A Unified Framework for Simultaneous Layout Decomposition and Mask Optimization

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Outline

Introduction

Algorithms

Experimental Results

Conclusion

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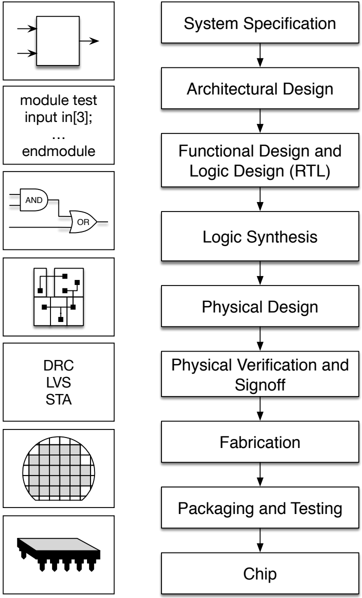
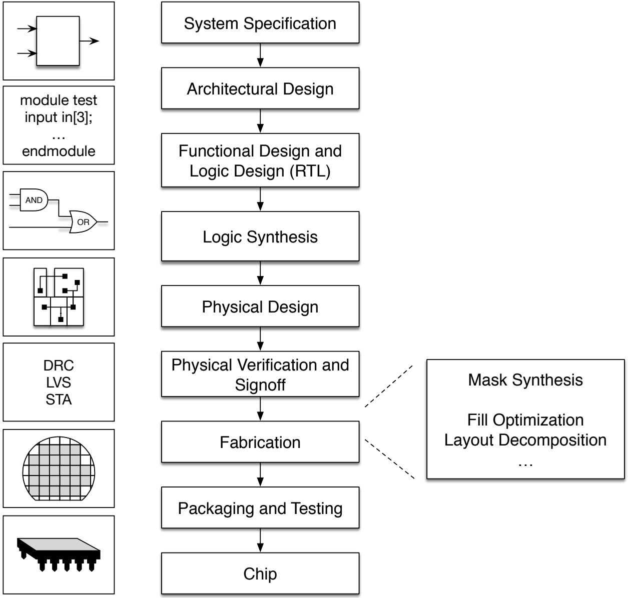
VLSI Chip Design Flow

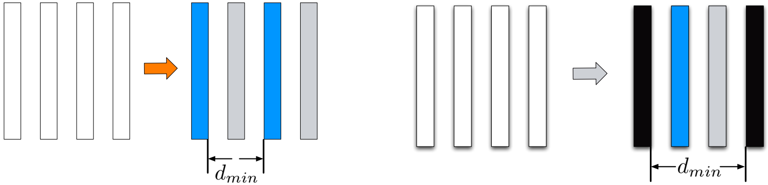


VLSI Chip Design Flow



Layout Decomposition (LD)

- Conflict: two features with the same color, while distance $< d_{min}$



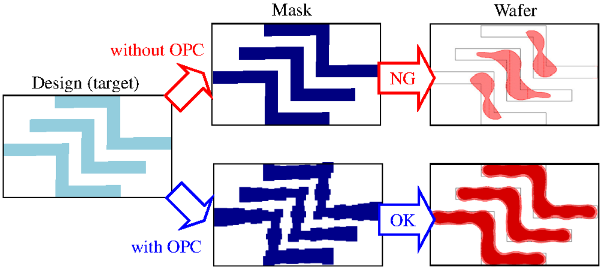
(a) LELE (b) LELELE

Problem Formulation

Input: layout and d_{min}

Output: decomposed layout, minimizing conflict #

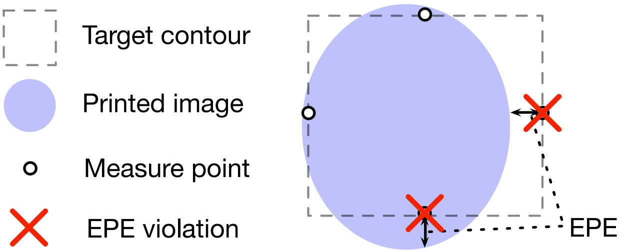
Mask Optimization (MO)



- The quality of printed image may be poor due to the diffraction effect of the light.
- Optical Proximity Correction(OPC): Refine the mask to compensate the diffraction effect.
- Method for OPC:
  - rule-based [Park+,ISQED'2010];
  - model-based [Kuang+,DATE'2015][Su+,TCAD'2016];
  - inverse lithography technique [Gao+,DAC'2014].

