IEEE/ACM 2024 INTERNATIONAL CONFERENCE ON COMPUTER-AIDED DESIGN ICCAD 43rd Edition

Enabling Robust Inverse Lithography with Rigorous Multi-Objective Optimization

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Outline

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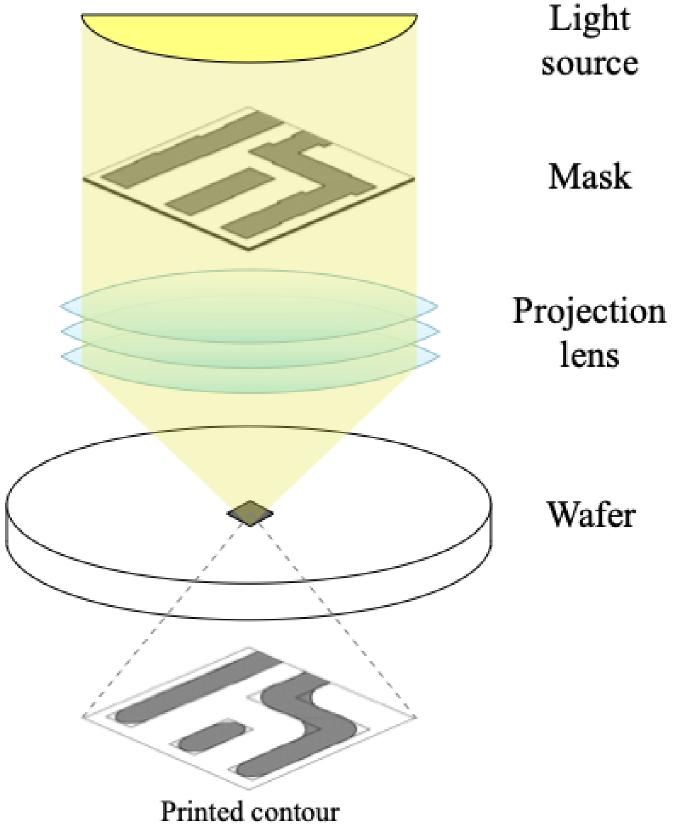
1. Introduction
2. Method
3. Experiments

Optical Proximity Correction (OPC)

- Lithography: pattern transferring
- Optical proximity effect results in yield loss[1]
- OPC: rectify mask patterns for compensation

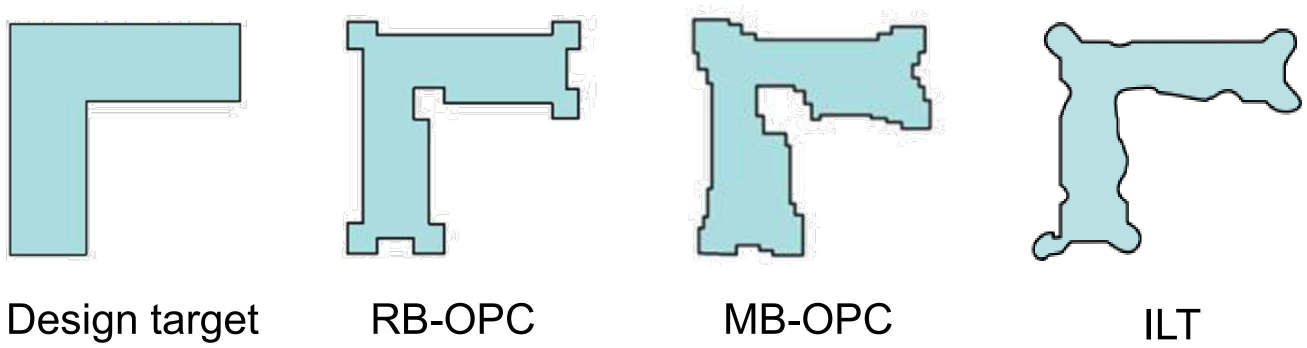
The optical proximity effect.



