EMOGen: Enhancing Mask Optimization via Pattern Generation

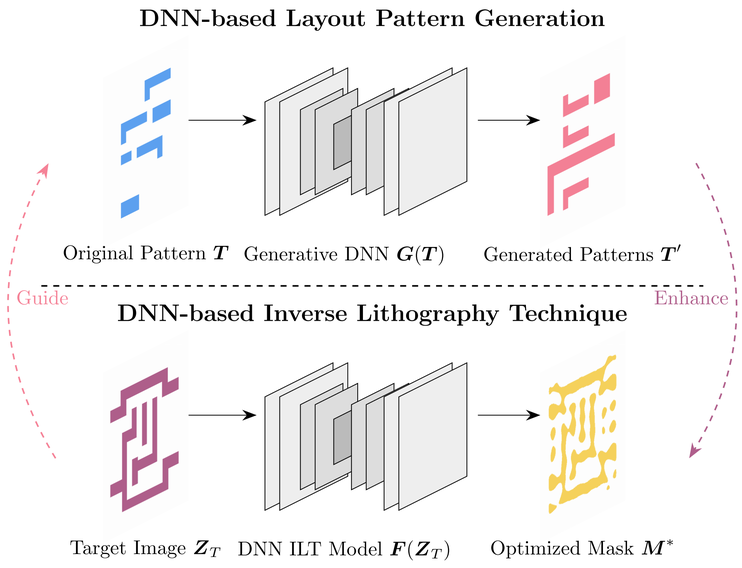
Su Zheng[1], Yuzhe Ma[2], Bei Yu[1], Martin Wong[3]

[1]Chinese University of Hong Kong

[2]Hong Kong University of Science and Technology (Guangzhou)

[3]Hong Kong Baptist University

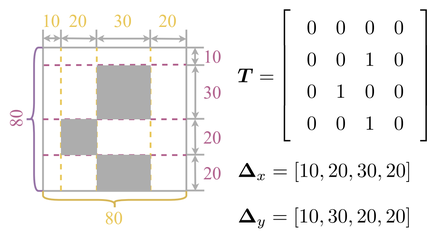
Motivation



- **Co-evolve** layout generation and mask optimization
  - Directly utilizes layout generation to improve DNN-based ILT methods
- ILT-aware training and legalization schemes
  - Discover the weaknesses of the DNN-based ILT model
- Extensive experiments verify the effectiveness
  - 39% enhancement in DNN-based ILT
  - 34% improvement in pattern legalization

Preliminaries

- Squish Pattern: efficiently represents layout patterns
  - A topology matrix + two geometry vectors



$$\boldsymbol{T} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\boldsymbol{\Delta}_x = [10, 20, 30, 20]$$

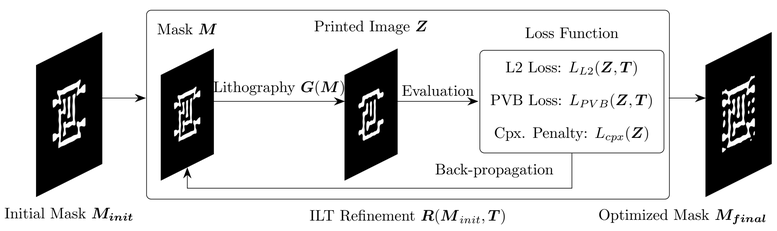
$$\boldsymbol{\Delta}_y = [10, 30, 20, 20]$$

- Layout Pattern Generation: autoencoder-based

$$\boldsymbol{T}' = \boldsymbol{f}_{dec}\left(\boldsymbol{f}_{enc}(\boldsymbol{T}) + \epsilon\mathcal{N}(0, \boldsymbol{I})\right). \quad (1)$$

  - Map the topology matrices to a latent space
  - Generate new patterns by perturbing latent features

- ILT for Mask Optimization



- Lithography simulation:
  $\boldsymbol{I} = \boldsymbol{H}(\boldsymbol{M}) = \sum_{k=1}^{K} \mu_k |\boldsymbol{h}_k \otimes \boldsymbol{M}|^2$.
- Objectives:
  $L2(\boldsymbol{Z}_{\text{nom}}, \boldsymbol{Z}_T) = \|\boldsymbol{Z}_{\text{nom}} - \boldsymbol{Z}_T\|^2$,
  $PVB(\boldsymbol{Z}_{\max}, \boldsymbol{Z}_{\min}) = \|\boldsymbol{Z}_{\max} - \boldsymbol{Z}_{\min}\|^2$.
- Metrics: L2, PVB, EPE (edge placement error)

Formulation

- Mask optimization problem

$$\boldsymbol{M}^* = \boldsymbol{f}_M(\boldsymbol{Z}_T|\boldsymbol{\theta}_M). \quad (2)$$

  - $\boldsymbol{Z}_T$ is the target image.
  - $\boldsymbol{M}^*$ represents the optimized masks given by the ILT model.

- Pattern generation problem

$$\boldsymbol{T}', \boldsymbol{\Delta}'_x, \boldsymbol{\Delta}'_y = \boldsymbol{f}_P(\boldsymbol{T}, \boldsymbol{\Delta}_x, \boldsymbol{\Delta}_y|\boldsymbol{\theta}_P). \quad (3)$$

  - $\boldsymbol{f}_P(\cdot)$ denotes the pattern generation model with the parameters $\boldsymbol{\theta}_P$.
  - $\boldsymbol{T}', \boldsymbol{\Delta}'_x, \boldsymbol{\Delta}'_y$ represent the generated topology and geometry.

