GAN-OPC: Mask Optimization with Lithography-guided Generative Adversarial Nets

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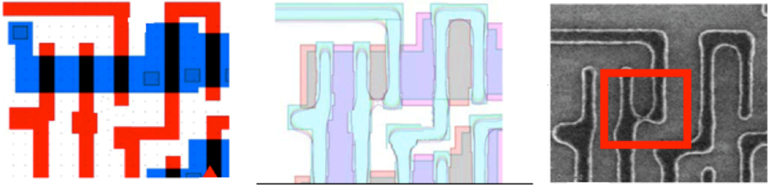
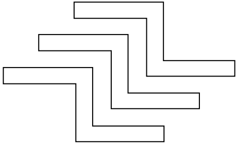
Lithography Proximity Effect



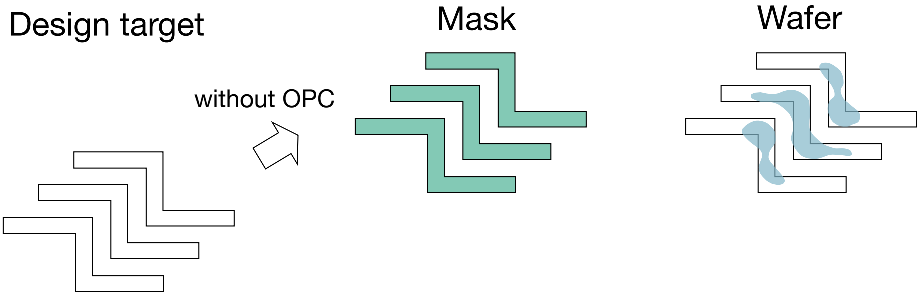
- What you see $\neq$ what you get
- Diffraction information loss
- RET: OPC, SRAF, MPL

Optical Proximity Correction (OPC)

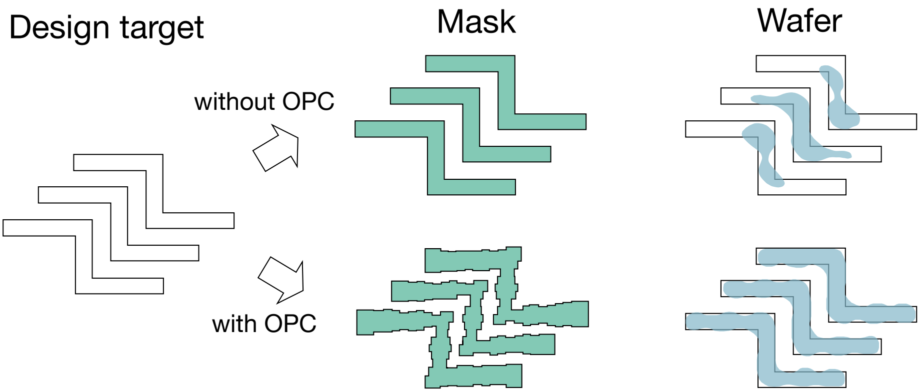
Design target



Optical Proximity Correction (OPC)



Optical Proximity Correction (OPC)



Previous Work

Classic OPC

- Model/Rule-based OPC
  [Kuang+,DATE'15][Awad+,DAC'16]
  [Su+,ICCAD'16]
  1. Fragmentation of shape edges;
  2. Move fragments for better printability.
- Inverse Lithography
  [Gao+,DAC'14][Poonawala+,TIP'07]
  [Ma+,ICCAD'17]
  1. Efficient model that maps mask to aerial image;
  2. Continuously update mask through descending the gradient of contour error.

Machine Learning OPC

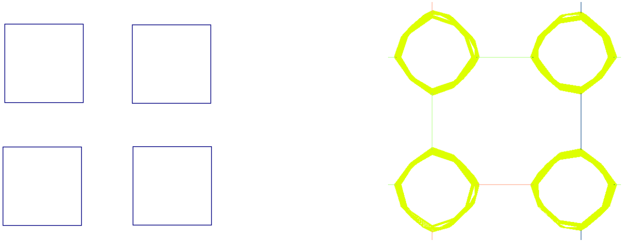
[Matsunawa+,JM3'16][Choi+,SPIE'16]
[Xu+,ISPD'16][Shim+,APCCAS'16]

1. Edge fragmentation;
2. Feature extraction;
3. Model training.

Preliminaries

Definition (PV Band)

Given the lithography simulation contours under a set of process conditions, the process variation (PV) band is the area between the outer contour and inner contour. PV Band reflects the robustness of the design to process window variations.