[1]Pan, D. Z., et al. (2013). "Design for manufacturing with emerging nanolithography." *In: IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems.*

Optical Proximity Correction (OPC)

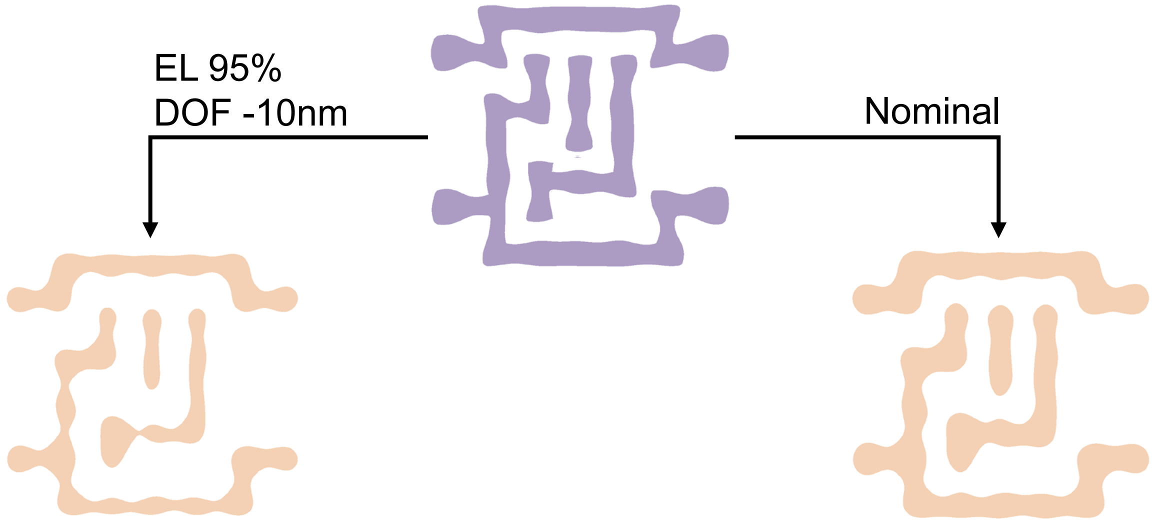
- Rule based OPC[2]: empirical rules
- Model based OPC[3] : iterative segment movement
- **ILT (Inverse Lithography Technique)** [4]: inverse imaging
- Deep learning based methods[5] : target-mask-pair dataset



[2]Otto, et al. (1994). “Automated optical proximity correction: a rules-based approach.” *In: Proc. SPIE. Vol. 2197.*
[3]Tetsuaki Matsunawa, et al. (2015). “Optical proximity correction with hierarchical Bayes model”. *In: Proc. SPIE. Vol. 9426.*
[4]Gao, J. R., et al. (2014). “MOSAIC: Mask optimizing solution with process window aware inverse correction.” *In: Proc. DAC (pp. 1-6).*
[5]Yang, H., et al. (2018). “GAN-OPC: Mask optimization with lithography-guided generative adversarial nets.” *In: Proc. DAC (pp. 1-6).*

Process Variation

- Process Variation
  - DOF (Depth of Focus)
  - EL (Exposure Latitude)
- The mask quality may fluctuate across different corners

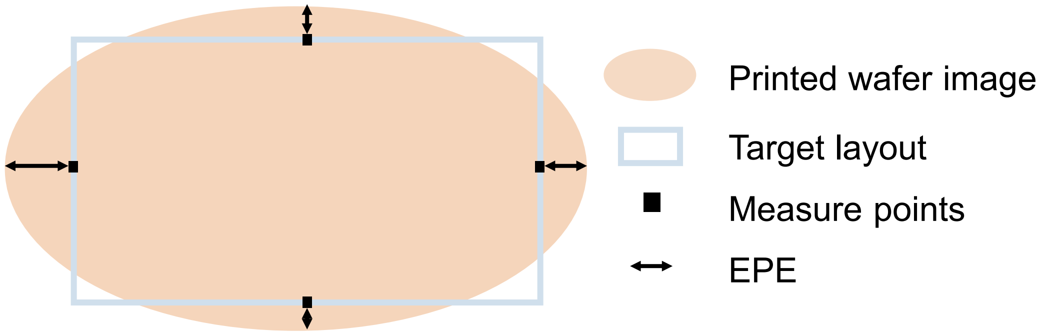


Printed images under two different process corners using the same mask.

Process Window

Process Window[6]

Characterizes the robustness against the process variation. Evaluated by measuring the variations among multiple process corners.



