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

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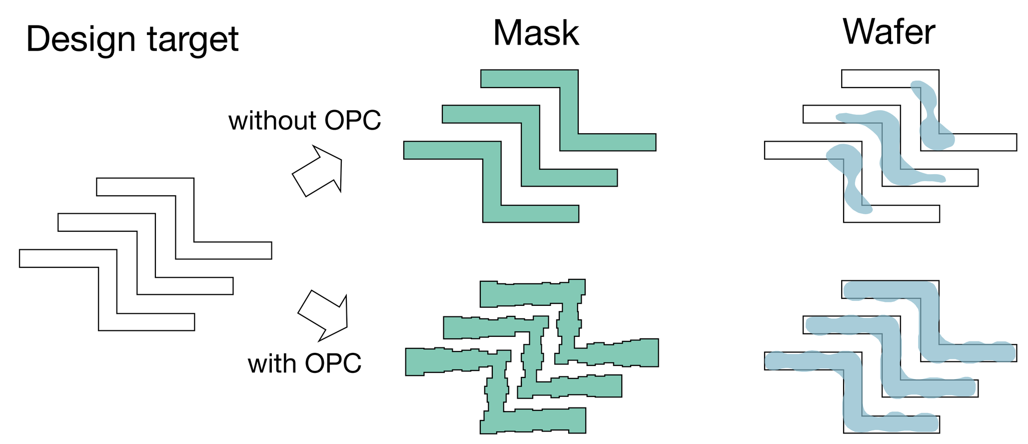
Backgrounds

Lithography Proximity Effects



- What you see $\neq$ what you get.
- Diffraction information loss.
- RET: Optical Proximity Correction (OPC), Scatter Bar and Multiple Patterning Lithography.

Classic OPC

Requires iterative call of lithography simulation engine.

- 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

Masks are updated segment-by-segment and cannot be done in one inference step. [Matsunawa+,JM3'16][Choi+,SPIE'16] [Xu+,ISPD'16][Shim+,APCCAS'16]

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

Preliminaries

Lithography Model

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

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

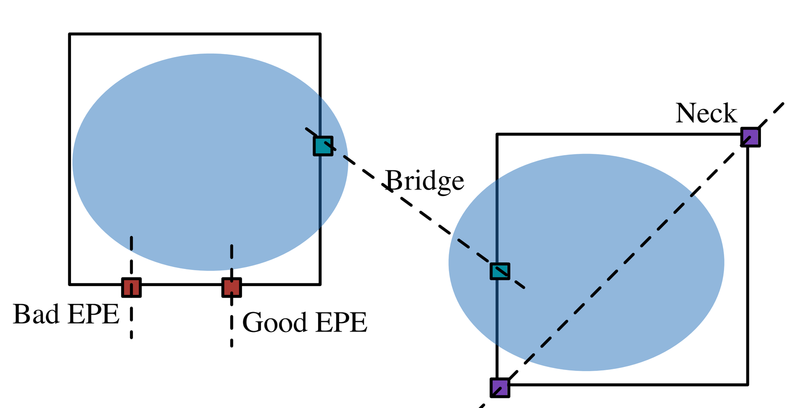
- Reduced Model [Gao+,DAC'14]

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

- Etch Model

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

Lithography Defects



- EPE measures horizontal or vertical distances from given points (i.e. OPC control points) on target edges to lithography contours.
- Neck detector checks the error of critical dimensions of lithography contours compared to target patterns.
- Bridge detector aims to find unexpected short of wires.

Inverse Lithography

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],

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

Mask can then be updated by descending the gradient derived in Equation (7),

$$\mathbf{M} = \mathbf{M} - \gamma \frac{\partial E}{\partial \mathbf{M}}. \tag{8}$$

Generative Adversarial Nets (GAN)

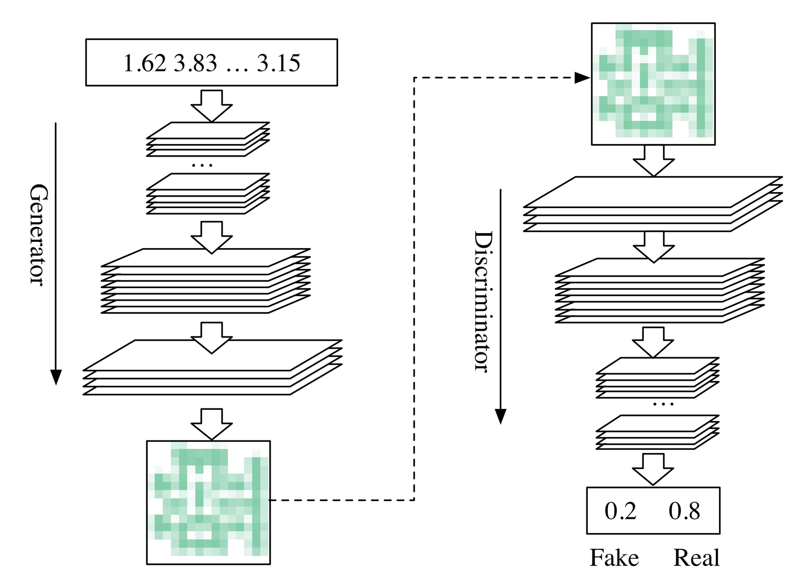
GAN Basis

- $\mathbf{x}$: 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 $p_{data}(\mathbf{x})$.

