ESANN 2020 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Online event, 2-4 October 2020, i6doc.com publ., ISBN 978-2-87587-074-2.
Available from http://www.i6doc.com/en/.

A Real-time PCB Defect Detector Based on Supervised and Semi-supervised Learning

Fan He[1], Sanli Tang[1,2], Siamak Mehrkanoon[3], Xiaolin Huang[1*], Jie Yang[1]

1- Shanghai Jiao Tong University - China 2- Hikvision Research Institute - China

3- Maastricht University - The Netherlands

Abstract. This paper designs a deep model to detect PCB defects from an input pair of a detect-free template and a defective tested image. A novel group pyramid pooling module is proposed to efficiently extract features in various resolutions to predict defects in different scales. To train the deep model, a dataset including 6 common types of PCB defects is established, namely DeepPCB, which contains 1,500 image pairs with annotations. Besides, a semi-supervised learning manner is examined to effectively utilize the unlabelled images for training the PCB defect detector. Experiment results validate the effectiveness and efficiency of the proposed model by achieving 98.6% mAP @ 62 FPS on DeepPCB dataset. DeepPCB is now available at: `https://github.com/tangsanli5201/DeepPCB`.

1 Introduction

With the rapid development of the consumer electronic products, printed circuit board (PCB) manufacturing has drawn more and more attentions. The quality of PCB has directly effects on the reliability of subsequent products. Thus, PCB defect detection is a key process in PCB production. In practice, a defect-free template image will usually be rectified manually from a defective PCB image and then be used in defect detection algorithms [1, 2] to inspect other PCB images in the same format. Earlier works on PCB defect detection focus on wavelet-based algorithms [3], which decrease the computation time compared to those based on image difference operation. Recently, [2] develops a hybrid algorithm by using morphological segmentation and simple image processing technique. [1] incorporates proper image registration to solve the alignment problem, which however consumes more processing time. These algorithms relying on image difference and logic inference sometimes fail due to: (a) the complicated or unaccounted defect patterns; (b) irregular image distortion and offset between the template and tested image pair; (c) over-sensitivity of hyper-parameters, e.g. the kernel size of erosion or dilation operation.

To enhance the generalization ability of the PCB defect detector, we consider to use deep neural network, which has shown its strong generalization aiblity on object detection task [4]. PCB defect detection is essentially an extension of object detection with slight difference: the pair-wise input, including a defect-free template image and a defective tested image. While deep methods [4, 5, 6] have

*This work is supported by Research and Demonstration Application of Monitoring and Management Technology of City Energy System Based on Large Data and Artificial Intelligence (SGIT0000YXJS1800395).

ESANN 2020 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Online event, 2-4 October 2020, i6doc.com publ., ISBN 978-2-87587-074-2.
Available from http://www.i6doc.com/en/.

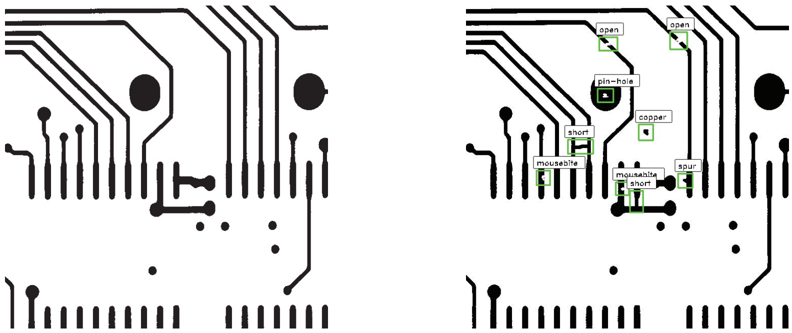

Fig. 1: A pair of (a) a defect-free template image and (b) a defective tested image with annotations of defect types and annotations in the DeepPCB dataset.

achieved promising progress, the requirements for large training data becomes a new challenge. To solve this problem, new datasets and some semi-supervised techniques are considered. The weight-averaged consistency is introduced in [7] with impressive results that the large amount of unlabeled samples can further boost the performance of deep models in a semi-supervised learning manner.