Edge Placement Error.

DOF (nm)	EL(%)				
	90	95	100	105	110
-10	N	N	Y	N	N
0	N	Y	Y	Y	N
10	N	Y	N	N	N

Process Window.

[6]Banerjee, S., et al. (2013). "ICCAD-2013 CAD contest in mask optimization and benchmark suite." *In: Proc. ICCAD (pp. 271-274).*

Lithography Modeling

- The forward lithography process
  - SVD-approximated Hopkins model[8,9]
  - Resist model

$$\mathbf{I}(x,y)=\sum_{k=1}^{K} w_k \left| \vec{h}_k(x,y)\otimes \mathbf{M}(x,y)\right|^2,$$

$$\mathbf{Z}(x,y)=f_{resist}(\mathbf{I})=\begin{cases}0, & \mathbf{I}(x,y)\le I_{th},\\ 1, & \text{otherwise.}\end{cases}$$

$\mathbf{M},\mathbf{I},\mathbf{Z}$: mask, aerial image, printed image

- Standard ILT formulation:

$$\begin{aligned}\min_{\mathbf{M}} \quad & \|\mathbf{Z}-\mathbf{Z}_t\|_2^2\\ \text{s.t.} \quad & \mathbf{Z}=f_{resist}(\mathbf{I})\\ & \mathbf{I}=f_{optic}(\mathbf{M})\\ & \mathbf{M}(x,y)\in\{0,1\}\,.\end{aligned}$$

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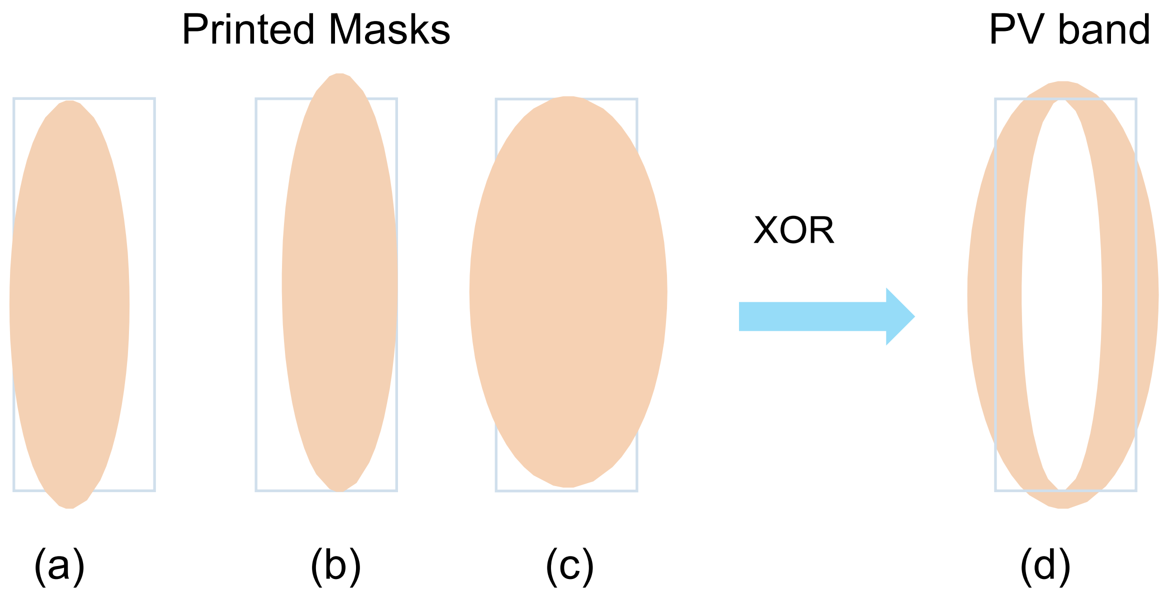
[8]Hopkins, H. H. (1951). “The concept of partial coherence in optics.” *In: Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences, Vol 208.*

[9]Cobb, N. B. (1998). “Fast optical and process proximity correction algorithms for integrated circuit manufacturing”. *University of California, Berkeley.*

Previous PV-aware ILT Methods

- Optimizes process variation band (PV band) for mask robustness
- PV band calculation uses **XOR**: non-differentiable
- Non-applicable for ILT methods



