classify them according to their void percentage. The deep learning model employed is a region-based convolutional neural network (R-CNN), namely, the Faster-R-CNN-ResNet-101 model (where 101 is the total layer depth) that is optimized for the pascal voc image data set [6] and is therefore deemed suitable for analysing X-ray images.

R-CNN uses a pre-trained convolutional neural network to generate a feature map from the image. Then, at each point of the feature map a set of bounding boxes of various aspect ratios is defined, called anchors. These are input for the Region Proposal Network (RPN) that determines for each anchor whether its contents are an object or belong to the background. Also, the anchor offset is determined that maximizes the overlap with the object. Finally, a region-based CNN is used to classify the features. The RPN and region-based CNN are trained on a dataset to minimize the overall loss function. See [7] for a detailed discussion on Faster R-CNN.

3.2. Data set

Ideally, the void identification model is capable of handling a diverse range of X-ray images of various products and tool settings. Such a