The organization of this paper are as follows. In next section, the first dataset for PCB defect detection is established, including 1,500 aligned image pairs with precise annotations. A PCB defect detection network is proposed in section 3 based on the novel group pyramid pooling (GPP) module, which improves the model's ability of detecting PCB defects in various scales. Extensive experiments are presented in section 4, which validates the effectiveness and efficiency of the proposed PCB defect detector and its semi-supervised learning framework.

2 The DeepPCB Dataset

We contribute DeepPCB to the community, which contains 1,500 PCB image pairs covering six types of PCB defects. Each pair consists a 640 x 640 defect-free template image and a defective tested image. We separate 1,000 image pairs as training set and the remaining 500 image pairs as test set.

We use the axis-aligned bounding box with a class ID for each defect in the tested images. As illustrated in Fig. 1, we annotate six common types of PCB defects: open, short, mousebite, spur, pin hole and spurious copper. Since there are only a few defects in the real tested images, we manually augment some artificial defects on each tested image according to the PCB defect patterns [8], which leads to around 3 to 12 defects in each image pair.

Following the popular benchmark on object detection datasets [9], average precision rate is used for evaluation. A detection is correct only if the intersection of unit (IoU) between the detected bounding box and any of the ground truth box with the same class is larger than 0.33.

ESANN 2020 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Online event, 2-4 October 2020, i6doc.com publ., ISBN 978-2-87587-074-2. Available from http://www.i6doc.com/en/.

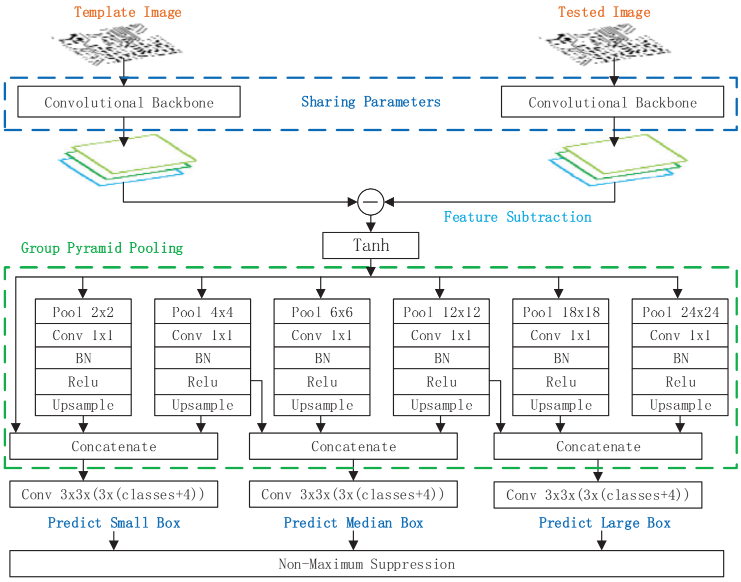

Fig. 2: An overview of the proposed model. The backbone is VGG16-tiny [10]. 'BN' denotes batch normalization. Up-sample is implemented by bilinear interpolation and the target size is the same as the first input of each concatenated group. Each feature group in GPP provides predictions in different scales.

3 Approach

3.1 Network Structure

Instead of directly calculating the difference between the input image pair, a convolutional backbone with max pooling operation is first deployed for extracting features from the input images. Then, the differences between the features of template and tested images are calculated. A novel group pyramid pooling module is followed to obtain features in various resolutions. Similar to [4, 11], we produce predictions of different scales from feature maps from the backbone. In Fig. 2, we show the structure of the proposed PCB defect detection model.

Group Pyramid Pooling (GPP) module Different from the feature pyramid network (FPN) [11], which merges features in different resolutions from coarse to fine with increasing computational and storage cost, GPP module obtains features of various resolutions from a pyramid pooling structure. Each group predicts PCB defects from the pre-generated default boxes [4] in a specific scale.

Prediction from convolutional feature maps Each output feature map from GPP module can produce a fixed set of detection predictions by several convolutional filters. As illustrated in the Fig. 2, at each location in output maps, it outputs the prediction of (i) classification: six types of PCB defects and one backgroud class, and (ii) localization: the translation offset between the centroids and the scaling ratios between the width and height of the default boxes

ESANN 2020 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Online event, 2-4 October 2020, i6doc.com publ., ISBN 978-2-87587-074-2. Available from http://www.i6doc.com/en/.

and the targets. Finally, non-maximum suppression (NMS) is applied to all the predictions from different scales to obtain the final prediction results.