PV band measurement

Previous PV-aware ILT Methods

- Minimize difference between wafer image variants and target pattern
- Previous PV-ILT mostly consider extreme process corners as "outermost" and "innermost"
- May not exist such corners

$$\begin{aligned} \min_{\mathbf{M}} \quad & \|\mathbf{Z} - \mathbf{Z}_t\|_2^2 \\ \text{s.t.} \quad & \mathbf{Z} = f_{resist}(\mathbf{I}) \\ & \mathbf{I} = f_{optic}(\mathbf{M}) \\ & \mathbf{M}(x, y) \in \{0, 1\} \,. \end{aligned}$$

$\Rightarrow$

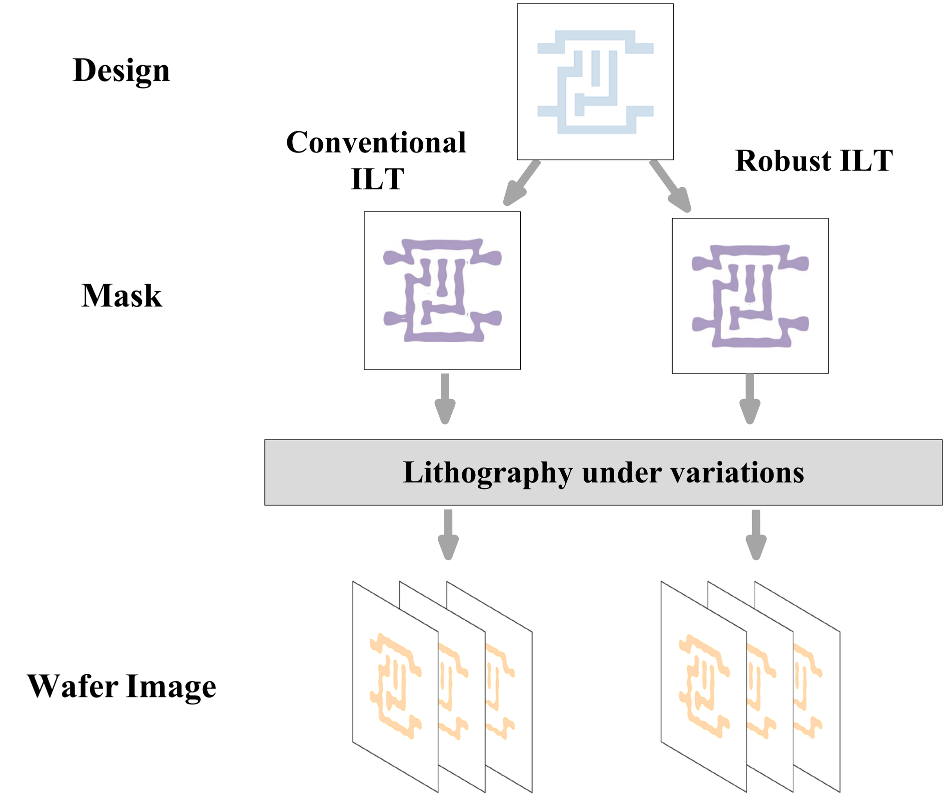
$$\begin{aligned} \min_{\mathbf{M}} \quad & \alpha\|\mathbf{Z} - \mathbf{Z}_t\|_2^2 + \beta \sum_{k=1}^{K} \|\mathbf{Z}_k - \mathbf{Z}_t\|^2 \\ \text{s.t.} \quad & \mathbf{Z} = f_{resist}(\mathbf{I}) \\ & \mathbf{I} = f_{optic}(\mathbf{M}) \\ & \mathbf{M}(x, y) \in \{0, 1\} \,. \end{aligned}$$

Motivation

Robust ILT

We consider all discrete process corners during rigorous optimization procedure.

- Direct optimization of process window
- Robust against process variations



Defocus	Dose 90%	95%	100%	105%	110%
-10	N	N	Y	N	N
0	N	Y	Y	Y	N
+10	N	Y	N	N	N

Defocus	Dose 90%	95%	100%	105%	110%
-10	N	Y	Y	Y	Y
0	N	Y	Y	Y	Y
+10	Y	Y	Y	Y	N

Robust ILT.