A PVBand Example: Lithography results of a 2×2 via/contact array under different process conditions.

Preliminaries

Definition (Squared-L_2 Error)

Let $\mathbf{Z}_t$ and $\mathbf{Z}$ as target image and wafer image respectively, the squared L_2 error of $\mathbf{Z}$ is given by $||\mathbf{Z}_t - \mathbf{Z}||_2^2$.

Problem (Mask Optimization)

Given a target image $\mathbf{Z}_t$, the objective of the problem is generating the corresponding mask $\mathbf{M}$ such that remaining patterns $\mathbf{Z}$ after lithography process is as close as $\mathbf{Z}_t$ or, in other word, minimizing the squared L_2 error of lithography images.

Lithography Model

- SVD Approximation of Partial Coherent System [Cobb,1998]

$$\mathbf{I} = \sum_{k=1}^{N^2} w_k |\mathbf{M} \otimes \mathbf{h}_k|^2. \tag{1}$$

- Reduced Model [Gao+,DAC'14]

$$\mathbf{I} = \sum_{k=1}^{N_h} w_k |\mathbf{M} \otimes \mathbf{h}_k|^2. \tag{2}$$

- Etch Model

$$\mathbf{Z}(x,y) = \begin{cases} 1, & \text{if } \mathbf{I}(x,y) \geq I_{th}, \\ 0, & \text{if } \mathbf{I}(x,y) < I_{th}. \end{cases} \tag{3}$$

Inverse Lithography Technique (ILT)

The main objective in ILT is minimizing the lithography error through gradient descent.

$$E = ||\mathbf{Z}_t - \mathbf{Z}||_2^2, \tag{4}$$

where $\mathbf{Z}_t$ is the target and $\mathbf{Z}$ is the wafer image of a given mask.
Apply translated sigmoid functions to make the pixel values close to either 0 or 1.

$$\mathbf{Z} = \frac{1}{1 + \exp[-\alpha \times (\mathbf{I} - \mathbf{I}_{th})]}, \tag{5}$$

$$\mathbf{M}_b = \frac{1}{1 + \exp(-\beta \times \mathbf{M})}. \tag{6}$$

Combine Equations (1)–(6) and the analysis in [Poonawala,TIP'07],

$$\begin{aligned} \frac{\partial E}{\partial \mathbf{M}} =& 2\alpha\beta \times \mathbf{M}_b \odot (1 - \mathbf{M}_b) \odot \\ & (((\mathbf{Z} - \mathbf{Z}_t) \odot \mathbf{Z} \odot (1 - \mathbf{Z}) \odot (\mathbf{M}_b \otimes \mathbf{H}^*)) \otimes \mathbf{H} + \\ & ((\mathbf{Z} - \mathbf{Z}_t) \odot \mathbf{Z} \odot (1 - \mathbf{Z}) \odot (\mathbf{M}_b \otimes \mathbf{H})) \otimes \mathbf{H}^*). \end{aligned} \tag{7}$$

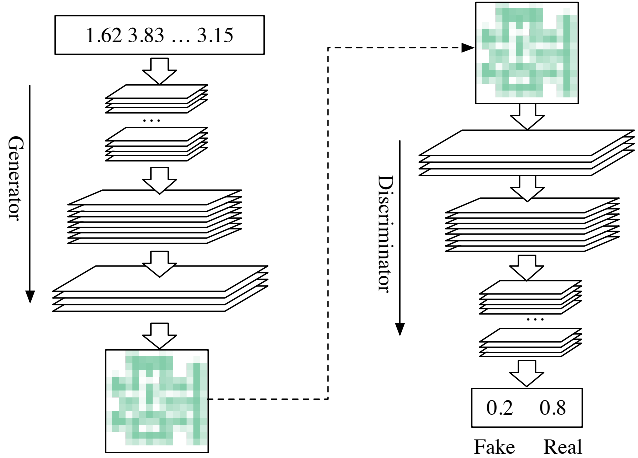
Genarative Adversarial Net (GAN)

- $\mathbf{x}$: Sample from the distribution of target dataset; $\mathbf{z}$: Input of G
- Generator $G(\mathbf{z};\theta_g)$: Differentiable function represented by a multilayer perceptron with parameters θ_g.
- Discriminator $D(\mathbf{x};\theta_d)$: Represents the probability that $\mathbf{x}$ came from the data rather than G.

