Lithography Hotspot Detection Based on Yolov5

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Introduction

Lithography hotspot detection plays an important role in the manufacturability design of integrated circuits, which affects the yield of the final product. The traditional detection methods, such as pattern matching and machine learning, usually are accompanied with the performance decrease with the increase of the layout complexity. And in lithography simulation-based method, the traditional geometric verification algorithm for measuring edge placement error (EPE) after simulation is too time-consuming in complex layout. In recent years, with the rapid development of deep learning, it has become one of the most popular methods for lithography hotspot detection[1].

In this work, we combine the advantages of lithography simulation and deep learning, and propose a lithography hotspot detection algorithm based on Yolov5 to realize fast and accurate location of lithography hotspot. The effectiveness of the method is verified on ICCAD 2012 contest benchmark 1[2].

METHODS

Since different types of hotspots may be corrected differently, it is necessary to classify and identify different types of hotspots. In this paper, six lithography hotspots are detected: missing, extra, hard bridging, soft bridging, hard pinching and soft pinching, as shown in Fig 1.

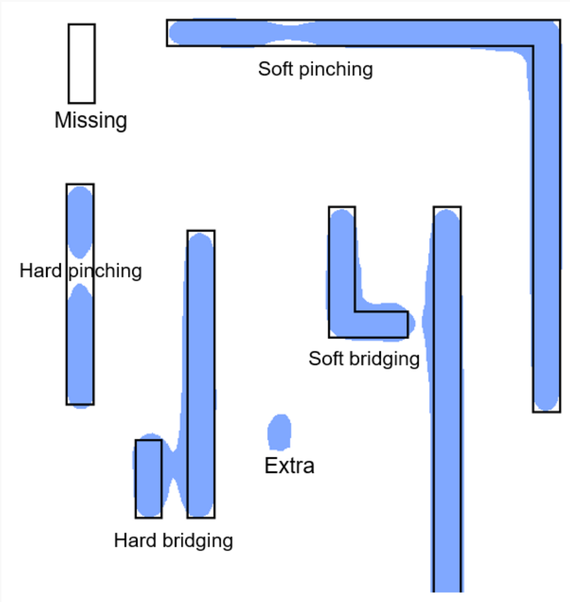

Fig 1 *Several different types of lithography hotspots (black boxes represent the mask pattern and the blue patterns indicate the shape of lithography patterns)*

We introduce the Yolov5 detection network to construct and train a hotspot detection model with a high prediction ability for realizing the fast and accurate localization of lithography hotspots. The network is shown in Fig 2.

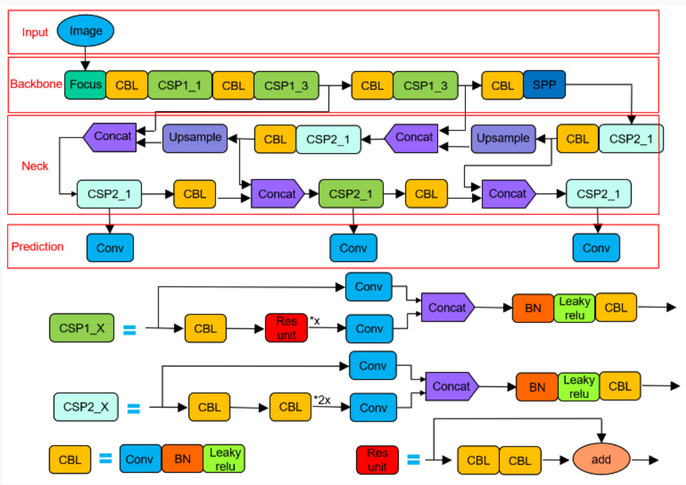

Fig 2 *The network structure of hotspot detection model*

The complete intersection over union (CIoU) loss function is used to calculate the bounding box regression loss. The binary cross entropy loss function (BCEWithLogitsLoss) is used to calculate the confidence loss and the classification loss.

$$CIoU_{\text{loss}} = 1 - CIoU = 1 - IoU + \frac{\rho^2(b, b^{\text{gt}})}{c^2} + \alpha \cdot v$$

CIoU loss function

$$Loss = -\frac{1}{n}\left[y_i \cdot \log\left(\sigma(x_i)\right) + (1 - y_i) \cdot \log\left(1 - \sigma(x_i)\right)\right]$$

BCEWithLogitsLoss function

EXPERIMENT

The experimental data set adopted in the paper was the layout benchmark 1 of ICCAD2012, which is a region of 12516 um^2 in total fabricated at 32 nm process node, and the simulation contour patterns were obtained by the lithography simulation based on Hopkins imaging principles. Since the data format of the benchmark is an OAS file, the 2D image is generated by the density coding of the layout. Then, about 1200 images with a size of 1000×1000 pixels, containing several lithography hotspots, are generated using the data enhancement methods mentioned above. Example images of hotspot detection dataset are shown in Fig 3.