$$\min_G \max_D \mathbb{E}_{\mathbf{x}\sim p_{data}(\mathbf{x})}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}\sim p_z(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))]. \tag{9}$$

GAN Architecture



GAN-OPC

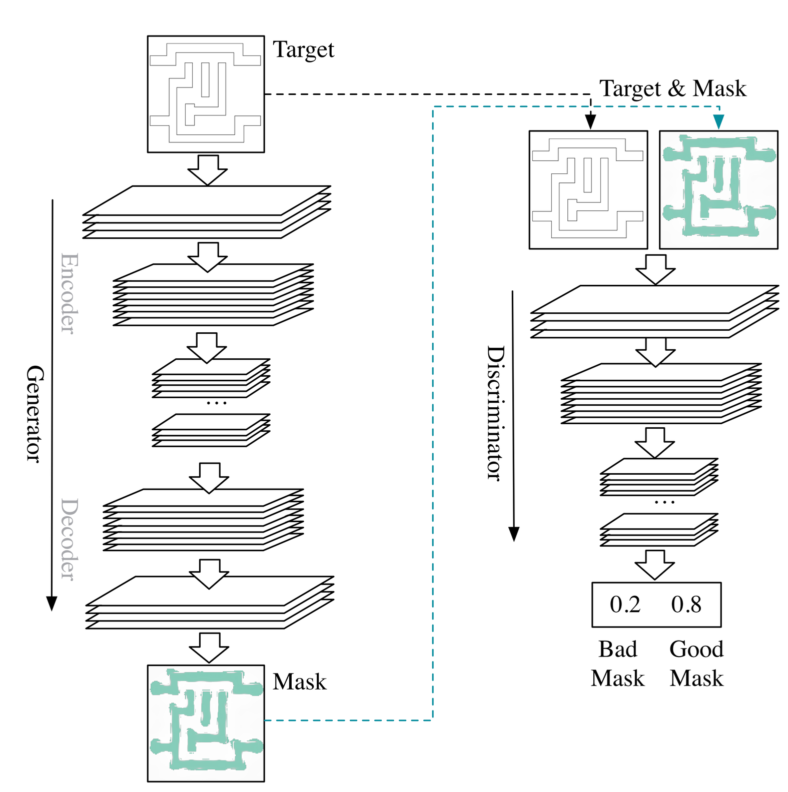
Generator Design

- Auto-encoder based generator which consists of an encoder and a decoder subnets.
- An encoder is a stacked convolutional architecture that performs hierarchical layout feature abstraction.
- A decoder operates in an opposite way that predicts the pixel-based mask correction with respect to the target.

Discriminator Design

- Take target-mask tuple as inputs: $(\mathbf{Z}_t, \mathbf{G}(\mathbf{Z})_t)$ or $(\mathbf{Z}_t, \mathbf{M}^*)$.

GAN-OPC Architecture



GAN-OPC Training

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

$$\max \mathbb{E}_{\mathbf{Z}_t\sim\mathcal{Z}}[\log(\mathbf{D}(\mathbf{Z}_t, \mathbf{G}(\mathbf{Z}_t)))], \tag{10}$$

$$\max \mathbb{E}_{\mathbf{Z}_t\sim\mathcal{Z}}[\log(\mathbf{D}(\mathbf{Z}_t, \mathbf{M}^*))] + \mathbb{E}_{\mathbf{Z}_t\sim\mathcal{Z}}[1 - \log(\mathbf{D}(\mathbf{Z}_t, \mathbf{G}(\mathbf{Z}_t)))]. \tag{11}$$

In addition to facilitate the training procedure, we minimize the differences between generated masks and reference masks when updating the generator as in Equation (12).

$$\min \mathbb{E}_{\mathbf{Z}_t\sim\mathcal{Z}}||\mathbf{M}^* - \mathbf{G}(\mathbf{Z}_t)||_n, \tag{12}$$

where $||\cdot||_n$ denotes the l_n norm. Combining (10), (11) and (12), the objective of our GAN model becomes

$$\begin{aligned}\min_{\mathbf{G}} \max_{\mathbf{D}} & \ \mathbb{E}_{\mathbf{Z}_t\sim\mathcal{Z}}[1 - \log(\mathbf{D}(\mathbf{Z}_t, \mathbf{G}(\mathbf{Z}_t))) + ||\mathbf{M}^* - \mathbf{G}(\mathbf{Z}_t)||_n^n] \\ & + \mathbb{E}_{\mathbf{Z}_t\sim\mathcal{Z}}[\log(\mathbf{D}(\mathbf{Z}_t, \mathbf{M}^*))].\end{aligned} \tag{13}$$

The generator and the discriminator are trained alternatively as follows.