Mask Optimization (cont.)

- Edge Placement Error (EPE): Geometric displacement between the image contour and the edge of target image on the layout.
- EPE Violation: The perpendicular displacement is greater than an EPE threshold value.



Problem Formulation

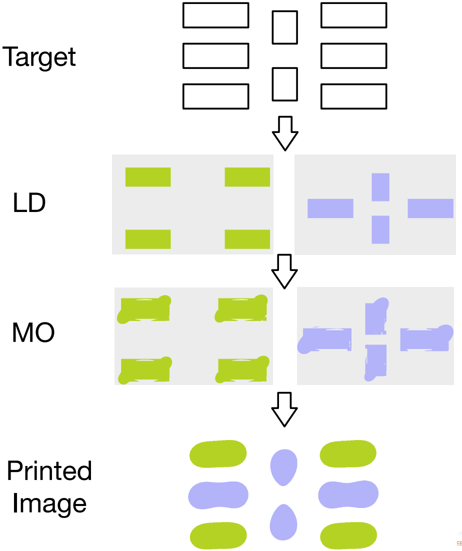
Input: target layout

Output: refined mask, minimizing EPE violation #.

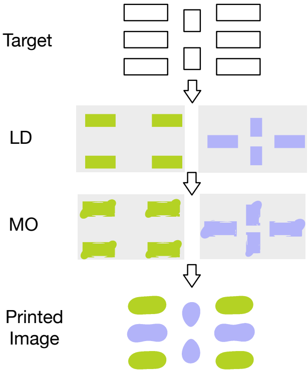
Two-Stage Flow for Layout Optimization

Two stages:

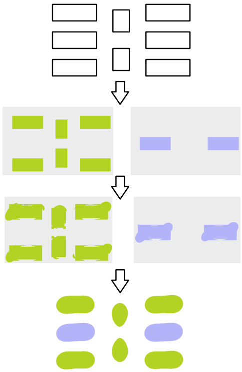
- Layout Decomposition (LD)
- Mask Optimization (MO)



Issues



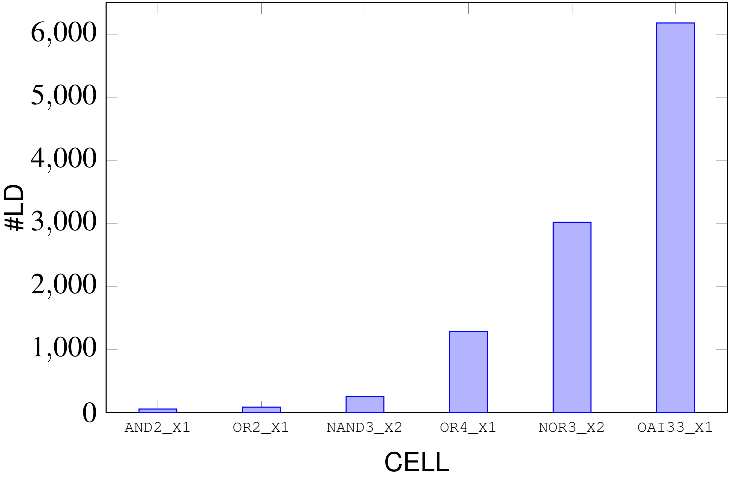
Solution 1: #EPE Violation = 1



Solution 2: #EPE Violation = 3

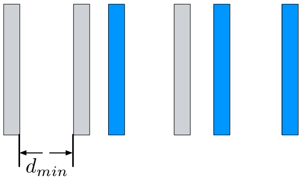
Options?