Semi-supervised settings for PCB defect detector Following [7], an extra teacher model sharing with the same network structure with the detector is designed to generate pseudo labels in the semi-supervised schedule. For the annotated image pairs, the detector is trained normally according to the supervised loss function. For the image pairs without labels, the consistency loss between the prediction of detector and the teacher model is used to train the detector. The teacher model updates its parameters according to the detector in an exponential moving average manner.

3.2 Objective Function

Following the matching strategy in SSD [4], each ground truth box is first matched to the default box [4] of the maximum jaccard overlap [12]. Then, the default boxes are matched with any ground truth box whose jaccard overlap is higher than 0.5, which can be described as $\mathcal{D} = \{(d, g)|\text{jaccard\_overlap}(d, g) > 0.5)\}$, where $d = (d^{cx}, d^{cy}, d^w, d^h)$ and $g = (g^{cx}, g^{cy}, g^w, g^h)$ are the central point, width and height of default box and ground truth box, respectively. Then, the objective function for box regression is defined as:

$$L_{\text{reg}} = \sum_{(d_n,g_n)\in\mathcal{D}} \sum_{i\in cx,cy,w,h} \text{smooth}_{\text{L1}}(l_n^i - t_n^i),$$

where $\text{smooth}_{\text{L1}}(\text{x}) = 0.5x^2, \text{if } |x| < 1 \text{ or } |x| - 0.5$ otherwise. l_n is the predicted offset between the default bounding box d_n and the matched ground truth box g_n. t_n is the target offset, which is normalized by the default box size: $t_n^j = (g_n^j - d_n^j)/d_n^j, \quad j \in \{cx, cy\}$, and $t_n^k = \log(g_n^k/d_n^k), \quad k \in \{w, h\}$.

The classification loss for the type of PCB defect is calculated by cross-entropy, where we randomly select background default boxes to keep the ratio of the background (Bg) to foreground (Fg) bounding boxes at around 3:1 :

$$L_{\text{cls}} = -\sum_{d_n\in\text{Fg}} \log(c_n^p) - \sum_{d_n\in\text{Bg}} \log(c_n^0),$$

where c_n^p is the predicted probability that the target in the box d_n belongs to class p. Notice that the class index for background box is set to 0.

The overall objective function for training the detector in supervised manner is $L(w^S; \mathcal{X}) = \sum_{\mathcal{X}}(L_{\text{reg}} + \alpha L_{\text{cls}})$ where w^S is the trainable parameters of the detector and $\mathcal{X}$ is the annotated samples. As for the semi-supervised scenario, let $\mathcal{U}$ be the unlabelled set, f^T and f^S be the teacher model and the detector. Then the objective function for semi-supervised framework is $L_{\text{semi}}(w^S; \{\mathcal{X}, \mathcal{U}\}) = L(w^S; \mathcal{X}) + \beta \sum_{x_u\in\mathcal{U}} ||f^T(x_u) - f^S(x_u)||^2$, where the parameters of the teacher model at t step w^T updates by $w_t^T = \gamma w_{t-1}^T + (1 - \gamma) w_t^S$.

ESANN 2020 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Online event, 2-4 October 2020, i6doc.com publ., ISBN 978-2-87587-074-2.
Available from http://www.i6doc.com/en/.

4 Experiments

In this section, based on DeepPCB dataset, extensive experiments are carried out to evaluate the proposed model for PCB defect detection as well as some advanced object detection models [4, 6, 5], for which we make slight modifications in the input and output: (i) a convolutional backbone, e.g., VGG-tiny [10] is first applied to efficiently extract features of both the template and tested image; (ii) feature subtraction is adopted to merge the last feature maps of the backbone from the input image pair. We train our model on a single Titan X GPU using Adam with initial learning rate 10^{-3}, 0.0005 weight decay, 500 epochs and batch size 16. The learning rate decays 0.33 every 100 epochs. The hyper-parameters are set as $\alpha = \beta = 1$ and $\gamma = 0.99$.

Results on Fully-Supervised Learning This section provides quantitative evaluations for various methods of PCB defect detection on DeepPCB dataset. For data augmentation of deep models, the template and tested image are simultaneously randomly horizontal/vertical flipped with probability of 0.5 and then they are randomly cropped into size of 512 x 512. In Table 1, we illustrate the evaluation result on DeepPCB dataset.

