02-19

16th International Conference on Machine Vision Applications (MVA)
National Olympics Memorial Youth Center, Tokyo, Japan, May 27-31, 2019.

PCB-METAL: A PCB Image Dataset for Advanced Computer Vision Machine Learning Component Analysis

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Abstract

We introduce PCB-METAL, a printed circuit board (PCB) high resolution image dataset that can be utilized for computer vision and machine learning based component analysis. The dataset consists of 984 high resolution images of 123 unique PCBs with bounding box annotations for ICs(5844), Capacitors(3175), Resistors(2670), and Inductors(542). The dataset is useful for image-based PCB analysis such as component detection, PCB classification, circuit design extraction, etc. We also provide baseline evaluations for IC detection and localization on state-of-the-art deep learning object detection algorithms.

1 Introduction

Printed Circuit Boards (PCBs) are the building blocks for the electronic industry. They find their place in every consumer electronics being produced, thus accounting for the need of mass production. Not all PCBs that are mass produced work and a significant amount of them turn out be defective. Automatic Optical Inspection (AOI) [10, 11] system has been widely used to inspect defects in PCBs during the manufacturing process to identify and eliminate those defective PCBs. These visual inspection systems find their applications in identifying defective IC chips and other components.

Circuit boards for electronic devices contain more circuits with components that are densely packed, causing difficulties with techniques that detect defects. The variability in the type of PCBs being analyzed creates constant challenges in developing an automated visual inspection system. These visual inspection systems use image processing techniques such as edge detection, key points, morphological operations, etc. for detecting and segmenting components, identifying breaks in electrical pathways, and classifying components, vias, and said electrical pathways. for detecting defects. However, such techniques heavily rely on the quality of the image and is prone to produce high false positives. Also, for training-based approaches, the quality of the training data is crucial to achieve a model that produces accurate detections. Hence, the need for a high-quality PCB image dataset arises for developing highly reliable automated inspection systems.

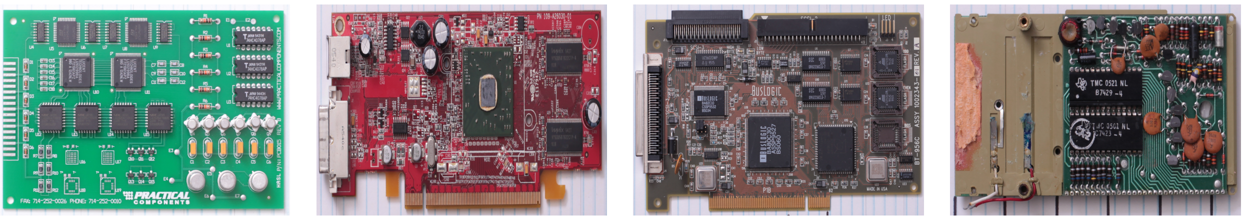
Figure 1. Image acquisition setup.

In this paper, we present a high quality PCB image dataset - PCB-METAL(PCB- Micro Electronics Taken Apart Logically) for researchers to develop techniques for automated inspection systems. The dataset comes with bounding box annotations of various components such as IC chips, Capacitors, Resistors, and Inductors. Such annotations are useful for systems that aim to detect these components using automation. Such techniques can also be utilized for reverse engineering a circuit board which is a challenging manual process. Further, we present baseline evaluations of state-of-the-art deep learning-based object detection techniques and their performance in detecting IC chips.

1.1 Contribution

Our contributions in this work are as follows.

(1) We provide a open access dataset (PCB-METAL) of high resolution PCB images for computer vision based analysis.



(a) Example Image 1 (b) Example Image 2 (c) Example Image 3 (d) Example Image 4

Figure 2. Example images from PCB-METAL dataset.

(2) We provide bounding box annotations in both text and xml formats for IC, capacitors, resistors, and inductors.

(3) We present a detailed baseline evaluation of state-of-the-art machine learning approaches on IC detection and localization using the PCB-METAL dataset.

The rest of the paper is organized as follows. Section 2 details existing approaches for automated PCB visual inspection. Section 3 explains our image acquisition setup and its statistics is presented in Section 4. Section 5 presents the baseline evaluations of state-of-the-art object detection approaches and Section 6 presents our conclusions.

