THE CHIPS TO SYSTEMS CONFERENCE

SHAPING THE NEXT GENERATION OF ELECTRONICS

JUNE 23-27, 2024

MOSCONE WEST CENTER
SAN FRANCISCO, CA, USA

THE CHIPS TO SYSTEMS CONFERENCE
SHAPING THE NEXT GENERATION OF ELECTRONICS

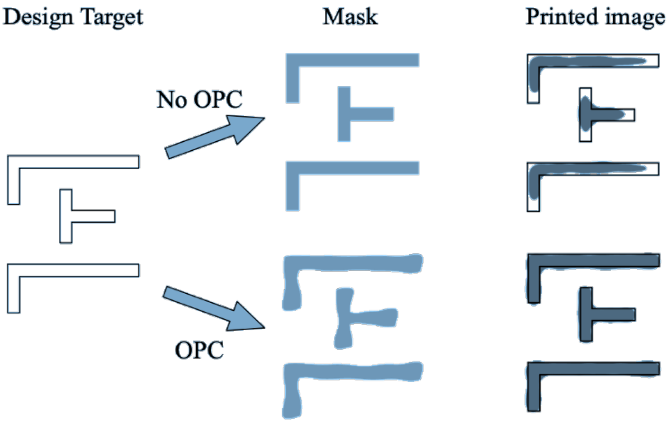
JUNE 23-27, 2024
MOSCONE WEST CENTER
SAN FRANCISCO, CA, USA

CAMO: Correlation-Aware Mask Optimization with Modulated Reinforcement Learning

Xiaoxiao Liang[1], Haoyu Yang[2], Kang Liu[3], Bei Yu[4], Yuzhe Ma[1]

[1]Hong Kong University of Science and Technology (GZ)
[2]NVIDIA [3]Huazhong University of Science and Technology
[4]Chinese University of Hong Kong

Background: Mask Optimization



The effect of mask optimization.

Background: Deep Learning-based OPC

- Supervised learning based method
  - Generative method[1]: image generation task
  - Regressive method[2]: learns from segment offset from other OPC engines
  - * Potential performance limitation due to dependency on pre-collected dataset
- Reinforcement learning based method[3]

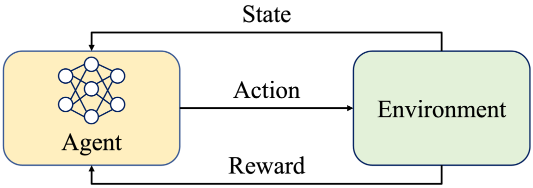
[1] Haoyu Yang, Shuhe Li, et al. (2018). "GAN-OPC: Mask Optimization with Lithography-guided Generative Adversarial Nets". In: *Proc. DAC*, 131:1–131:6.

[2] Tetsuaki Matsunawa, Bei Yu, and David Z. Pan (2015). "Optical proximity correction with hierarchical Bayes model". In: *Proc. SPIE*. vol. 9426.

[3] Xiaoxiao Liang et al. (2023). "RL-OPC: Mask Optimization With Deep Reinforcement Learning". In: *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*.

Reinforcement Learning

Reinforcement Learning investigates how intelligent agents makes sequential decisions and interacts with RL environment to fetch the scores of the latest decision.
Objective: maximize accumulative reward

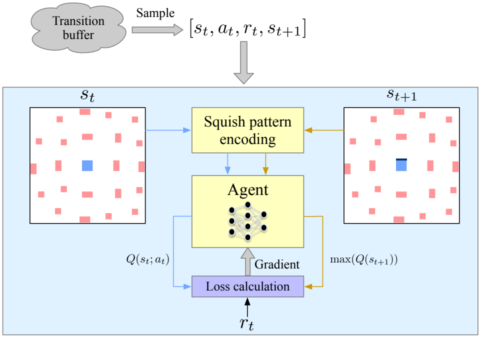


RL overview[4].

[4] Xiaoxiao Liang et al. (2023). "RL-OPC: Mask Optimization With Deep Reinforcement Learning". In: *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*.

Background: Deep Learning-based OPC

- RL-OPC[5]: encodes the local feature as input, decides segment movements, learns the mapping from mask updating to mask quality improvement.

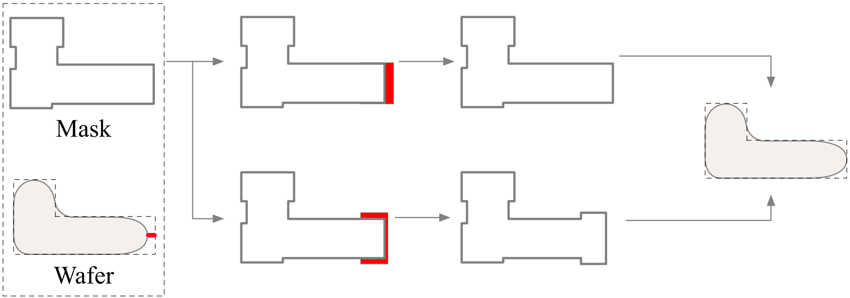


RL-OPC flow.