Problem Formulation

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Robust ILT with Rigorous Multi-Objective Optimization

Given a target layout $\mathbf{Z}_t$, the objective of robust inverse lithography technique is to obtain a mask $\mathbf{M}^*$ by solving the following N-dimensional **M**ulti-**O**bjective **O**ptimization **P**roblem (MOOP).

- Accommodate process variations based on basic ILT solutions:

$$
\begin{aligned}
\min_{\mathbf{M}} \quad & \mathcal{L}(\mathbf{M}) = [\mathcal{L}_1(\mathbf{M}), \mathcal{L}_2(\mathbf{M}), ..., \mathcal{L}_N(\mathbf{M})]^T \\
\text{s.t.} \quad & \mathcal{L}_n(\mathbf{M}) = \|\mathbf{Z}_n - \mathbf{Z}_t\|_2^2, \quad \forall n \in \{1, 2, ..., N\}, \\
& \mathbf{Z}_n = f_{resist}(\mathbf{I}_n), \quad \forall n \in \{1, 2, ..., N\}, \\
& \mathbf{I_n} = \sum_{k=1}^{K} w_k \mid \vec{h}_{n_k} \otimes \mathbf{M} \mid^2, \quad \forall n \in \{1, 2, ..., N\}, \\
& \mathbf{M}(x, y) \in \{0, 1\},
\end{aligned}
$$

Robust ILT

Optimization Perspective

Non-trivial[10], due to a complicated priority balance, avoiding *Pareto dominated point*

Conflict gradients direction[11] ✗

Dominated gradients scale[12] ✗

Computational Cost Perspective

Introduces **more computation overhead** on lithography simulation and backward optimization

Low scalability ✗

[10] Emmerich, M. T., & Deutz, A. H. (2018). "A tutorial on multi-objective optimization: fundamentals and evolutionary methods." *In: Natural computing. Vol. 17.*
[11] Yu, T., Kumar, et al. (2020). "Gradient surgery for multi-task learning." *In: NIPS, Vol. 33.*
[12] Liu, L., et al. (2021). "Towards impartial multi-task learning." *In: ICLR.*

Robust ILT

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Optimization Perspective

Non-trivial, due to a complicated priority balance, avoiding *Preto dominated point*

- Conflict gradients direction ✗
- Dominated gradients scale ✗

Computational Cost Perspective

Introduces **more computation overhead** on lithography simulation and backward optimization

- Low scalability ✗

Propose a **uniform gradient optimization method**

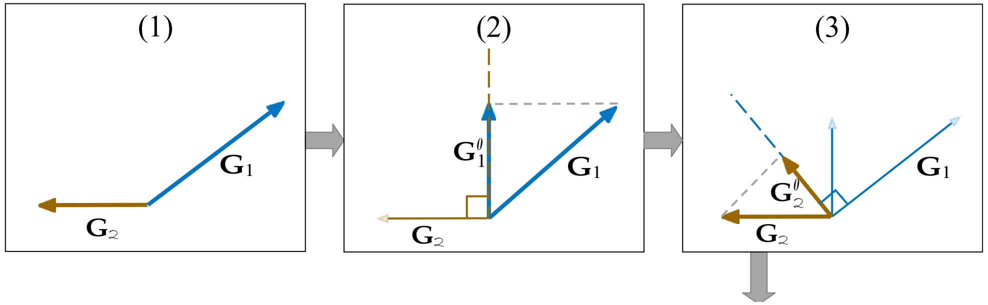
- ✓ Uniform gradient direction
- ✓ Gradient magnitude-balancing

Improve the algorithm efficiency from both the **implementation** and **algorithm** level