- Co-optimization problem → two players competing with each other

$$\min_{\boldsymbol{\theta}_M} \max_{\boldsymbol{\theta}_P} L_{ILT}\left(\boldsymbol{f}_M(\boldsymbol{X}|\boldsymbol{\theta}_M), \boldsymbol{X}\right) \ s.t.\ \boldsymbol{X} = \boldsymbol{r}\left(\boldsymbol{f}_P(\boldsymbol{T}, \boldsymbol{\Delta}_x, \boldsymbol{\Delta}_y|\boldsymbol{\theta}_P)\right). \quad (4)$$

  - L_{ILT} is the loss function of ILT.
  - $\boldsymbol{r}(\cdot)$ converts the generated pattern to ILT input.

- Legalization of the generated patterns

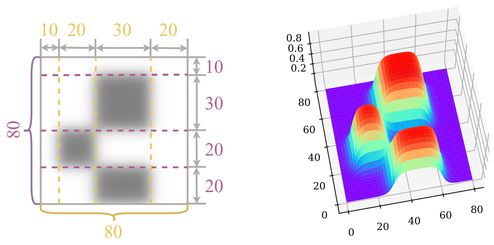
$$\sum_{k\in\boldsymbol{k}_x} \Delta'_{x,k} \geq \text{Space}_{\min}, \sum_{k\in\boldsymbol{k}_y} \Delta'_{y,k} \geq \text{Space}_{\min}, \forall \boldsymbol{k}_x, \boldsymbol{k}_y \in \boldsymbol{S}_{\min}, \quad (5)$$

$$\sum_{l\in\boldsymbol{l}_x} \Delta'_{x,l} \geq \text{Width}_{\min}, \sum_{l\in\boldsymbol{l}_y} \Delta'_{y,l} \geq \text{Width}_{\min}, \forall \boldsymbol{l}_x, \boldsymbol{l}_y \in \boldsymbol{W}_{\min}, \quad (6)$$

$$\sum_{(i,j)\in\boldsymbol{p}} \Delta'_{x,i}\Delta'_{y,j} \in [\text{Area}_{\min}, \text{Area}_{\max}], \forall \text{ polygon } \boldsymbol{p}. \quad (7)$$

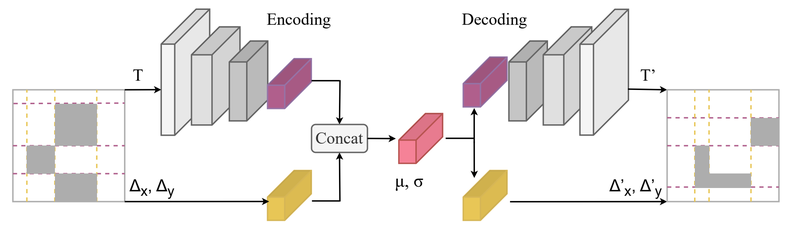
Training

- Make it differentiable with $\boldsymbol{r}(\cdot)$, the bell-shape function



Models

- Pattern Generation Model

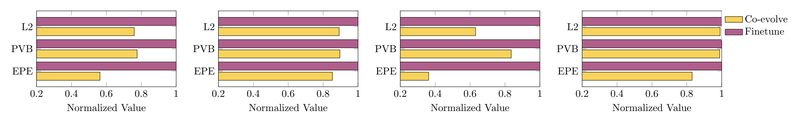


- Mask Optimization Models
  - **GAN-OPC** It follows the design of generative adversarial network (GAN).
  - **Neural-ILT** A UNet is utilized in Neural-ILT to predict the optimized mask.
  - **DAMO** It improves the GAN for ILT with the backbone based on UNet++ and a multiscale discriminator.
  - **CFNO** Combining the basic principles of Vision Transformer (ViT) and Fourier Neural Operator (FNO).
- Codebase from OpenILT and LithoBench
  - https://github.com/OpenOPC/OpenILT
  - https://github.com/shelljane/LithoBench

Experiments

- Comparison Between ILT Models With and Without Co-evolution

Method	GAN-OPC		NeuralILT		DAMO		CFNO		Ratio	
Setting	Finetune	Co-evolve	Finetune	Co-evolve	Finetune	Co-evolve	Finetune	Co-evolve	Finetune	Co-evolve
L2	50,388	**38,288**	50,804	**45,313**	53,448	**33,757**	46,280	**45,863**	1.00	**0.81**
PVB	69,549	**53,987**	61,464	**55,082**	65,447	**54,703**	62,514	**61,811**	1.00	**0.87**
EPE	7.1	**4.0**	7.5	**6.4**	10.2	**3.7**	5.9	**4.9**	1.00	**0.61**



- Comparison on the Legalization of Generated Patterns

Metric	μ_V	L2	PVB	EPE
No legalization	0.094	51777	57149	22.0
Design Rules Only	0.070	50782	57335	21.4
Design Rules + ILT (ours)	**0.062**	**64800**	**65394**	**44.1**