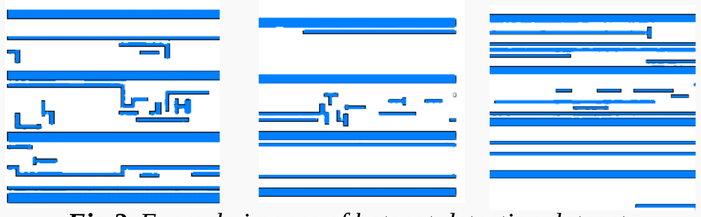

Fig 3 *Example images of hotspot detection dataset*

In this experiment, the weight file yolov5s.pt was used to initialize the weight parameters, the input image size was 640 px, the batch-size was set to 16, and the number of epochs was set to 500. The experimental computer is configured with an Intel i7-11800H CPU and a 16G RAM, and a GPU of NVIDIA GeForce RTX 3060.

RESULTS & DISCUSSION

The following Fig 4 shows the changes in several relevant parameters in the model during the training process. The model begins to converge and tends to be stable after 400 epochs. These results indicate that the network is fully trained without overfitting.

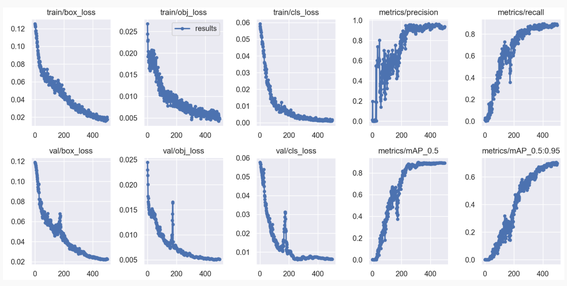

Fig 4 *Changes of relevant parameters of training model*

The precision, the recall, and the F1 score are used as the performance metrics. In order to check the effectiveness of the proposed method, we compare the performance parameters of the proposed method with that of three other lithography hotspot detection methods based on deep learning. They are the method combining clustering and CNN, the method combining HDAM and GoogLeNet, and the method based on Faster R-CNN, respectively. Besides, the runtime of our approach has been compared with that of the geometric algorithm based on the EPE measurement. The detection results are shown in Table I. Fig 5 shows the results of lithography hotspot detection on the test set.

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

performance metrics formula

Table 1 *Experimental results*

Method	Precision(%)	Recall(%)	F1-score(%)	Runtime ($h \cdot mm^{-2}$)
CNN	30.6	95.1	46.3	25.2
GoogLeNet	32.4	99.5	48.9	-
Faster R-CNN	52.4	94.7	67.5	0.7
EPE	-	-	-	1.0
The proposed method	95.3	96.3	95.8	0.7

a. The runtime of all methods does not consider the simulation time.

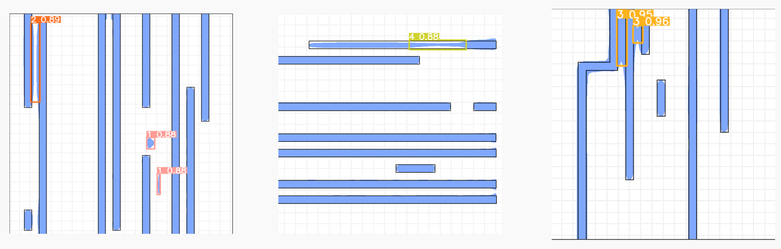

Fig 5 *The results of lithography hotspot detection*

Conclusions

In summary, a Yolov5-based detection method for the lithography hotspots has been proposed. The fast localization of various lithography hotspots can be realized by using the Yolov5 model. Meanwhile, it can realize the classification and recognition of different types of lithography hotspots. Both the effectiveness and feasibility of the method have been verified. The experimental results show that the precision, the recall, and the F1 score of the method reach 95.3%, 96.3% and 95.8%, respectively. Moreover, the average detection time of the proposed approach is 0.7 h/mm^2, which is reduced by 30.0% compared with that of traditional algorithms based on the EPE measurement. We believe that the proposed method has great application potential in dealing with the lithography hotspot detection problem concerned by the industry.

References

[1] Shin M and Lee J-H, “CNN Based Lithography Hotspot Detection”, International Journal of Fuzzy Logic and Intelligent Systems, vol. 3, no. 3, Sep 2016.

[2] A. J. Torres, "ICCAD-2012 CAD contest in fuzzy pattern matching for physical verification and benchmark suite, " in Proc. IEEE/ACM Int. Conf. Comput.-Aided Design (ICCAD), 2012, pp. 349–350.

Acknowledgements

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