- **Exhaustive MO** for all LD solutions.
  - Running time overhead due to thousands of LD solutions.

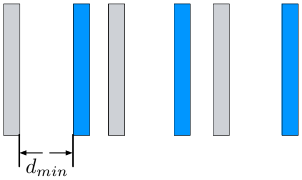


Options? (cont.)

- **Heuristic selection** among LD solutions.
  - Local region density [Yu+,ICCAD'13]: balance the pattern density on each mask.



  - Spacing vector [Chen+,ISQED'13]: maximize minimum distance between patterns.

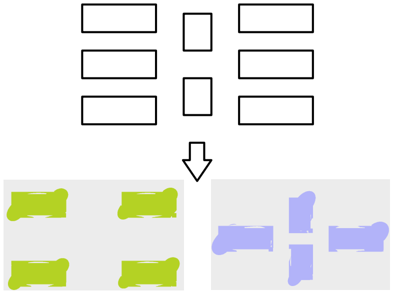


  - Limited effectiveness.

Motivation

How about combining LD and MO together?

Target



LDMO

- It is an open problem.
- It is expected to be more effective and more efficient.

Outline

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Preliminaries

- Lithography model:
  - The aerial image is formed by a series of convolution operation between mask $\mathbf{M}$ and lithography kernel $\mathbf{h}$.

$$\mathbf{I} = f_{optical}(\mathbf{M}) = \sum_{k=1}^{K} w_k \cdot |\mathbf{M} \otimes \mathbf{h}_k|^2$$

- Photo-resist model
  - Set a threshold I_{th} to binarize aerial image.

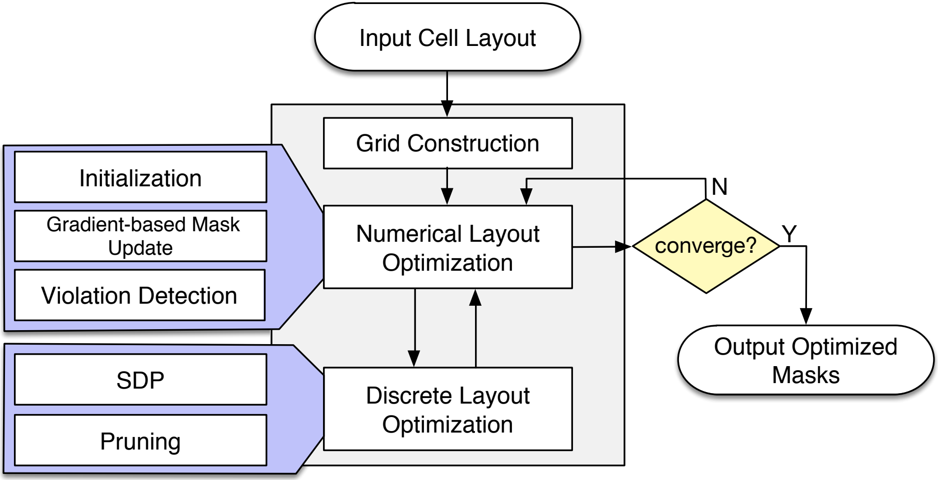
$$\mathbf{Z}(x,y) = f_{resist}(\mathbf{I}) = \begin{cases} 1, & \text{if } \mathbf{I}(x,y) \geq I_{th}, \\ 0, & \text{otherwise.} \end{cases}$$