Table 1: Evaluation results of AP(%) on DeepPCB dataset. 'AP' or 'MP' denotes the contrastive settings of average pooling or max-pooling in GPP module.

Method	mAP	open	short	mousebite	spur	copper	pin-hole	FPS
I.P. [2]	89.3	88.2	87.6	90.3	88.9	91.5	89.2	78
SSD [4]	95.9	93.1	94.5	95.7	96.7	96.9	98.7	64
YOLO [6]	92.6	90.5	92.0	93.1	93.3	94.9	92.6	34
Faster [5]	97.6	96.8	95.4	97.9	98.7	97.4	99.5	4
ours-AP	97.1	97.0	93.5	98.7	96.6	97.4	**99.9**	62
ours-MP	**98.6**	**98.5**	**98.5**	**99.1**	**98.2**	**98.5**	99.4	62

Results on Semi-Supervised Learning We also evaluate the detector trained in semi-supervised manner by randomly removing the annotations of some training samples. Table 2 shows the performance of the detector via different numbers labeled samples, which demonstrates the effectiveness the semi-supervised learning in PCB defect detection task.

Table 2: Evaluation results in the semi-supervised setting. SSD_{full} refers to only using the certain number of labeled samples to train the detector in a fully-supervised manner, while SSD_{semi} refers to using both the labeled and the rest unlabelled samples in the semi-supervised way.

labeled samples	50	100	200	300	1000
SSD_{full}	86.5	90.7	92.1	94.6	98.6
SSD_{semi}	89.3	92.4	93.5	95.2	98.6

ESANN 2020 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Online event, 2-4 October 2020, i6doc.com publ., ISBN 978-2-87587-074-2.
Available from http://www.i6doc.com/en/.

5 Conclusion

This work contributes DeepPCB, a large-scale PCB dataset containing six common types of PCB defects with annotations of positions. A novel deep module is proposed, namely group pyramid pooling, that efficiently combines features in different resolutions and makes predictions for detecting PCB defects in various scales. Through extensive experiments, we demonstrate that the proposed architecture with GPP module can achieve state-of-the-art performance while consuming very low computational time.

References

[1] Fabiana R. Leta, Flavio F. Feliciano and Flavius P. R. Martins. Computer vision system for printed circuit board inspection. In *ABCM Symposium Series in Mechatronics*, pages 623–632 vol.3, 2018.

[2] S. H Indera Putera and Z. Ibrahim. Printed circuit board defect detection using mathematical morphology and matlab image processing tools. In *International Conference on Education Technology and Computer*, pages V5–359–V5–363, 2010.

[3] JoaquÃn Santoyo, J. Carlos Pedraza, L. Felipe MejÃa, and Alejandro Santoyo. Pcb inspection using image processing and wavelet transform. *Lecture Notes in Computer Science*, 4827:634–639, 2007.

[4] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng Yang Fu, and Alexander C. Berg. Ssd: Single shot multibox detector. In *European Conference on Computer Vision*, pages 21–37, 2016.

[5] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: towards real-time object detection with region proposal networks. In *International Conference on Neural Information Processing Systems*, pages 91–99, 2015.

[6] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In *Computer Vision and Pattern Recognition*, pages 779–788, 2016.

[7] Antti Tarvainen and Harri Valpola. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In *Neural Information Processing Systems*, pages 1195–1204, 2017.

[8] Madhav Moganti, Fikret Ercal, Cihan H. Dagli, and Tsunekawa Shou. Automatic pcb inspection algorithms. *Computer Vision and Image Understanding*, 63(2):287–313, 1996.

[9] Mark Everingham, Luc Van Gool, Christopher K. I. Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *International Journal of Computer Vision*, 88(2):303–338, 2010.

[10] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *International Conference on Learning Representations*, 2015.

[11] Tsung Yi Lin, Piotr Dollar, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie. Feature pyramid networks for object detection. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 936–944, 2017.

[12] Dumitru Erhan, Christian Szegedy, Alexander Toshev, and Dragomir Anguelov. Scalable object detection using deep neural networks. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 2155–2162, 2014.