- ✓ Objective sampling strategy
- ✓ Parallel implementation with multi-GPUs

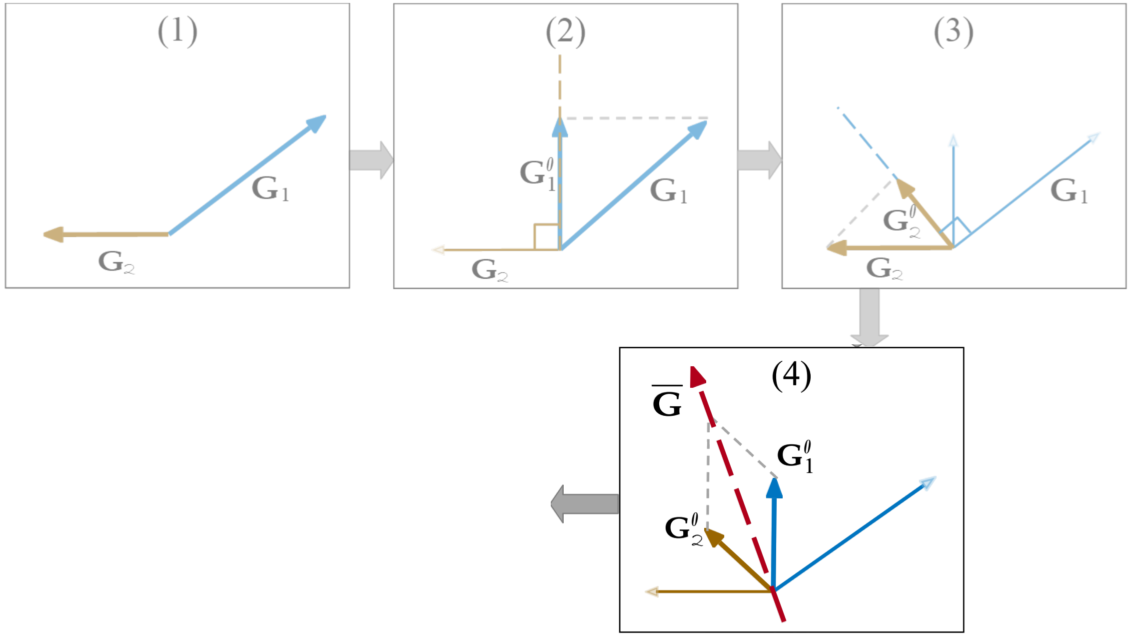
Uniform Gradient Direction

- Explicitly handle the diverged directions among different gradients
- Solve gradient conflicts by projecting each gradient onto the orthogonal direction of the others
- Alleviate projection ordering bias by random perturbation



Uniform Gradient Direction

- Normalize aggregated gradient to obtain uniform update direction

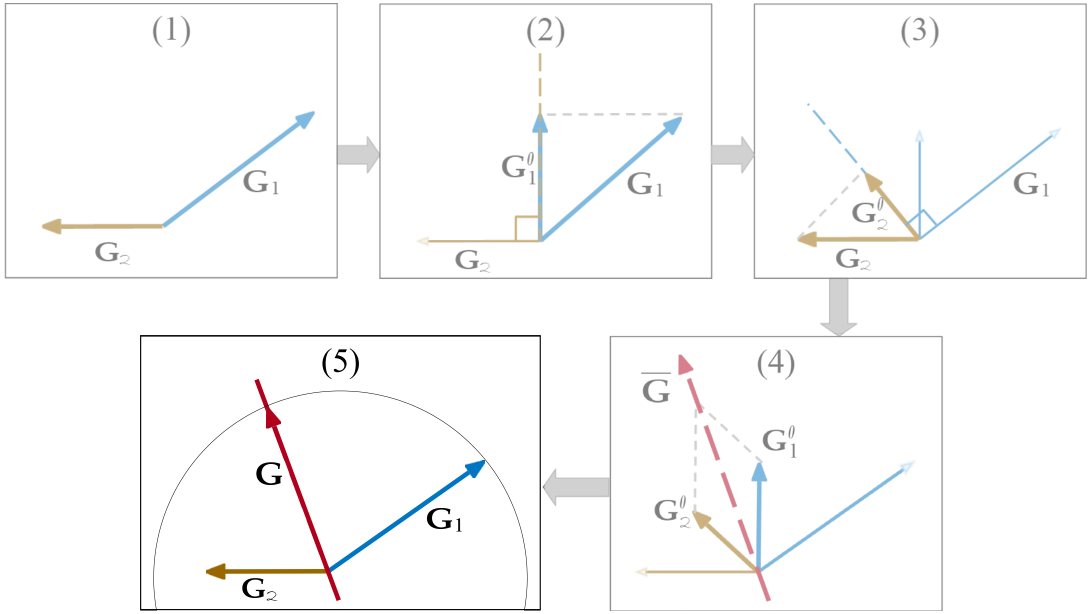


Gradient Magnitude-balancing

Observation

There are significant discrepancies between the printed images and the target layout, and some gradients have large magnitudes.