[5] Xiaoxiao Liang et al. (2023). "RL-OPC: Mask Optimization With Deep Reinforcement Learning". In: *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*.

Insights

- Observations:
  - Distinct masks may yield similar contours:

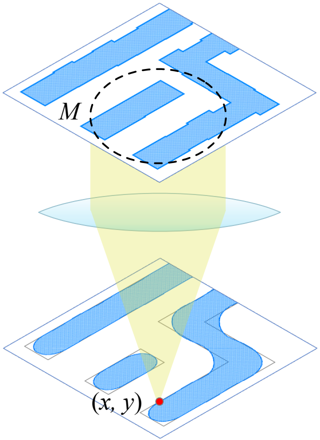


Insights

- Light proximity effect: in the lithography process, the local light intensity is determined by mask patterns within a larger **neighborhood**.

$$Z(x, y) = f_{optical}(M)$$

  - Consistent with the fact that the forward lithography process can be approximated by convolutional operations.



Gap

- Regression-based OPC and RL-OPC decide segment movement solely by analyzing its local features - frequent mask evaluation
- Enlarged solution space: effects of the neighboring segments' movements are neglected.

Gap

- Regression-based OPC and RL-OPC decide segment movement solely by analyzing its local features - frequent mask evaluation
- Enlarged solution space: effects of the neighboring segments' movements are neglected.
- Motivation:
  - Based on observations, consider the neighboring segments as spatially **correlated**.
  - When processing multiple segments, regard them as **coordinated** in fixing the contour displacement.

Method: RL Preparation

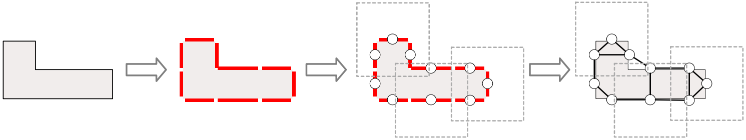
- State: layout geometrical information, encoded by squish pattern[6];
- Action: inward / outward movement for individual segment;
- Reward: the mask quality improvement after mask updating in each iteration:

$$r_t = \frac{|EPE_t| - |EPE_{t+1}|}{|EPE_t| + \varepsilon} + \beta \frac{PVB_t - PVB_{t+1}}{PVB_t}. \quad (1)$$

[6] Haoyu Yang, Piyush Pathak, et al. (2019). "Detecting multi-layer layout hotspots with adaptive squish patterns". In: *Proc. ASPDAC*, pp. 299–304.

Method: RL Decision Network

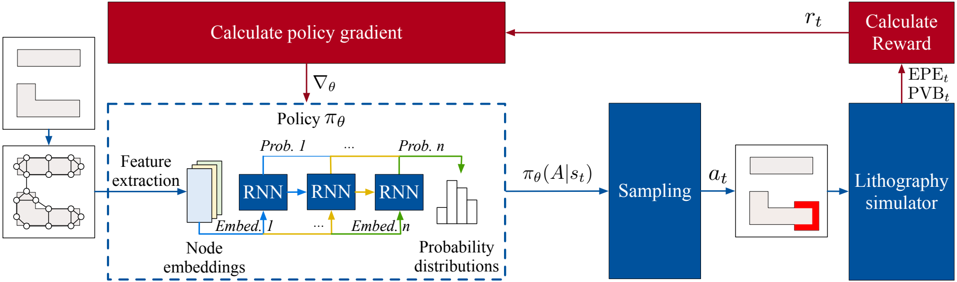
- Graph Neural Network (GNN): after segmentation, formulate the layout into a graph, fuse the node features along the graph edges.
  - Vertices: each individual segment;
  - Graph edges: determined by segments distance;
  - Node features: encoded neighborhood of each segment.



- Recurrent Neural Network (RNN): sequentially processes the input embeddings and recurrently records the historical contexts for deciding future incoming segments.

Method: Correlation-aware Decision Framework

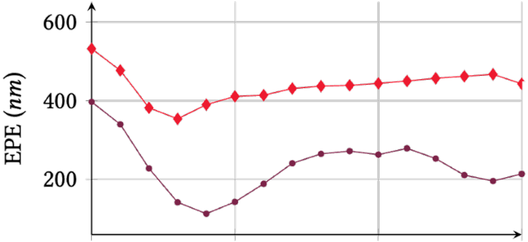
- Two attempts for capturing the spatial correlation:
  - Graph encoding & feature fusing: graph edges determined by proximity
  - Sequential decision using RNN, coordinately considers segments movements on the fly



The correlation-aware mask updating framework.