Problem Formulation

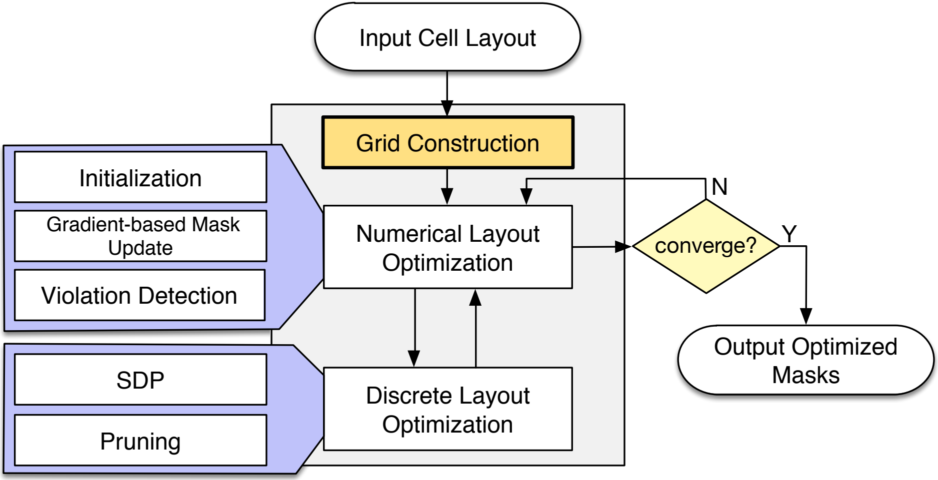
LDMO: Given a target image $\mathbf{Z}_t$, find two masks $\mathbf{M}_1$ and $\mathbf{M}_2$ which can form printed image with high fidelity.

$$
\begin{aligned}
\min_{\mathbf{M}_1,\mathbf{M}_2} \quad & F = \|\mathbf{Z}_t - \mathbf{Z}\|_2^2 \\
\text{s.t.} \quad & \mathbf{M}_1(x,y) \in \{0,1\}, \quad \forall x,y, \\
& \mathbf{M}_2(x,y) \in \{0,1\}, \quad \forall x,y, \\
& \mathbf{I}_1 = \sum_{k=1}^{K} w_k \cdot |\mathbf{M}_1 \otimes \mathbf{h}_k|^2, \\
& \mathbf{I}_2 = \sum_{k=1}^{K} w_k \cdot |\mathbf{M}_2 \otimes \mathbf{h}_k|^2, \\
& \mathbf{Z} = f_{resist}(\mathbf{I}_1) \vee f_{resist}(\mathbf{I}_2).
\end{aligned}
$$

Overall Flow

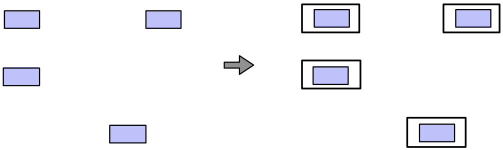


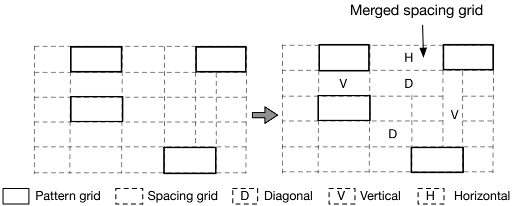
Overall Flow



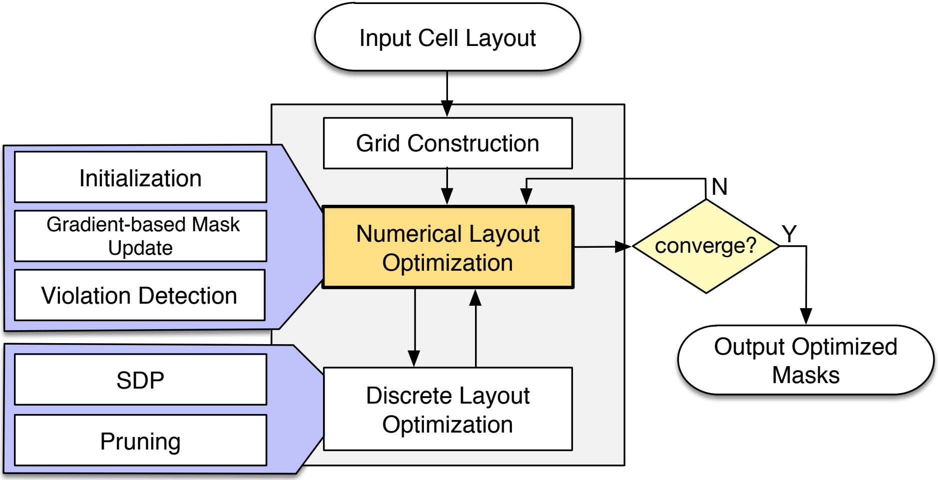
Grid Construction

- Extract target pattern.
- Add bounding box.
- Construct grid.
- Merge grid.