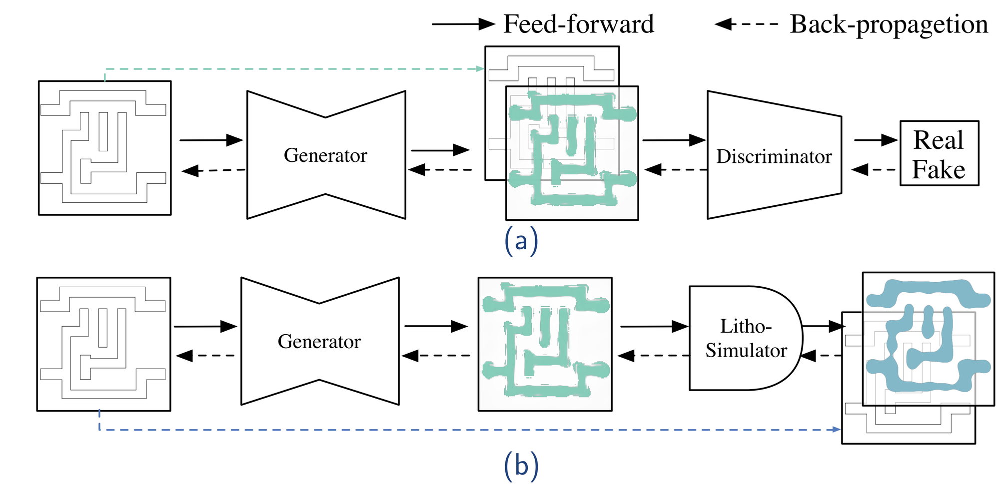
The GAN-OPC Training Algorithm

for number of training iterations **do**
  Sample m target clips $\mathcal{Z} \leftarrow \{\mathbf{Z}_{t,1}, \mathbf{Z}_{t,2}, \dots, \mathbf{Z}_{t,m}\}$;
  $\Delta\mathbf{W}_g \leftarrow \mathbf{0}, \Delta\mathbf{W}_d \leftarrow \mathbf{0}$;
  for each $\mathbf{Z}_t \in \mathcal{Z}$ **do**
    $\mathbf{M} \leftarrow \mathbf{G}(\mathbf{Z}_t; \mathbf{W}_g)$;
    $\mathbf{M}^* \leftarrow$ Groundtruth mask of $\mathbf{Z}_t$;
    $l_g \leftarrow -\log(\mathbf{D}(\mathbf{Z}_t, \mathbf{M})) + \alpha||\mathbf{M}^* - \mathbf{M}||_2^2$;
    $l_d \leftarrow \log(\mathbf{D}(\mathbf{Z}_t, \mathbf{M})) - \log(\mathbf{D}(\mathbf{Z}_t, \mathbf{M}^*))$;
    $\Delta\mathbf{W}_g \leftarrow \Delta\mathbf{W}_g + \frac{\partial l_g}{\partial \mathbf{W}_g}$; $\Delta\mathbf{W}_d \leftarrow \Delta\mathbf{W}_d + \frac{\partial l_d}{\partial \mathbf{W}_g}$;
  end for
  $\mathbf{W}_g \leftarrow \mathbf{W}_g - \frac{\lambda}{m}\Delta\mathbf{W}_g$; $\mathbf{W}_d \leftarrow \mathbf{W}_d - \frac{\lambda}{m}\Delta\mathbf{W}_d$;
end for

ILT-guided Pretraining

Why Pretraining?

- ILT and neural networks optimization share similar gradient descent procedure.
- Let the generator get prior knowledge from the lithography engine.