Method: OPC-inspired RL Modulator

- Observations:
  - Solution space explosively grows with complex layout
  - A purely data-driven learning scheme may not be efficient enough
  - Fluctuated mask quality



The EPE curve fluctuates on complex layout.

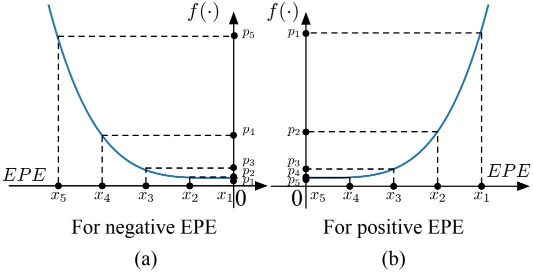
- Solution: integration of OPC domain knowledge for RL guidance.

Method: OPC-inspired RL Modulator

- OPC principle: reduce the gap between light intensity and the threshold at target pattern edges.
  - Example: Large inner EPE $\rightarrow$ Intensity lacking $\rightarrow$ more light needed $\rightarrow$ may prefer outward movement; vice versa.

Method: OPC-inspired RL Modulator

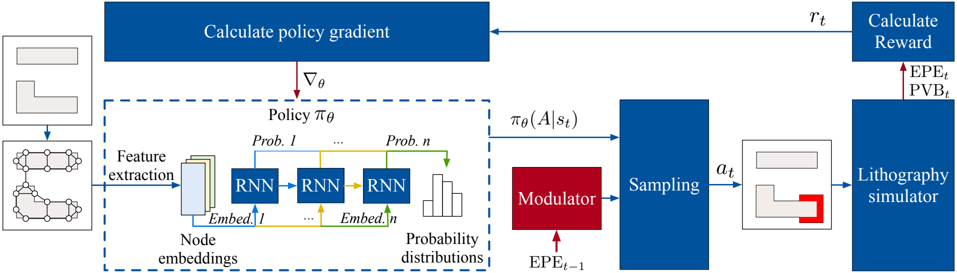
- Design a modulator to modulate the likelihood of each movement being selected when deciding single segment.
- Based on the current EPE at each segment, generates a vector using a projector, formulate its *preference* towards each movement:



The projection function to derive the modulator for each segment by their EPE.

Methodology: CAMO Framework

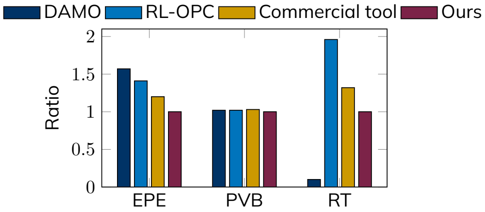
- Modulator: generates preference vector, element-wise multiplies with policy's prediction



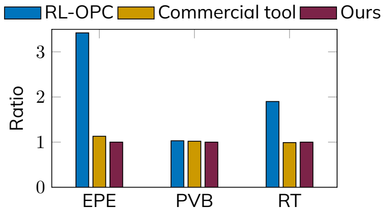
The CAMO framework

Results: Numerical Comparisons

- Experimental settings:
  - Dataset: via & metal layer cases
    - Via: $2\mu m \times 2\mu m$ clips, # vias 2 to 6
    - Metal: $1.5\mu m \times 1.5\mu m$ clips, by OpenROAD, standard cells from NanGate 45nm PDK
  - EPE measurement: 60nm evenly

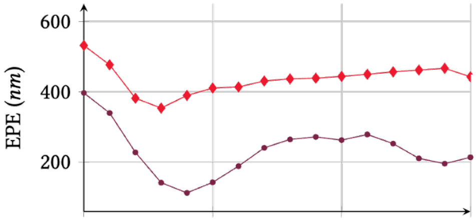


Mask quality comparison on the via layer.

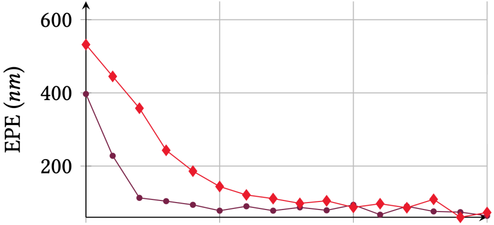


Mask quality comparison on the metal layer.

Results: Modulator Effectiveness



(a)



(b)

The EPE trajectories of two testcases, (a) without modulator, and (b) with modulator.

THE CHIPS TO SYSTEMS CONFERENCE

SHAPING THE NEXT GENERATION OF ELECTRONICS

JUNE 23-27, 2024

MOSCONE WEST CENTER
SAN FRANCISCO, CA, USA

Thanks!