Overall Flow



Formulation Relaxation

- Relaxation on binary constraints with *sigmoid* function.

$$\mathbf{M}_1(x,y) \in \{0,1\} \rightarrow \mathbf{M}_1(x,y) = \mathrm{sig}(\mathbf{P}_1(x,y)) = \frac{1}{1+\exp[-\theta_M \mathbf{P}_1(x,y)]}$$

$$\mathbf{Z}_1(x,y) = f_{resist}(\mathbf{I}_1) \rightarrow \mathbf{Z}_1(x,y) = \mathrm{sig}(\mathbf{I}_1(x,y)) = \frac{1}{1+\exp[-\theta_Z(\mathbf{I}_1(x,y) - I_{th})]}$$

- Relaxation on $\mathbf{Z}$.

$$\mathbf{Z} = f_{resist}(\mathbf{I}_1) \vee f_{resist}(\mathbf{I}_2) \rightarrow \mathbf{Z}(x,y) = \min\{\mathbf{Z}_1(x,y) + \mathbf{Z}_2(x,y), 1\}$$

Gradient-Based Optimization

Algorithm 1 Gradient-Based Mask Update

```
function MaskUpdate(P1, P2)
    Initialize stepsize t;
    Compute the relaxed masks M1, M2;
    Compute Z according to current P1 and P2;
    Compute the gradient ∇P1 F, ∇P2 F
    P1 ← P1 − t × ∇P1 F;
    P2 ← P2 − t × ∇P2 F;
    return P1,P2, ∇P1 F, ∇P2 F;
end function
```

function MaskUpdate($\mathbf{P}_1$, $\mathbf{P}_2$)

  Initialize stepsize t;

  Compute the relaxed masks $\mathbf{M}_1, \mathbf{M}_2$;

  Compute $\mathbf{Z}$ according to current $\mathbf{P}_1$ and $\mathbf{P}_2$;

  Compute the gradient $\nabla_{\mathbf{P}_1} F$, $\nabla_{\mathbf{P}_2} F$

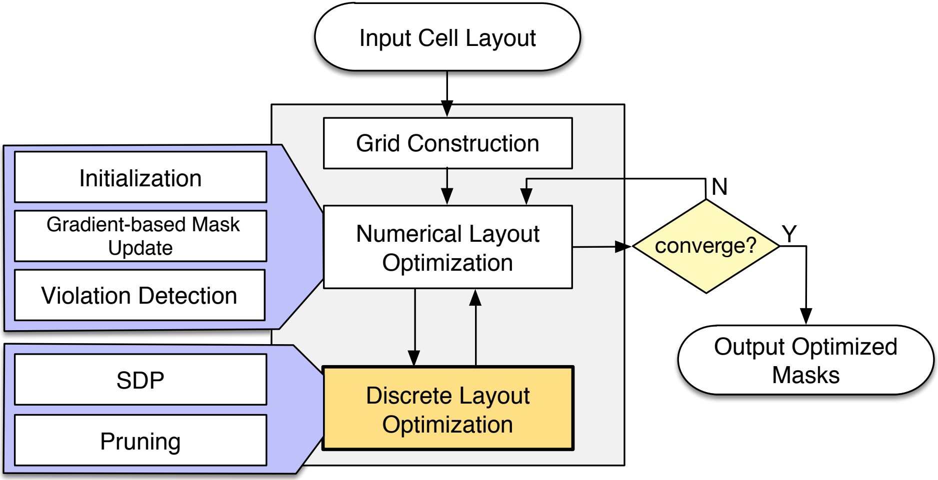
  $\mathbf{P}_1 \leftarrow \mathbf{P}_1 - t \times \nabla_{\mathbf{P}_1} F$;

