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THE CHIPS TO SYSTEMS CONFERENCE

SHAPING THE NEXT GENERATION OF ELECTRONICS

JUNE 23-27, 2024

MOSCONE WEST CENTER
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EMOGen: Enhancing Mask Optimization via Pattern Generation

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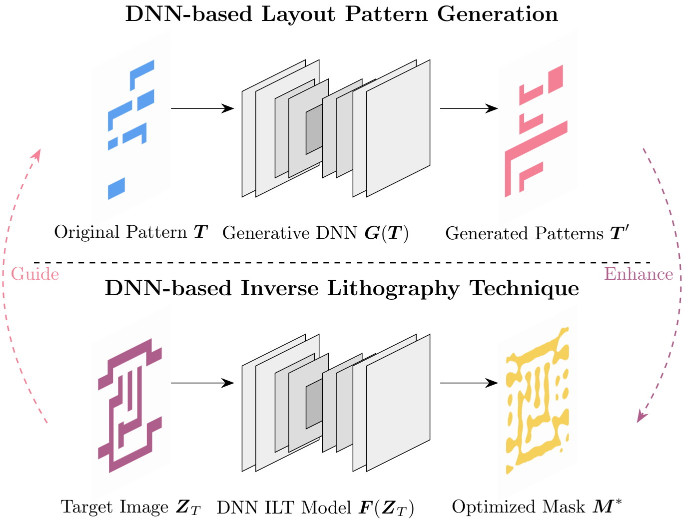
Outline

Introduction

Motivation



DNN-based Layout Pattern Generation
Original Pattern $\boldsymbol{T}$
Generative DNN $\boldsymbol{G}(\boldsymbol{T})$
Generated Patterns $\boldsymbol{T}'$
Guide
Enhance
DNN-based Inverse Lithography Technique
Target Image $\boldsymbol{Z}_T$
DNN ILT Model $\boldsymbol{F}(\boldsymbol{Z}_T)$
Optimized Mask $\boldsymbol{M}^*$

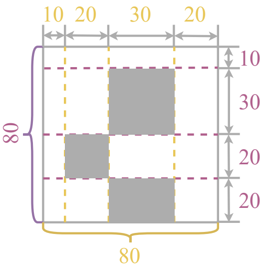
Contributions

- EMOGen: **co-evolution** of layout generation and mask optimization
  - Use 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 of EMOGen
  - 39% enhancement in DNN-based ILT
  - 34% improvement in pattern legalization

Preliminaries

Squish Pattern

- Efficient representation of the layout patterns
  - A topology matrix + two geometry vectors



(a)

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

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

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

(b)

Layout Pattern Generation

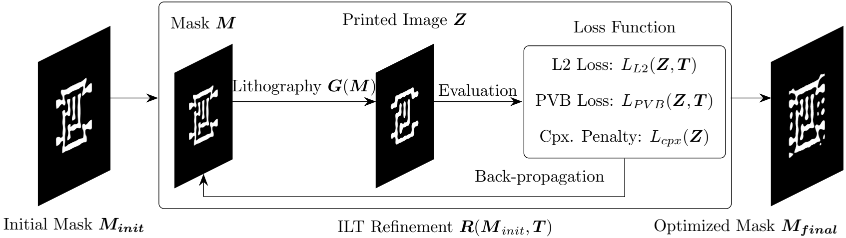
- Autoencoder-based approaches

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

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

Mask Optimization

- 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: $L2(\mathbf{Z}_{\text{nom}}, \mathbf{Z}_T) = \|\mathbf{Z}_{\text{nom}} - \mathbf{Z}_T\|^2$,

$$PVB(\mathbf{Z}_{\max}, \mathbf{Z}_{\min}) = \|\mathbf{Z}_{\max} - \mathbf{Z}_{\min}\|^2.$$

Method

Mathematical Formulation

- Mask optimization problem

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

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

Mathematical Formulation

- Pattern generation problem

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

  - $\boldsymbol{f}_P(\cdot)$ 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.

Mathematical Formulation

- Co-optimization problem $\rightarrow$ two players competing with each other

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

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

Mathematical Formulation

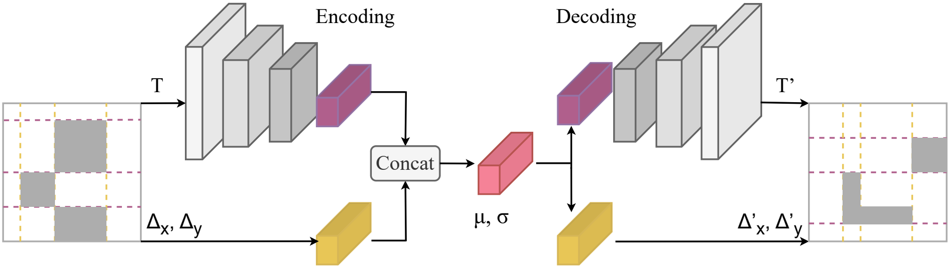
- Legalization of the generated patterns

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

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

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

Pattern Generation Model



ILT Models

- **GAN-OPC**[1] It follows the design of generative adversarial network (GAN).
- **Neural-ILT**[2] A UNet is utilized in Neural-ILT to predict the optimized mask.
- **DAMO**[3] It improves the GAN for ILT with the backbone based on UNet++ and a multiscale discriminator.
- **CFNO**[4] Combining the basic principles of Vision Transformer (ViT) and Fourier Neural Operator (FNO).