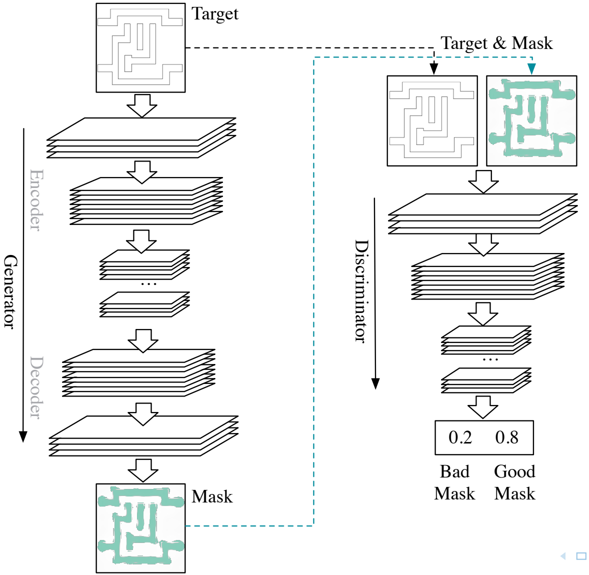
1. Train D to maximize the probability of assigning the correct label to both training examples and samples from G.
2. Train G to minimize $\log(1-D(G(\mathbf{z})))$, i.e. generate faked samples that are drawn from similar distributions as $p_{data}(\mathbf{x})$.

$$\min_G \max_D \mathbb{E}_{\mathbf{x}\sim p_{data}(\mathbf{x})}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(1-D(G(\mathbf{z})))]. \tag{8}$$

GAN Architecture



GAN-OPC



Target
Target & Mask
Encoder
Generator
Decoder
Mask
Discriminator
0.2
0.8
Bad Mask
Good Mask

GAN Training

Based on the OPC-oriented GAN architecture in our framework, we tweak the objectives of $\mathbf{G}$ and $\mathbf{D}$ accordingly,

$$\max_{\mathbf{G}} \mathbb{E}_{\mathbf{Z}_t \sim \mathcal{Z}}[\log(\mathbf{D}(\mathbf{Z}_t, \mathbf{G}(\mathbf{Z}_t)))], \tag{9}$$

$$\max_{\mathbf{D}} \mathbb{E}_{\mathbf{Z}_t \sim \mathcal{Z}}[\log(\mathbf{D}(\mathbf{Z}_t, \mathbf{M}^*))] + \mathbb{E}_{\mathbf{Z}_t \sim \mathcal{Z}}[1 - \log(\mathbf{D}(\mathbf{Z}_t, \mathbf{G}(\mathbf{Z}_t)))]. \tag{10}$$

In addition to facilitate the training procedure, we minimize the differences between generated masks and reference masks when updating the generator as in Equation (11).

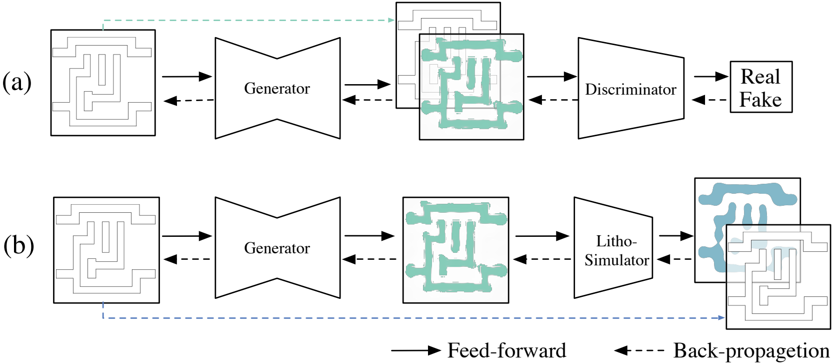
$$\min_{\mathbf{G}} \mathbb{E}_{\mathbf{Z}_t \sim \mathcal{Z}} ||\mathbf{M}^* - \mathbf{G}(\mathbf{Z}_t)||_n, \tag{11}$$

where $||\cdot||_n$ denotes the l_n norm. Combining (9), (10) and (11), the objective of our GAN model becomes