2 Related Work

In this section, we provide details of existing datasets that are suited for automated PCB visual analysis. There are not many publicly available PCB datasets designed for the purpose of automated analysis. The PCB-DSLR [8] dataset is the first publicly available dataset with 748 images of PCBs from a recycling facility. The images are annotated for bounding boxes for IC chips which account for 9313 samples (including duplicates). The other publicly available dataset is from [9] includes 480 images of 80 different PCBs, but consist of low-quality images that are inadequate for analysis at the component level. Herchenbach et al. [5] and Li et al. [6] used private datasets that included 21 PCB images and 128 ICs in total respectively. Herchenbach et al. [5] used a combination of PGB camera and a depth sensor to detect components via depth and color-based segmentation, while Li et al. [6] proposed a method to identify surface mounted devices and focused on IC segmentation. The authors in another work [7] performed text recognition on both boards and mounted components. The dataset used by them consists of 860 PCB segments with text. However, no specific details were available on the number of boards used.

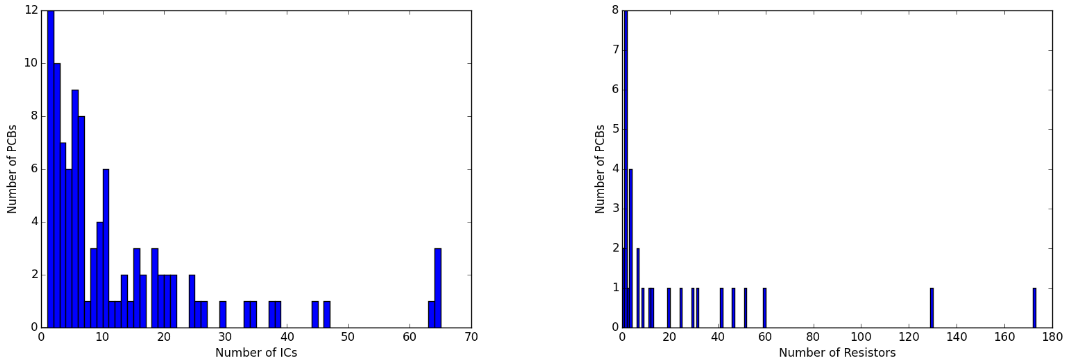
3 Dataset Acquistion

Our image acquisition system was designed with a high quality images of boards in a consistent, reatable, manner. The resolution of the capture is sufficient for detailing the smallest surface mount component. Also, these images are free from effects such as blur, poor lighting, etc. and from PCB that is clear of dust and other debris unlike PCB-DSLR dataset, whose images are those of boards from a recycling facility. The PCBs in the PCB-METAL dataset is obtained from various electronic devices ranging from a computer to a cellphone. The dataset acquisition process is detailed below.

The acquisition system is shown in Figure 1. The acquisition system includes a professional Canon EOS 5D Mark II DSLR camera setup with a shutter speed of 1/60, aperture of 5.6, and an ISO of 125. The setup also includes a professional lighting system - Interfit EX150 with a flash strength of $6th$ dial tick. The camera and the lighting setup overlook a stable white board on which the PCBs are placed for imaging. The camera and the lights are controlled simultaneously using a remote control. The lighting system ensures constant illumination thus avoiding shadows and specular reflections on the board.

Our dataset is composed of images from 123 unique boards that were imaged both front and back with four degrees of rotation (0°, 90°, 180°, 270°), thus accounting for 8 images per board. This is to account for a complete visualization of all the components from all its sides. The PCB boards were collected from various electronic devices that were defective or to be recycled with devices ranging from a laptop to a cellphone. Figure 2 shows examples of images from the dataset.