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[1] Haoyu Yang, Shuhe Li, et al. (2018). "GAN-OPC: Mask optimization with lithography-guided generative adversarial nets". In: *Proc. DAC*.

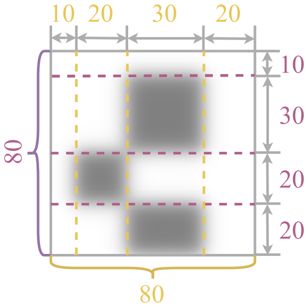
[2] Bentian Jiang et al. (2020). "Neural-ILT: Migrating ILT to neural networks for mask printability and complexity co-optimization". In: *Proc. ICCAD*.

[3] Guojin Chen et al. (2020). "DAMO: Deep agile mask optimization for full chip scale". In: *Proc. ICCAD*.

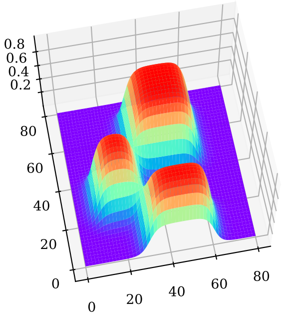
[4] Haoyu Yang and Haoxing Ren (2023). "Enabling Scalable AI Computational Lithography with Physics-Inspired Models". In: *Proc. ASPDAC*, pp. 715–720.

Combining Pattern Generation and ILT Models

- Make it differentiable

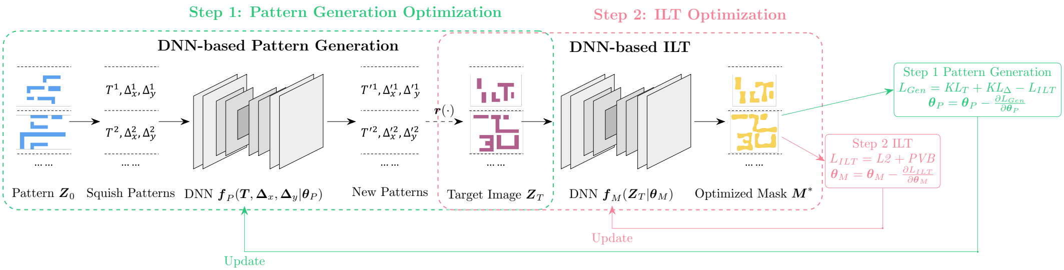


(c)



(d)

Overview of EMOGen Training

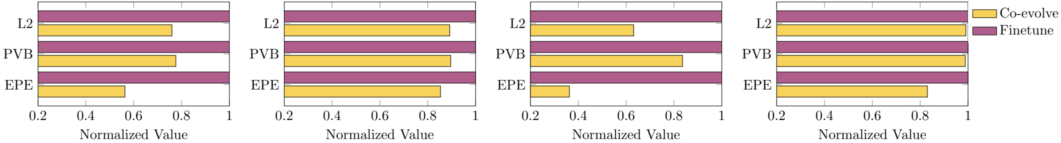


Experiments

Comparison Between ILT Models With and Without Co-evolution

- Better ILT performance.

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**



(a) GAN-OPC (b) NeuralILT (c) DAMO (d) CFNO

Comparison on the Legalization of Generated Patterns

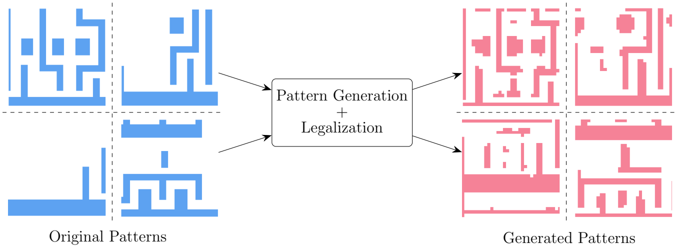
- Better pattern generation: effectively deteriorate the ILT performance.
- Better pattern legalization: the generated results have a smaller average number of design rule violations.

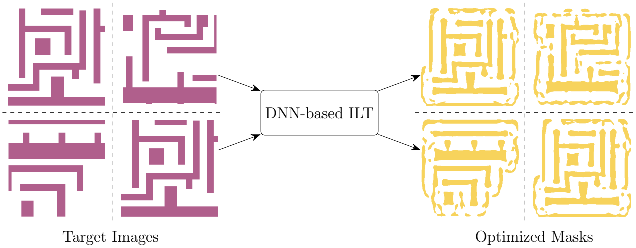
Metric	μ_V	L2	PVB	EPE
No Legalization[5]	0.094	51777	57149	22.0
Design Rules Only[6]	0.070	50782	57335	21.4
Design Rules + ILT (ours)	**0.062**	**64800**	**65394**	**44.1**

[5] Haoyu Yang, Piyush Pathak, et al. (2019). "DeePattern: Layout pattern generation with transforming convolutional auto-encoder". In: *Proc. DAC*.

[6] Zixiao Wang et al. (2023). "DiffPattern: Layout Pattern Generation via Discrete Diffusion". In: *Proc. DAC*.

Examples from the Trained Pattern Generation and ILT Models





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