Faster Region-based Hotspot Detection

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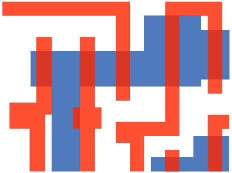
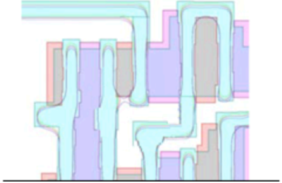
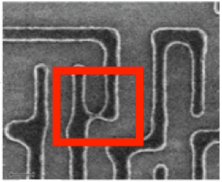
Lithography Hotspot Detection



Pre-OPC Layout

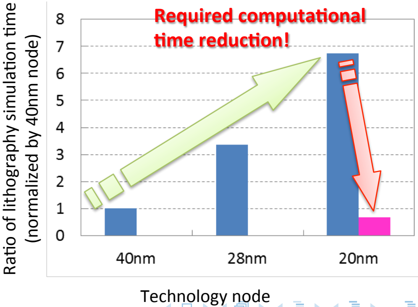


Post-OPC Mask

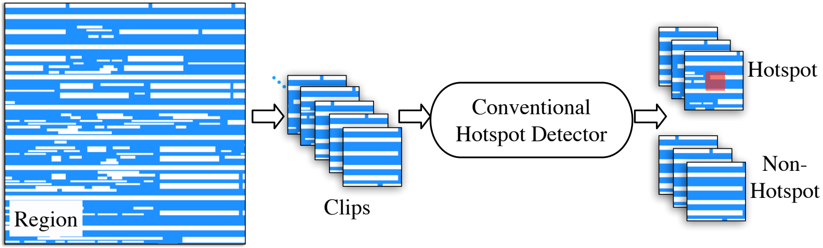


Hotspot on Wafer

- RET: OPC, SRAF, MPL
- Still hotspot: low fidelity patterns
- Simulations: extremely CPU intensive



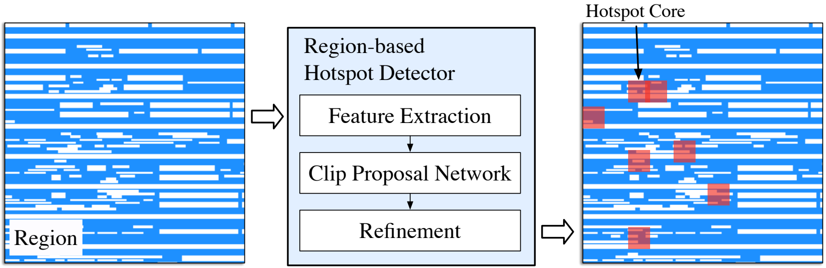
Previous Solution



- A binary classification problem.
- Scan over whole region.
- Single stage detector.

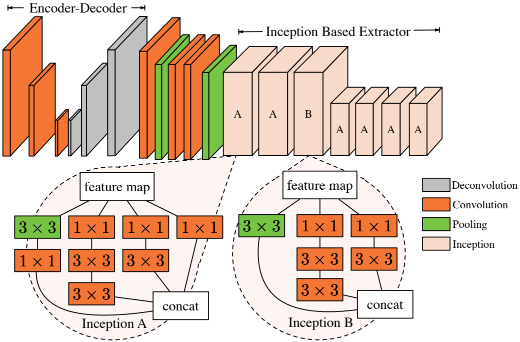
- Scanning is time consuming and single stage is not robust to false alarm.

Region based approach



- Learning what and where is hotspot at same time.
- Classification Problem -> Classification & Regression Problem.

Feature Extraction



Encoder-decoder preprocess

- Symmetric Structure for feature encoding and decoding.
- Much faster than discrete cosine transformation.

Inception based structure

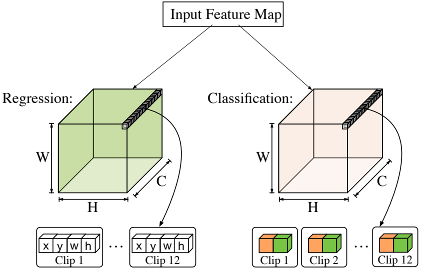
- Multi threads feature extraction.
- Prune the depth of the output channel for each stage.
- Downsample the feature map size in height and width direction.