- Current step size: the maximum magnitude of gradients
  - While small step size is to maintain performance when all gradient magnitudes diminish



Acceleration

- Through objective sampling, in each ILT iteration:

- Compute sub-gradients $G_{1\sim N}$
- For corner n from 0 to N:
  - **Sample** M corners over the index set $\{1, 2, \ldots, N\}\backslash n$
  - For m in **sampled set**:
    - Obtain the uniform gradient direction using G_n and G_m
  - Sum the M directions
- Magnitude $= \max||G_{1\sim N}||$
- Obtain the final aggregated gradient with direction and magnitude

Acceleration

- Through multiple GPUs parallelization
  - Parallel lithography forward simulation and backward propagation under various process conditions

Comparison with Previous Methods

- Benchmark: ICCAD2013 CAD Contest[6] (2048×2048)
- Comparison between ours and previous SOTA methods on EPE
  - MOSAIC[4]
  - Deep learning-based method: NeuralILT[13], GANOPC[5] and CFNOILT[14]

Design	MOSAIC				NeuralILT				GANOPC				CFNOILT				Ours			
	Nominal	Worst	Mean	Std	Nominal	Worst	Mean	Std	Nominal	Worst	Mean	Std	Nominal	Worst	Mean	Std	Nominal	Worst	Mean	Std
Case 1	8	23	15	5.02	8	19	13.83	3.92	17	41	26.33	9.71	17	39	24.83	8.26	**6**	**13**	**8.67**	**3.33**
Case 2	**0**	11	5.5	3.62	8	25	15.67	6.89	4	24	14.33	8.64	17	49	27.83	13.12	**0**	**6**	**2.5**	**2.26**
Case 3	49	**60**	49.33	**6.25**	**42**	62	50.5	8.04	47	74	56.17	10.65	67	98	76.67	12.27	47	61	**49**	7.46
Case 4	2	5	3	1.26	**1**	5	2.5	1.64	2	10	4.67	2.94	9	27	13.67	7.94	**1**	**2**	**1.83**	**0.41**
Case 5	**0**	7	1.5	2.74	2	5	3.67	1.21	2	7	3.17	2.14	4	47	15.67	17	**0**	**3**	**0.67**	**1.21**
Case 6	3	4	**1.67**	1.86	4	5	3.5	1.22	3	17	8.67	5.24	3	41	17.5	14.39	**2**	**3**	**1.67**	**0.82**
Case 7	2	19	5.83	7.86	**0**	**6**	**1.67**	**2.34**	**0**	18	4.17	6.88	**0**	21	5	8	**0**	16	3.17	6.4
Case 8	**0**	**0**	**0**	**0**	**0**	4	1.17	1.47	2	11	4.33	4.23	1	13	5.83	4.58	**0**	1	0.17	0.41
Case 9	1	6	2.5	1.87	4	18	9.17	5.81	6	25	15	7.56	7	24	13.17	5.78	**0**	**3**	**1.17**	**1.17**
Case 10	**0**	**0**	**0**	**0**	4	5	2.83	2.04	5	14	7	4.86	**0**	3	0.83	1.33	**0**	**0**	**0**	**0**
Average	6.5	13.5	8.43	-	7.3	15.4	10.45	-	8.8	24.1	14.38	-	12.5	36.2	20.1	-	**5.6**	**10.8**	**6.89**	-

[13] Jiang, B., et al. (2020). “Neural-ILT: Migrating ILT to neural networks for mask printability and complexity co-optimization.” *In: Proc ICCAD (pp. 1-9).*

[14] Yang, H., & Ren, H. (2023). “Enabling scalable AI computational lithography with physics-inspired models.” *In: Proc. ASPDAC (pp. 715-720).*

Overall Runtime

- Comparison between previous SOTA methods and ours, w. and w.o. multiple GPUs acceleration