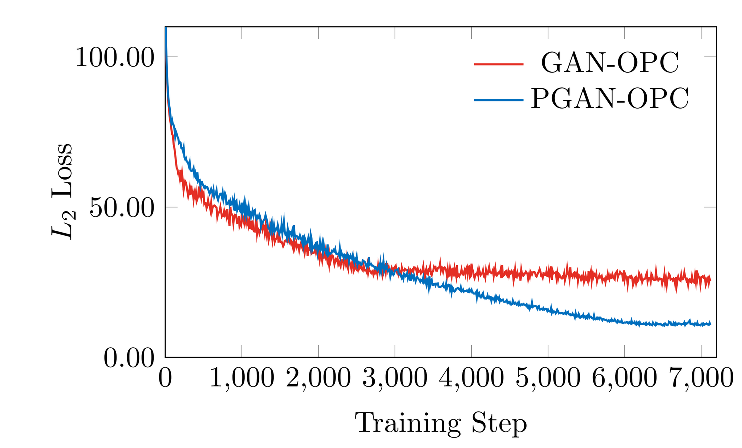
ILT-guided Pretraining

Equation (8) is naturally compatible with mini-batch gradient descent, if we create a link between the generator and ILT engine, the wafer image error can be back-propagated directly to the generator as illustrated above.

ILT-guided Pretraining

for number of pre-training iterations **do**
  Sample m target clips $\mathcal{Z} \leftarrow \{\mathbf{Z}_{t,1}, \mathbf{Z}_{t,2}, \dots, \mathbf{Z}_{t,m}\}$;
  $\Delta\mathbf{W}_g \leftarrow 0$;
  for each $\mathbf{Z}_t \in \mathcal{Z}$ **do**
    $\mathbf{M} \leftarrow \mathbf{G}(\mathbf{Z}_t; \mathbf{W}_g)$;
    $\mathbf{Z} \leftarrow$ `LithoSim`$(\mathbf{M})$ ▷ Equations (2)–(3)
    $E \leftarrow ||\mathbf{Z} - \mathbf{Z}_t||_2^2$;
    $\Delta\mathbf{W}_g \leftarrow \Delta\mathbf{W}_g + \frac{\partial E}{\partial \mathbf{M}}\frac{\partial \mathbf{M}}{\partial \mathbf{W}_g}$; ▷ Equation (7)
  end for
  $\mathbf{W}_g \leftarrow \mathbf{W}_g - \frac{\lambda}{m}\Delta\mathbf{W}_g$; ▷ Equation (8)
end for

Training Behavior:

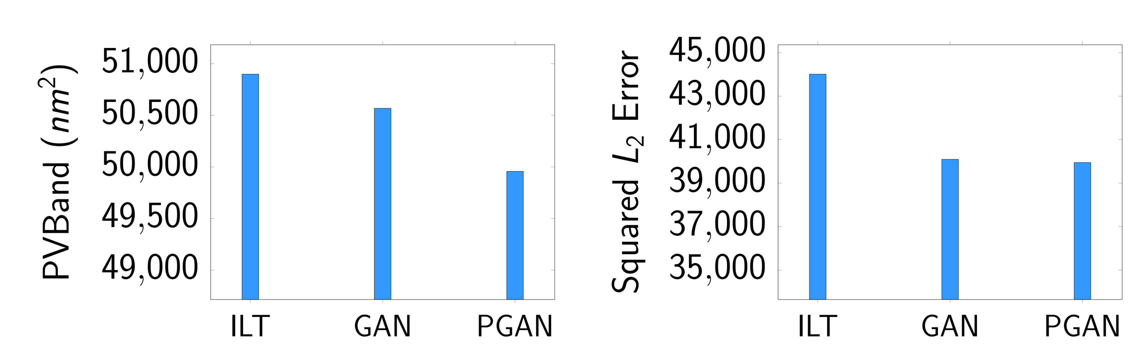


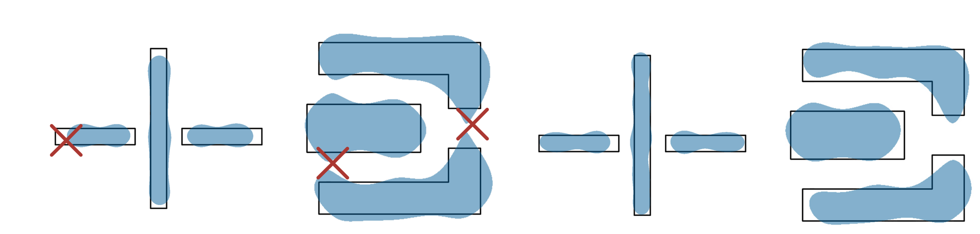
Experimental Results

The Dataset

- The lithography engine is based on the `lithosim v4` package from ICCAD 2013 CAD Contest.
- Manually generated 4000 instances based on the design specfication from existing $32nm$ M1 layouts.

Mask Optimization Results





(a) (b)

Visualizing PGAN-OPC and ILT:

(a) masks of [Gao+,DAC'14]; (b) masks of PGAN-OPC; (c) wafer images by masks of [Gao+,DAC'14]; (d) wafer images by masks of PGAN-OPC; (e) target patterns.