$$\begin{aligned} \min_{\mathbf{G}} \max_{\mathbf{D}} \mathbb{E}_{\mathbf{Z}_t \sim \mathcal{Z}}[1 - \log(\mathbf{D}(\mathbf{Z}_t, \mathbf{G}(\mathbf{Z}_t))) + ||\mathbf{M}^* - \mathbf{G}(\mathbf{Z}_t)||_n^n] \\ + \mathbb{E}_{\mathbf{Z}_t \sim \mathcal{Z}}[\log(\mathbf{D}(\mathbf{Z}_t, \mathbf{M}^*))]. \end{aligned} \tag{12}$$

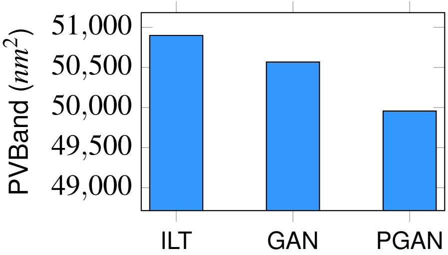
ILT-guided Pre-training

Observing that both ILT and neural network optimization share similar gradient descent procedure, we propose a jointed training algorithm that takes advantages of ILT engine, as depicted in Figure (b). We initialize the generator with lithography-guided pre-training to make it converge well in the GAN optimization flow thereafter.

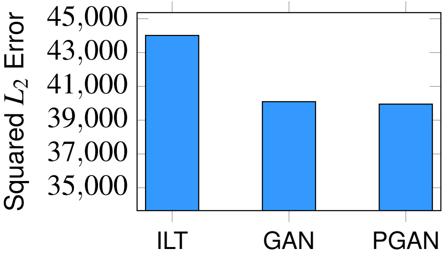


(a) Standard GAN training flow (GAN); (b) Pretraining generator with lithography engine (PGAN).

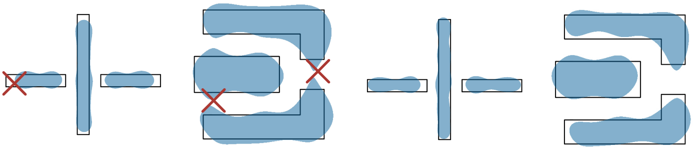
Results



(a)

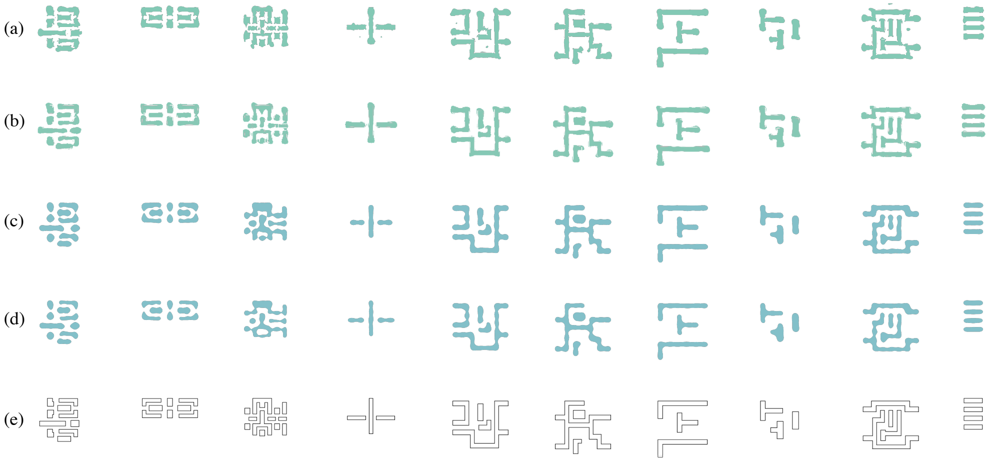


(b)



ILT PGAN

Results



(a) Masks of ILT; (b) Masks of PGAN; (c) Wafer Images of ILT; (d) Wafer Images of PGAN; (e) Targets.

Conclusion

- An OPC-oriented GAN architecture and associated loss function are proposed.
- We facilitate the training procedure by initializing the generator with an ILT engine.
- Experimental results show better printability of layout masks generated by our flow.
- Demonstrate the potential of GAN being an candidate of RET solutions.

Thank You