Design	MOSAIC	NeuralILT	GANOPC	CFNOILT	Ours	
					Ori.	Accel.
Case1	7.50s	4.92s	6.19s	5.46s	41.40s	17.72s
Case2	7.55s	5.25s	5.75s	5.11s	41.70s	15.16s
Case3	7.45s	4.95s	6.05s	5.13s	41.03s	15.13s
Case4	7.48s	5.12s	5.82s	5.26s	41.43s	16.28s
Case5	7.66s	4.94s	5.88s	5.32s	41.42s	16.10s
Case6	7.60s	4.90s	5.89s	5.51s	41.47s	14.96s
Case7	7.52s	4.92s	5.72s	5.05s	42.04s	15.87s
Case8	7.56s	5.08s	5.77s	5.12s	41.19s	16.05s
Case9	7.78s	5.17s	5.84s	5.00s	41.84s	14.97s
Case10	8.03s	4.87s	5.82s	4.95s	42.44s	16.42s
Average	7.61s	5.01s	5.87s	5.19s	41.60s	15.86s

Objective Sampling

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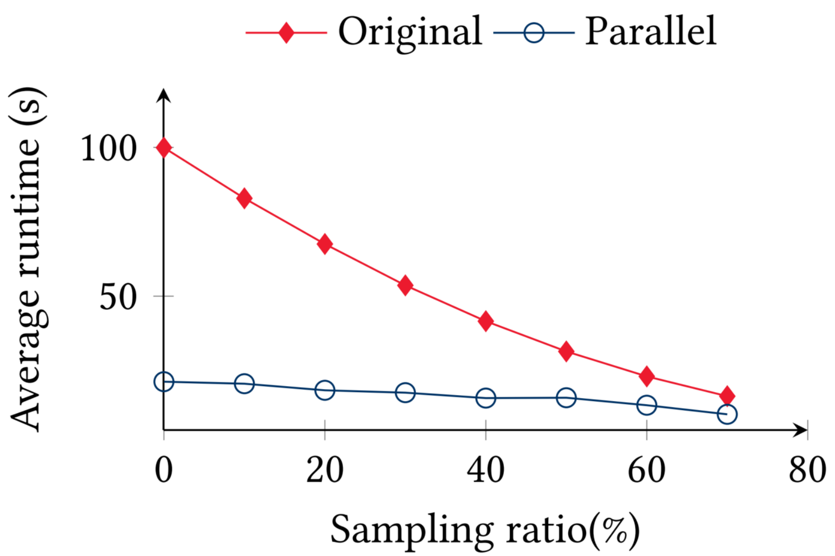
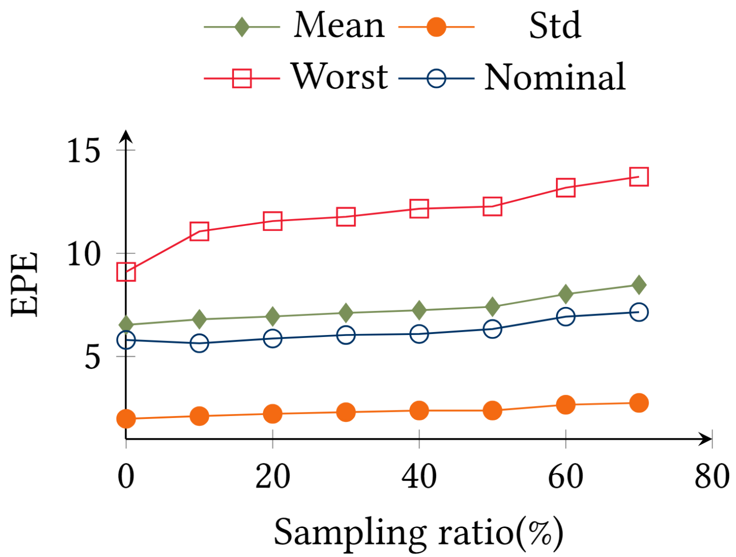
- Trade-off between performance and runtime
- Robust against sampling: EPE deviation remains relatively constant as the sampling ratio increasing





Runtime with objective sampling.

Mask quality with objective sampling.

Conclusion

- A rigorous MOOP solution for robust ILT, explicitly optimizes all process corners
- A uniform gradient computation approach
- Efficiency improvement: algorithm level & implementation level
- Achieves substantial process window improvement

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THANK YOU!

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