  $\mathbf{P}_2 \leftarrow \mathbf{P}_2 - t \times \nabla_{\mathbf{P}_2} F$;

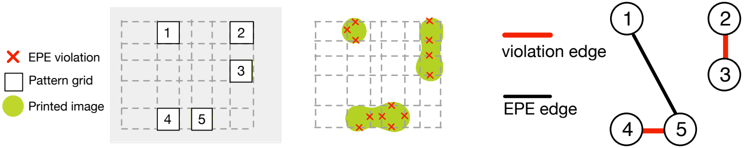
  return $\mathbf{P}_1$,$\mathbf{P}_2$, $\nabla_{\mathbf{P}_1} F$, $\nabla_{\mathbf{P}_2} F$;

end function

Overall Flow



Violation Graph



(a) (b) (c)

$$w_{ij} = \begin{cases} 1, & \text{if } v_i \text{ and } v_j \text{ have conflict,} \\ \beta, & \text{if } v_i \text{ and } v_j \text{ have large \#EPEV,} \\ 0, & \text{otherwise.} \end{cases}$$

$$\mathbf{W} = \begin{bmatrix} 0 & 0 & 0 & 0 & \beta \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ \beta & 0 & 0 & 1 & 0 \end{bmatrix}$$

Semidefinite Programming

- Use $\mathbf{x} = [x_1, x_2, \cdots, x_n]^\top$ to denote the grid assignment solution.
- Max-Cut:

$$\begin{aligned} \max_{x_i} \quad & \sum_{(i,j)\in E} w_{ij}(1 - x_i x_j) \\ \text{s.t.} \quad & x_i \in \{-1, 1\}, \quad \forall v_i \in V \end{aligned}$$

Relax to Semidefinite Programming:

$$\begin{aligned} \min_{\mathbf{X}} \quad & \mathbf{W} \bullet \mathbf{X} \\ \text{s.t.} \quad & \text{diag}(\mathbf{X}) = \mathbf{e}, \\ & \mathbf{X} \succeq \mathbf{0} \end{aligned}$$

Semidefinite Programming (cont.)

- Randomized rounding [Goemans+,JACM'1995]
  - Obtain $\mathbf{X}^*$ by solving SDP.
  - Cholesky decomposition with $\mathbf{X}^*$.

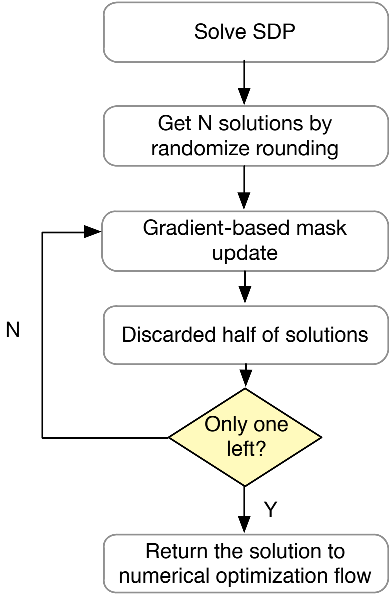
$$\mathbf{X}^* = \mathbf{U}^\intercal \mathbf{U}$$

  - Get x_i as follows. $\mathbf{u}_i$ is the i-th column of $\mathbf{U}$ and $\mathbf{r}$ is random unit vector.

$$x_i = \operatorname{sgn}(\mathbf{u}_i^\intercal \mathbf{r}) = \begin{cases} 1, & \text{if } \mathbf{u}_i^\intercal \mathbf{r} \geq 0, \\ -1, & \text{otherwise.} \end{cases}$$

Pruning

- Obtain multiple solutions by randomized rounding.
- Efficient pruning.