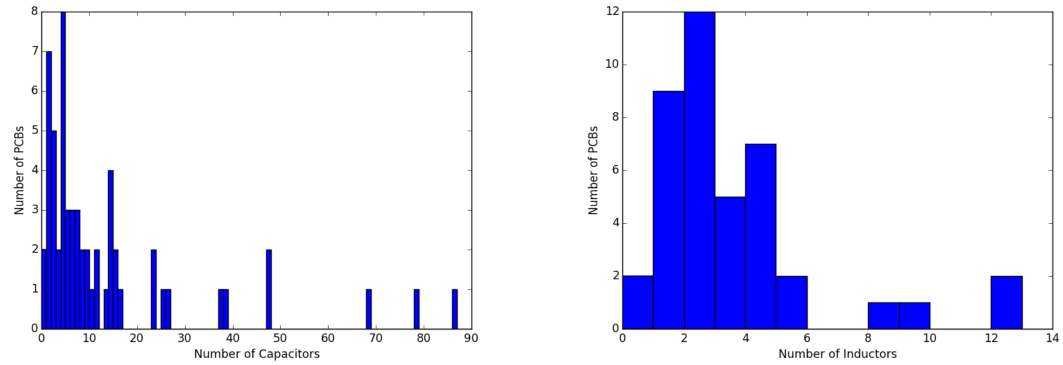
In addition to these raw images our dataset provides hand annotated bounding box locations (x, y, width, height) for each component for all 8-images per board. The annotations were quality checked by an external reviewer, i.e. a trained person who did not perform the orginal annotation. This includes 5,844 ICs, 3,175 Capacitors, 2,679 Resistors, and 542 Inductors. This information can be used to train and test object detection techniques that would identify and localize these components. These annotations are available in standard



(a) IC Statistics

(b) Resistor Statistics

Figure 3. Distribution of IC and Resistors in PCB-METAL Dataset.



(a) Capacitor Statistics

(b) Inductor Statistics

Figure 4. Distribution of Capacitors and Inductors in PCB-METAL Dataset.

text and xml formats that can be readily consumed by most of the object detection machine learning algorithms. The xml format follows the PASCAL VOC data annotation format. This mode of presentation of the annotation data provides the users with the ability to use an annotation API of their choice in parsing the data. Table 1 shows the comparison in statistics between the PCB-DSLR and PCB-METAL datasets.

4 Dataset Statistics

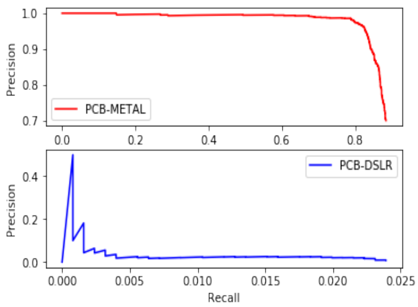
In this section we present the statistics on the PCB-METAL dataset. All statistics were obtained using the 0° rotated image of each unique PCB, resulting in 123 images in total. There are 1,226 IC chips, 788 capacitors, 666 resistors, and 127 inductors that are uniquely labeled in the dataset.

Figures 3 and 4 show the distribution of the number of ICs, capacitors, Resistors, and Inductors per PCB. From the figures it can be seen that the majority of the boards have fewer than 20 IC chips and capacitors. Also, it is to be noted that the density of resistors and capacitors are less for these boards. However, it can be noted that there are two boards that have more than 120 resistors each and three boards that have more than 70 capacitors each. The largest number of IC chips (more than 60) can be found in three of the boards.

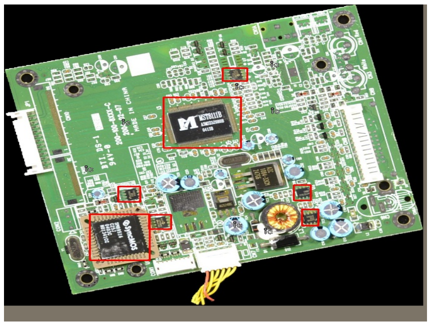
The PCB boards themselves vary in shape and size providing a large variance in the size and aspect ratio of these images. Since these images have been imaged with a white background, it becomes easier to apply techniques such as background subtraction, boundary detection, etc. easily to these images to segment the PCB image.

Table 1. Comparison between PCB-DSLR and Our (PCB-METAL) dataset.

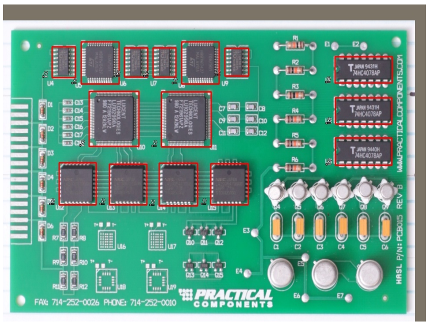
Dataset	No. of Images	ICs	Capacitors	Resistors	Inductors
PCB-DSLR	748	9313	None	None	None
PCB-METAL	984	5844	3175	2679	542



(a) Performance of Retinanet-50 [4] on PCB-DSLR and PCB-METAL



(b) Prediction from PCB-DSLR dataset



(c) Prediction from PCB-METAL dataset

Figure 5. Performance on PCB-DSLR vs PCB-METAL using Retinanet-50 [4]

5 Component Detection - Baseline Evaluation

In this section we present a baseline evaluation of the state-of-the-art deep learning-based object detection approaches. The motivation behind this analysis is to show the usefulness of our dataset for the design and evaluation of learning-based approaches for PCB analysis. Also, these baseline evaluations may help researchers in identifying the strengths and weaknesses involved in existing methods for detection of tiny objects as a function of pixel size.

