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Synthetic Data for Deep Learning: Segmentation of PCB X-Ray Images

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Reverse engineering, defect analysis, and inspection are important tasks in the field of electronic devices. In the process of electronic device inspection, X-ray imaging has proven to be one of the most effective non-destructive techniques for obtaining a 3D view of the sample with good resolution. However, the data obtained by X-ray imaging is generally large, and manual inspection of the data can be a time-consuming task. To overcome this challenge, an automatic segmentation system can be implemented to assist with the inspection.

In order to inspect a printed circuit board (PCB), the board should first be segmented to differentiate between copper and other materials in the PCB, such as glass fiber. Different image processing techniques can be used for this task, including Otsu's thresholding [1], active contour models [2], and k-means clustering [3]. While these methods are capable of effectively segmenting the circuits in a PCB X-ray scan, there is still a significant challenge in accurately differentiating between nodes and connections in order to automatically extract the net list.

Several studies have been conducted toward PCB reverse engineering, such as [4, 5, 6, 7, 8]. For example, Botero et al. proposed a via detection framework that utilizes the Hough circle transform for the initial detection, followed by an iterative false removal process developed specifically for detecting vias. They compared their proposed methodology to an adjustment of a Mask R-CNN network [8].

Deep learning methods offer excellent segmentation capabilities that can be applied to specific tasks such as the segmentation of nodes and connections in PCB X-ray images. However, these methods require large training datasets, which can be a very time-intensive task. To address this challenge, we propose a method of training a deep learning network with synthetic data to segment the nodes and connections in a 2D X-ray image of a PCB sample. Our network is able to segment the nodes with high accuracy, without seeing any real PCB data.

We utilized a U-net network [9] with a VGG16 backbone [10] for our segmentation purposes. The training data for our model was generated by drawing simple disks as nodes and lines connecting some of them as connections. We used various larger intensities (near white) for drawing the nodes and connections and various smaller intensities (near black) for the background. To simulate the noisy image collected by the X-ray machine, we added some noise to the generated images.

We trained two similar networks separately on 20,000 synthetic images to segment the nodes and the contents of the X-ray image. After training for 100 epochs, the networks were able to segment the nodes and the contents of real X-ray images with high accuracy. With the content and the locations of the nodes, a graph traversal algorithm like depth-first search can be utilized to find the connections between the nodes in the segmented content of the image.

The method we proposed is a crucial solution in the semiconductor industry, where preparing an annotated dataset can be very expensive, and the dataset can be very unbalanced as images of fault locations are very limited. The method can also be applied to other types of electronic devices. Additionally, the method can be extended to other fields, such as medical image segmentation, where training data is limited.

References

1. N Otsu, *IEEE Transactions on Systems, Man, and Cybernetics* **9** (1979), p. 62.
2. M Kass, A Witkin and D Terzopoulos, *International Journal of Computer Vision* **1** (1988), p. 321.
3. J Macqueen, *5th Berkeley Symp. Math. Statist. Probability* (1967), p. 281.
4. RC Mata *et al.*, 2006 International Conference on Computing & Informatics (2006).
5. N Asadizanjani *et al.*, International Symposium for Testing and Failure Analysis (2015).
6. N Asadizanjani, M Tehranipoor and D. Forte, IEEE Transactions on Components, Packaging and Manufacturing Technology (2017), p. 1.
7. S Kleber, HF Nölscher and F Kargl, Workshop on Offensive Technologies (2017).
8. UJ Botero *et al.*, International Symposium for Testing and Failure Analysis (2020).
9. O Ronneberger, P Fischer and T Brox, Lecture Notes in Computer Science (2015), p. 234.
10. K Simonyan and A Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, arXiv (2014).