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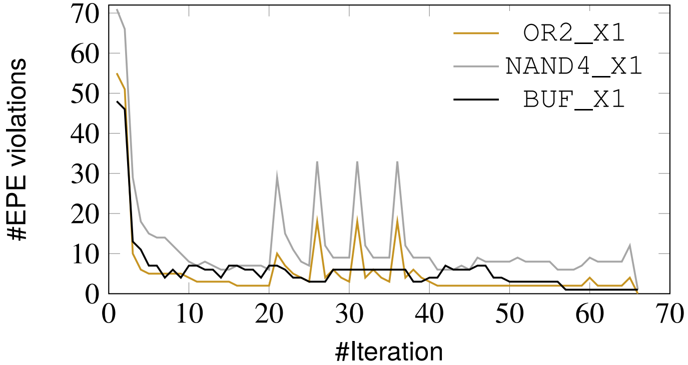
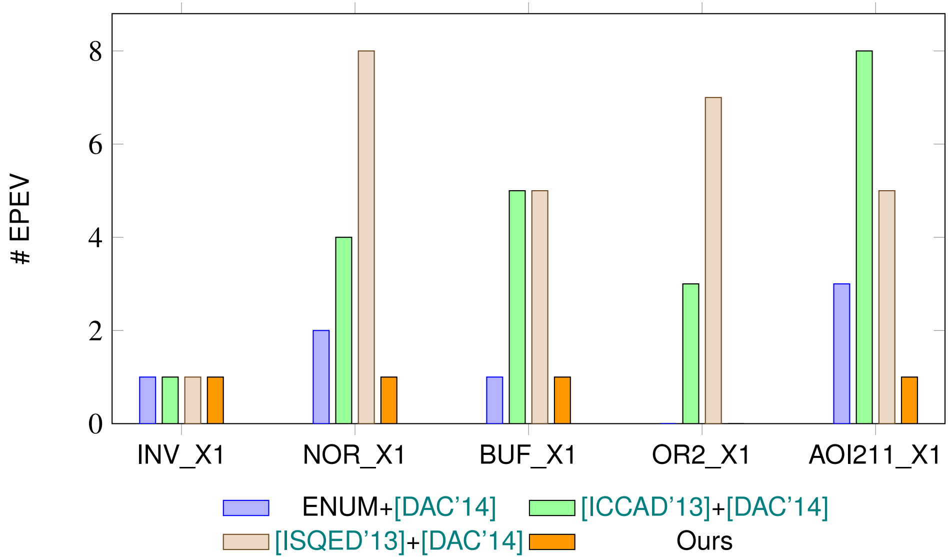
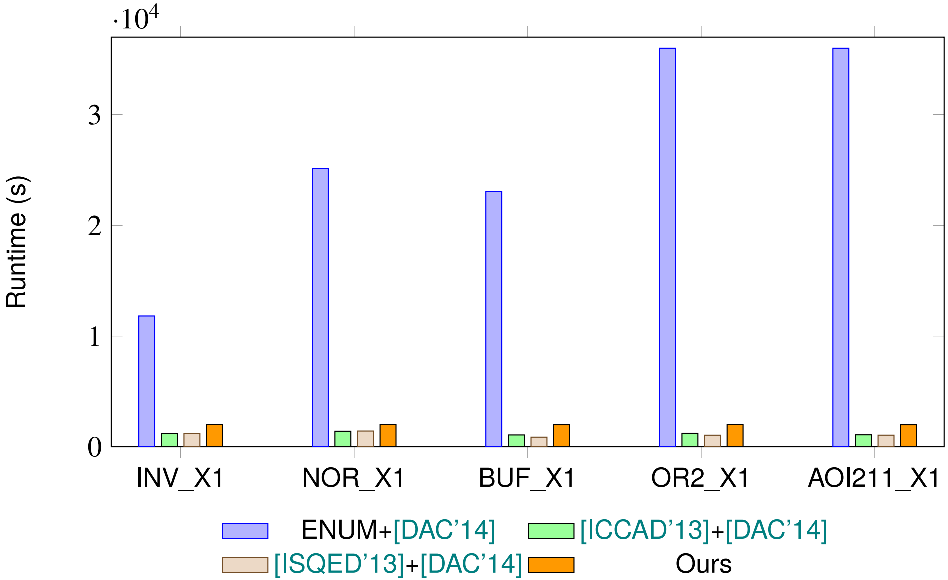
#EPE Violation Convergence Curve