Clip Proposal Network

Definition

- **Clip**: Predefined box to crop hotspot features in region.
- **Proposal**: Selected clip which contribute to classification and regression.

- Based on extracted features, Clip Proposal Network is designed to locate and classify hotspots.
- Classification and regression branches share features.



Details on Clip Proposal Network

- To a classifier, we have to balance the positive and negative samples.
- As a regression task on location, we need to select reasonable clips as proposals.
- We also need to consider efficiency and quality of features.

Solutions

- Clip Pruning
- Hotspot Non Maximum Suppression.

Details on Clip Proposal Network

Intersection over Union (IoU)

$$\mathrm{IoU} = \frac{clip_{groundtruth} \bigcap clip_{generated}}{clip_{groundtruth} \bigcup clip_{generated}}.$$

Clip generation: generate group of clips with different aspect ratios and scales in dense.

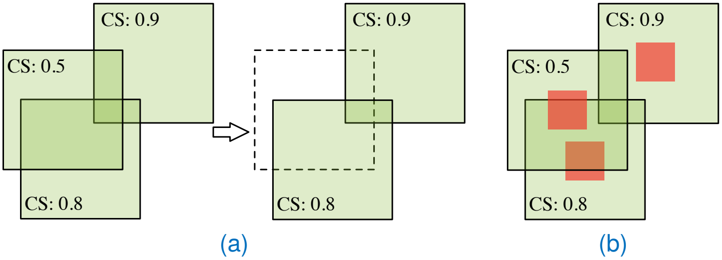
- Number of clips: $w \times h \times$ clips per location

Clip Pruning before Classification and Regression.

- IoU > 0.7, reserved as positive sample;
- IoU with any ground truth highest score should be reserved as positive sample;
- IoU < 0.3, reserved as negative sample;
- Rest of clips do no contribution to the network training.

Details on Clip Proposal Network

- Hotspot Non maximum suppression
- CS: classification score
- Take advantage of the structural relation between core region and clips
- Avoid error dropout during the training



Examples of (a) conventional non-maximum suppression, and (b) the proposed hotspot non-maximum suppression.

Loss Function Design

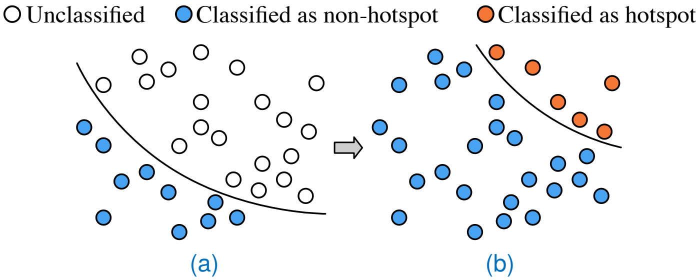
- Regression Loss for target i:

$$l_{loc}(l_i, l_i') = \begin{cases} \frac{1}{2}(l_i - l_i')^2, & \text{if } |l_i - l_i'| < 1, \\ |l_i - l_i'| - 0.5, & \text{otherwise}, \end{cases} \tag{1}$$

- Classification Loss for target i:

$$l_{hotspot}(h_i, h_i^{'}) = -(h_i \log h_i^{'} + h_i^{'} \log h_i). \tag{2}$$

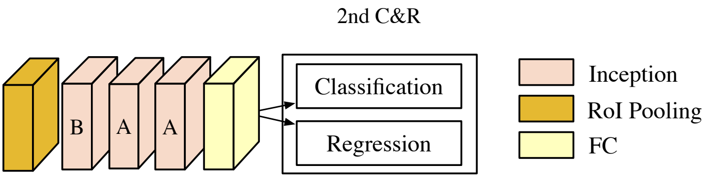
Refinement



(a) 1st hotspot classification in clip proposal network; (b) The labelled hotspots are fed into 2nd hotspot classification in refinement stage to reduce false alarm.

- We get a rough prediction with the clip proposal network.
- Refinement stage is applied to further decrease the false alarm.