In order to measure the performance of the approaches without the bias of the training data, we performed a 10-fold cross validation on all of the approaches for IC detection. The PCB-METAL dataset was randomly divided into 10 sets of training and testing sets. The training set in each fold included 80% of the PCB images and the remaining 20% for the testing set. The training and testing sets were mutually exclusive in terms of the images from the same PCB. This ensures that these approaches never see the testing data during training.

5.1 Object Detection Approaches

In this section we employ our dataset to evaluate three state-of-the-art deep learning techniques suited for object detection. These techniques have been shown to provide superior performance for detecting objects and their bounding boxes. The first approach is YOLO [1] (You Look Only Once) is an object detection algorithm that uses a single convolutional neural network for simultaneous prediction of bounding boxes and class probabilities for those boxes. YOLO is designed to be fast since it frames the detection problem as a regression problem. For our evaluation, we use YOLO v3 [2] which includes prediction across scales for an improved prediction.

The second approach is Faster-RCNN [3] uses a Region Proposal Network (RPN) that shares full-image convolutional features with detection network. The RPN is a fully convolutional network that simultaneously predicts object boundaries and detection scores at each position. The third approach is RetinaNet [4] which is a single, unified network composed of a backbone network and two task-specific sub-networks. The backbone computes a feature map over an entire image, whereas the two sub-networks (classification and box regression) predicts the class scores for the object and the bounding box location respectively.

Pre-trained models (trained using ImageNet dataset) were used for all the three algorithms for each fold. The performance of these approaches is presented in terms of mean of mean average precision (mAP) scores of all the folds from the PCB-METAL dataset. The mAP score is based on the Intersection Over Union (IOU) of the predicted bounding box with that of ground truth. Table 2 shows the mAP scores from various machine learning approaches. It can be noted from the mAP scores that these algorithms provide a good performance in detecting ICs from minimal training data with a pre-trained model for initialization. However, we noted that performance degradation was mainly due to mis-classification of other components similar in look as IC. Also, the bounding boxes for some predictions were not tightly bound as the ground truth.

Table 2. Performance of object detection algorithms on PCB-METAL dataset.

Technique	Mean mAP
YOLOv3 [2]	0.698
faster-rcnn [3]	0.783
Retinanet-50 [4]	0.833

5.2 Comparison with PCB-DSLR

In order to compare the performance of these approaches on PCB-DSLR dataset, we performed IC detection on images from the PCB-DSLR dataset using the best performing approach (Retinanet-50 [4]) on the PCB-METAL dataset. Similar to our previous experiment, we performed a 10-fold cross validation on the images from PCB-DSLR dataset. The performance is reported in terms of mean of mAP and an average precision-recall curve (shown in Figure 5(a)). The mean mAP for PCB-DSLR dataset is 0.001 while the mean mAP for PCB-METAL is 0.833. The poor performance on the PCB-DSLR dataset is attributed to the inconsistency in capture of the boards, i.e. test images rotated at non-standard angles in the PCB-DSLR. Figures 5(b) and 5(c) shows example predictions on a test image from the PCB-DSLR and PCB-METAL dataset respectively. From the figure it can be seen that the predictions on PCB-METAL are superior than the predictions from PCB-DSLR dataset.

6 Conclusion

In this work we introduced a publicly available PCB image dataset with bounding box annotations for various components. This dataset would facilitate computer-vision and machine learning based approaches for various PCB analysis. We have also provided baseline evaluations of state-of-the-art machine learning object detection approaches on our dataset. The dataset combined with the baseline evaluations will provide researchers a means to evaluate their approaches for PCB analysis. In future, we will be extending this dataset with more images and also provide the user with depth information of the components which would provide an additional mode of information for detailed defect detection.

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