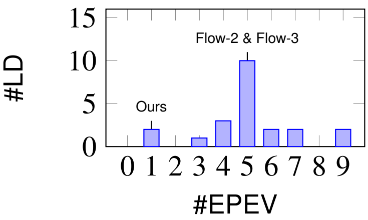
Comparison – EPE Violation Num



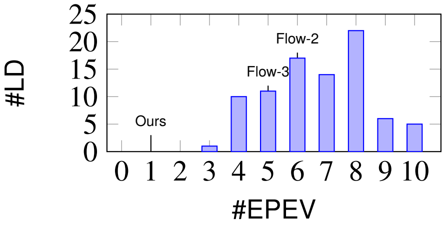
Comparison – Runtime



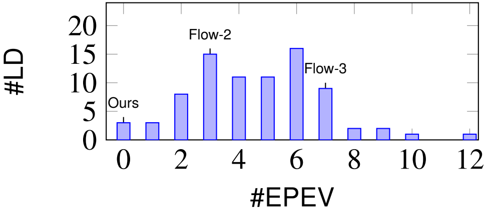
Distribution of #EPE violations



(a) BUF_X1



(b) NAND4_X1

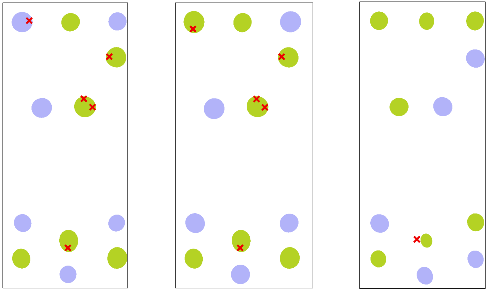


(c) OR2_X1

- Flow-2 [ICCAD'13] + [DAC'14];
- Flow-3 [ISQED'13] + [DAC'14];

Examples of Printed Image

(a) [ICCAD'13] + [DAC'14];
(b) [ISQED'13] + [DAC'14];
(c) Ours.



(a) (b) (c)

BUF_X1

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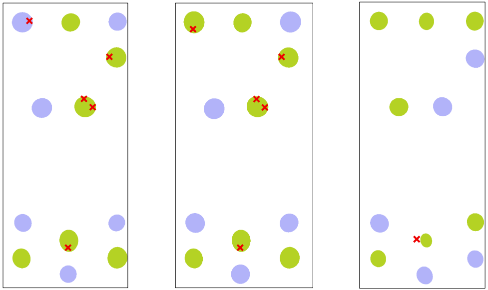
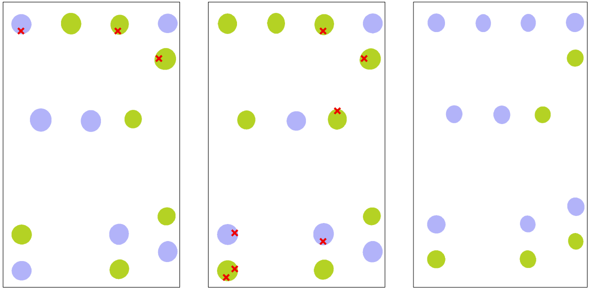
Examples of Printed Image

(a) [ICCAD'13] + [DAC'14];
(b) [ISQED'13] + [DAC'14];
(c) Ours.



(a) (b) (c)

BUF_X1



(a) (b) (c)

OR2_X1

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Conclusion

- A unified framework is proposed for solving LDMO problem.
- Two collaborative flows are designed:
  - A gradient-based numerical optimization
  - A set of discrete optimization.
- Effectiveness and efficiency are verified.

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- A unified framework is proposed for solving LDMO problem.
- Two collaborative flows are designed:
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  - A set of discrete optimization.
- Effectiveness and efficiency are verified.

Future Exploration

- More advanced lithography process, e.g., triple patterning lithography.
- More optimization targets, such as process variation band.

Thank You

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