Refinement



- RoI (Region of Interest) Pooling is a resize operation to transform feature maps to fixed size.
- Only clips selected from first stage contribute to refinement.

Experimental Result

- Benchmarks from ICCAD Contest 2016.
- Ground truth hotspot locations are label according to the results of industrial 7nm metal layer EUV lithography simulation under a given process window.
- No defects found with lithography simulation on `Case1`.

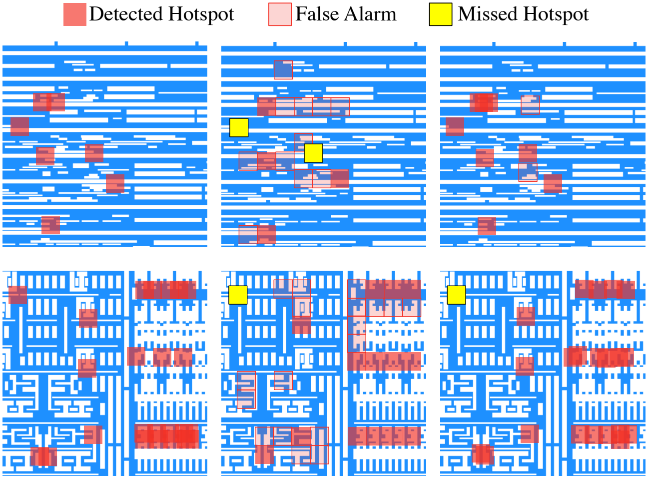
Bench	TCAD'18∗			Faster R-CNN†			SSD‡			Ours		
	Accu (%)	FA	Time (s)	Accu (%)	FA	Time (s)	Accu (%)	FA	Time (s)	Accu (%)	FA	Time (s)
`Case2`	77.78	48	60.0	1.8	3	1.0	71.9	519	1.0	93.02	17	2.0
`Case3`	91.20	263	265.0	57.1	74	11.0	57.4	1730	3.0	94.5	34	10.0
`Case4`	100.00	511	428.0	6.9	69	8.0	77.8	275	2.0	100.00	201	6.0
Average	89.66	274.0	251.0	21.9	48.7	6.67	69.0	841.3	2.0	95.8	84	6.0
Ratio	1.00	1.00	1.00	0.24	**0.18**	0.03	0.87	3.07	**0.01**	**1.07**	**0.31**	**0.02**

∗Haoyu Yang et al. (2018). "Layout hotspot detection with feature tensor generation and deep biased learning". In: *IEEE TCAD*.

†Shaoqing Ren et al. (2015). "Faster R-CNN: Towards real-time object detection with region proposal networks". In: *Proc. NIPS*, pp. 91–99.

‡Wei Liu et al. (2016). "SSD: Single shot multibox detector". In: *Proc. ECCV*, pp. 21–37.

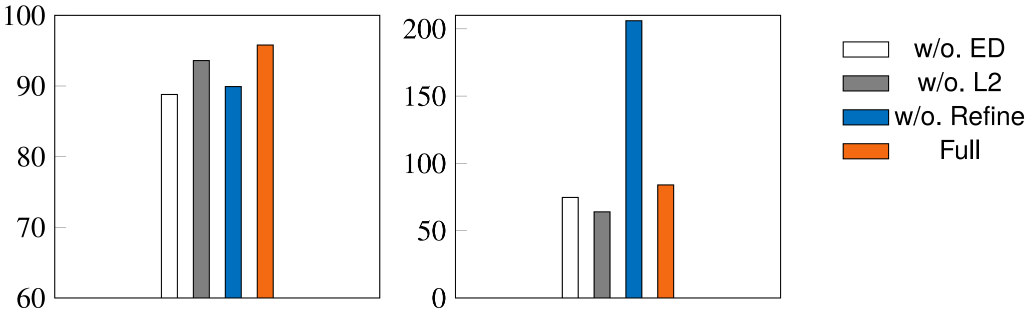
Experimental Result



(a) Ground-truth (b) TCAD'18 (c) Ours

Visualization of different hotspot detection results.

Ablation Study



(a) Accuracy (%) (b) False Alarm

Comparison among different settings on (a) average accuracy and (b) average false alarm.

Thank You